

Perfecting Visibility with Retailer Data

By

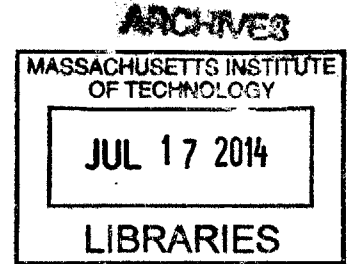
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Master of Engineering in Logistics

at the

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June 2014

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Abstract

This thesis investigates the utility of using retailer point of sales (POS) data in the production planning process of a consumer-packaged goods (CPG) manufacturing company. The quantitative measurements of utility include the improvement of production forecasting, reduction of inventory costs, and reduction of equipment changeover costs. Qualitatively, we evaluate the effectiveness of using POS to drive a more collaborative relationship between the retailer and the manufacturer. The POS data include items sold, store inventory, and warehouse inventory of a retail partner for specific stock keeping units (SKUs) produced by the manufacturer. We develop production-planning models by combining POS data with customer orders, current production plans, and existing inventory positions to optimize manufacturing and inventory costs. The results illustrate that if the aggregate volume of customer orders approximately equaled to that of the POS, then the integration of POS data into manufacturing planning offers opportunities to reduce production and inventory costs. The analysis also points to situations where POS data and customer orders vary significantly; in these situations the proposed production-planning model does not apply, but the POS data provide useful evidence for aligning plans between the manufacturer and the retailer.

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1 Introduction

This thesis addresses a key opportunity in today's supply chain of CPG companies: how to effectively use large volume of demand data to improve overall supply chain performance. In particular this study focuses on the use of Point of Sales (POS) data to adjust production-planning schedule of a CPG manufacturing company, which we are going to label from now on as our sponsor company. We started this project by first interviewing the key stakeholders in our sponsor company's key divisions such as manufacturing, transportation, inventory management, IT, demand planning, finance and sales. Once we understood their needs and expectations we collected POS data on specific SKUs from one of the manufacturer's largest retailer customer. The intent was to find meaningful relationship between downstream demand data and retailer orders. Using the two datasets we created a production plan and scheduling model that would emulate and improve on the current planning process of our sponsor company; the objective, in fact, was to identify and quantify the added value of integrating POS data in the supply planning process.

1.1 Sponsor Company Background: Current Planning Process

The sponsor company is a Fortune 500 CPG corporation primarily focused on food products. The company markets many different brands in the United States and it manufactures on shore. The main distribution channel is large retailers, and the sponsor company ships to the retailer's warehouses via its regional distribution centers. The sponsor company is presently collecting POS data but it has not integrated them yet into the Sales and Operation Planning (S&OP) process.

The unconstrained demand in the demand planning process is generated by a statistical forecast based on historical Customer Orders. Then the forecast is reviewed by different stakeholders to produce a final demand consensus. This in turn is fed into an optimization software to generate a

weekly production schedule by SKU; the optimization algorithm takes into account all the constraints on the supply side with the intent of meeting the consensus demand at minimum cost and at an established item fill rate target. The software is in fact calculating the target Days of Supply (DOS) for any given planning period. This target is resulting from the defined inventory policy whereby the inventory level for any given planning period should not be less than a desired amount. The review of the overall demand and supply planning process is performed monthly while the production planning is reviewed weekly. For the majority of the products the production planning schedule has a freeze period of two to three weeks. This implies that the master production schedule could only be adjusted, if needed, beyond this planning period.

1.2 Problem Statement and Scope of Project

The fundamental question of our sponsor company is the following:

“How can manufacturers use retailer POS data to drive upstream decisions?”

The sponsor company has at its disposal a vast amount of retailer POS data as it collects demand signals from retailers on a daily basis. The key question was how to extract value from those demand signals by directly affecting the manufacturing production schedule and cycles. The scope was intentionally narrowed by the sponsor company to a particular production platform to test the usability and added value of POS data. The initial list of more than 40 SKUs was narrowed down to a key list of four SKUs to be the most representative of the production platform selected for this research. Despite the nature of POS data, the main focus of the sponsor company was not to produce a new forecasting technique or to change the current demand planning process. On the other hand, the emphasis was to produce a methodology and a framework to justify and prove the validity of the use of POS data for adjusting the upstream manufacturing planning process. To

illustrate the value of POS data, we focused on the impact of our model on two key relevant manufacturing costs: change over costs and inventory holding costs. We therefore focused on how POS data integration in the supply planning process could produce direct benefits for those costs while maintaining the item fill rate target.

1.3 Hypothesis: Expecting and Managing the Bullwhip Effect

Our expectation is that by analyzing POS data the sponsor company can better understand the reasons behind the behavior of the retailer orders and eventually have a better visibility on the very downstream segment of the supply chain. Our main hypothesis is that as the Customer Orders are driven by the inventory policy of the retailer, our sponsor company should face a bullwhip effect when it comes to generating a forecast and generating a production planning schedule against the Customer Orders. Consequently, we are expecting to see a POS data historical pattern exhibiting a degree of volatility lower than the historical demand pattern of retailer orders to the manufacturer. We therefore tested this hypothesis to see if we could encounter a bullwhip effect, quantify it and take advantage of it by better planning for the production schedule. The existence of the bullwhip in fact could lead to two different usages of POS data:

- i. A better prediction of Customer Orders, thus planning for the bullwhip
- ii. A better prediction of future POS therefore reducing the bullwhip

We focused primarily on the first point in line with the key requirements and expectations of our sponsored company while also providing further insights on the advantages of choosing the second approach.

1.4 Project Goal and Approach in Building the Model

The main goal of the project was therefore to share with our sponsor company a model that could be used to provide a framework and a methodology in leveraging POS data and capturing their value in the production planning process. We first built a conversion rate by observing and measuring the POS data relationship with the Customer Orders. This rate would convert a set of observed POS data into a projected set of Customer Orders by injecting the noise of the bullwhip effect into the downstream sales signals. This conversion allowed us to integrate the POS data in a production planning model that was built to recreate the current scheduling environment of the sponsor company. We designed an optimization problem, which in the literature is referred as a multi-period production planning linear program. Through the model, we solved for the optimal production scheduling of the SKUs by minimizing holding and change over costs while keeping a target item fill rate. We then compared the results of the optimization with two other versions of the model where we simulated two different environments: a modelling of the as is process of our sponsor company and a modelling of an optimal integrated supply chain. The final results showed the potential gains of integrating POS data in the production planning process and helped define a framework for the sponsor company on how to spot opportunities in leveraging POS data depending on the characteristic of the individual SKU.

2 Literature Review

2.1 Introduction

The use of Point of Sale (POS) data to perfect forecasting has always generated a great amount of hype. The latest reincarnation of this hype is being associated with “BIG DATA”. In order for POS data to be used to create real value, one must prove the benefits outweigh the costs and convince internal business units and external trade partners to support the gathering and use of it. The recent developments in technology have allowed POS data to be collected, transferred, stored and analyzed to improve forecasts. Essential questions to ask are how the POS data be used, how they should be analyzed, and how it is useful integrating them in the supply chain planning process.

The purpose of this thesis is to develop the scope of what POS data can be used for and also develop a model based on the POS data to improve the processes described in the scope. We analyzed the existing research based on the effectiveness of results and based on our academic knowledge and professional experience.

2.2 Past: Lack of POS Data and Poor Collection Efforts

The ability for manufacturers to start collecting POS data is a recent innovation in the supply chain planning process. As Kiely (Kiely, Winter 1998-1999) correctly points out, the lack of POS data in the past forced companies to produce a forecast and demand planning based merely on shipment data out of the factory on a monthly basis. This type of information available at the most upstream

echelon of the supply chain is far from the truth in predicting the actual product consumption of the end costumers.

According to Trepte (Trepte, Winter 2008-2009) forecast accuracy has historically remained flat as many suppliers have not been focusing in what he refers as a “consumer-centric approach”. Despite gaining visibility of POS data from the retailers, many suppliers did not have the capacity at their system level to absorb such volume of new data and therefore they were not able in the past to leverage them. In addition they were not comfortable using them as they were getting just a fraction of the total volume of sales. According to the author it could be a weakness to use POS data just as a set of extra data points without fully integrating them into the planning process.

Andres (Andres, Winter 2008-2009) also highlights the difficulty in the past of collecting POS data, which was primarily due to the lack of today’s technology in effectively collecting such data, as well as the high number of retailers that populated the market few decades ago.

2.2 Present: Methods of POS Collection and Different Contents

Although the notion of whether to use POS data to improve supply chain operations is generally supported, the actual implementation of integrating POS data into the supply chain is still in its infancy. Companies are still defining the benefits of POS while at the same time appropriating the cost, time, and effort of collecting, analyzing, and using the data. Larry Lapide (Lapide L. , Spring 2011) explains that POS implementation requires a companywide IT system integration and also the buy-in from each department to participate and use the data. Jeff Brown, Senior Demand Planner of Brown Shoe makes an even more extreme claim that successful POS

implementation requires the collaboration of not only internal business units but also that of the entire supply chain from end customers to suppliers (Brown, Winter 2008-2009).

The advance of technology and the consolidation of retailers in few big players has significantly reduced the cost of collecting POS data today, according to Andres (Andres, Winter 2008-2009). Not only is POS data now shared more easily and effectively between the retailer and the manufacturer, but the proliferation of third parties, such as Nielsen, have contributed to a vast collection of data which is then sold across the different stakeholders of the supply chains. POS data are usually collected at the SKU level where each product has a unique universal product code (UPC). A typical query from a POS database would be able to generate information such as price, inventory level in store, inventory level at distribution center and the number of units sold. In some cases it is possible to identify with flags those items on promotion.

According to S. Aiyer (Gentry, January 2004) POS data do not necessarily have to be collected on a real time basis as it is sufficient for a manufacturer to receive such data from retailers on a daily or weekly basis depending on the way retailers collect and distribute their information.

Shapiro (Shapiro, Winter 2008-2009) provides a general overview of the different types of POS data currently available. In some cases POS data come from proprietary software available at the retailer level. This type of data that is usually used by the retailer to generate the forecast. POS data can also be generated through the transmission of EDI documents. Shapiro points out the difficulties in managing such data as the lack of normalization can further complicate how manufacturers can collect and interpret the data for their purposes. There can also be issues in the transmission of the data itself and the lack of standardization across the different retailers. Finally, in some cases, POS data are transmitted via Excel spreadsheet. In this latter case the accuracy and the usability of the data is more compromised than the ones generated through EDI transmission.

Kiely accurately describes the different sets of data available in the supply chain and how the POS data is indeed one of the most appropriate indicators of the final customer product consumption (Kiely, Winter 1998-1999). Total demand for a product can in fact be captured by the different material and document flows throughout the supply chain, starting from the shipment data out of the factory, then moving into the order requests from the manufacturer's DC and retailer's DC, then into the customer's warehouse movements from their DC to the final stores, and finally reaching the last piece of information demand, the POS data, which represent the better indication of the end consumer purchasing choice.

2.3 Future: Usage and Benefits for a Perfect Visibility in the Supply Chain

Brent Williams of Auburn University and Matthew Waller of the University of Arkansas set out to examine quantitative differences in forecast accuracy between using POS and order history (Williams & Waller, Creating Order ForecastL Point of Sale or Order History?, 2010). The study, conducted on grocery stores, revealed results that were both expected and counter to conventional thought. It concluded that POS data can generate forecasts that were more accurate more frequently, although order history was producing a more accurate forecast, the magnitude of the benefits was much higher. This result signifies that human input (order history) still generates a tremendous value but the amount of skilled human resources cannot be compared to the ever-available POS data. The resulting action is to use human input to generate forecasts that have a major impact on the business.

The most useful conclusion of this study is that POS data and Order History should be used in combination and used to complement each other. To do so, companies can generate more accurate

forecasts more frequently and increase the magnitude of the benefits. Companies can also reduce bullwhip by using the two datasets to offset each other.

A “perfect synchronization” is what Gruman (Gruman, 2005) defines as the ultimate result in supply chain when POS data is incorporated into the demand planning process. The perfect synchronization could allow a company to better harmonize its marketing, sales, manufacturing and distribution efforts. According to the author, POS data is a powerful tool in accounting for seasonality, promotional events and measuring any significant deviations from the foreseen regular pattern.

Andres (Andres, Winter 2008-2009) shares a clear and simple idea about the reasons behind the added value of POS data in the supply chain: POS data by their nature do provide the most independent piece of demand information. POS data, in fact, are not affected by any inventory decisions across the chain as they are driven only by the final consumer’s willingness to buy. On the other hand, any other piece of demand information across the supply chain would hide replenishment and inventory policies that might mask the real sale patterns. According to the author, using POS data to generate forecast models is the main driver for a better visibility in the supply chain. As a complement to the design of a forecast model of multilinear regression, a store replenishment model has to be developed to fully capture the added value of POS data. The author is suggesting to calculate a safety stock level during a week period to be added to the sum of a daily forecast which will then in turn generate the optimal order quantity. The impact will be an optimization of the transportation planning, inventory management and an overall reduction of stock outs.

According to S. Aiyer (Gentry, January 2004) the future of supply chain planning is to move from a collaborative planning, forecasting and replenishment (CPFR) environment to a “consumer-

driven replenishment (CDR)” approach whereby the new information available with POS data can be leveraged to increase the level of visibility of the final consumer. While for items where the demand is sporadic or slow moving the application of a CDR has its limitations, for commodity products with seasonality features, POS data can be truly powerful to predict the demand pattern. One of the benefits of the CDR approach as defined by Aiyer is the increase in inventory turnovers and an increase of the level of forecast accuracy. POS data is therefore critical in enhancing the collaboration between manufacturer and retailer.

In emphasizing the role of POS data to produce a more consumer-centric planning approach, Trepte (Trepte, Winter 2008-2009) proposes three distinct solutions. The first focuses on using POS data to produce a comparative dashboard with shipment data. For example POS data can be used to quickly identify any significant deviation with the trend and growth in shipment data. This approach can help spot any issues that would need rapid attention from the management. The second solution provides a way to use POS data in calculating the inventory level of the retailer and predicting the next orders. POS data is indeed used to generate a forecast which are combined with the shipment forecast and produce a replenishment model to optimize the inventory level and better predict the customer’s orders. Finally POS data can be used to enhance the collaboration between manufacturers and retailers by designing risk-sharing types of contracts (pay back solution for example).

Gallucci and Mccarthy (Gallucci & McCarthy, Winter 2008-2009) praise the POS data as the most valuable piece of information that would dramatically reduce the bullwhip effect. POS data change less significantly over time compared to the order history. By having order forecasts as close as possible to the POS data pattern, the overall demand planning can reduce the noise in the regression model and improve its stability and accuracy. One of the most important benefits according to the

author is the level of insights that POS data can especially provide in predicting customer behavior during promotional or seasonal activities. The impact is therefore truly beneficial not only for the entire supply chain but also for the marketing and sales department when planning their commercial initiatives. The authors, in line with other scholars, describe POS data usage as favorable for comparison and analytical purposes but also instrumental in transforming and integrating the forecast methods. The authors see a great potential in modelling POS data forecasts and integrating those in the overall demand planning process. A new consensus would be generated as a validation process between POS-based forecasts and order history based forecasts. This approach would be extremely successful as it would consider the two types of forecasts independently thus allowing the manufacturer to craft different planning scenarios.

Similarly, Shapiro (Shapiro, Winter 2008-2009) stresses the importance of using POS data to complement and refine the forecasting process of a manufacturer especially when it comes to identifying seasonality indices. Like many other scholars he is also supporting the usage of POS forecast to assess the inventory level of the retailers and thus predict their order patterns.

Like other authors, Kiely (Kiely, Winter 1998-1999) also emphasizes the virtues of POS data as the most independent, granular and stable source of demand. According to the author, a consumer-driven planning system has to take into account the POS data and blend them with their current demand planning system.

2.4 Conclusion

There is no doubt that POS data represent a powerful tool in the hands of supply chain planners. The collection of such data has been considerably improved over the last decades and its volume has become a significant portion of the overall available information for a manufacturer to make

intelligent decisions about its supply chain planning. It is now time to leverage this increased visibility in the supply chain which provides more insights into the final customer's frequency and willingness to buy a given product. Our thesis explores the different POS data available in our sponsor company and provides a unique methodology on how integrating the data in the current production planning process with the final objective of reducing costs while keeping a target service level. The model we proposed takes inspiration from the lessons learned in the literature to design a new integrated customer driven supply demand process.

3 Methodology

This section explores how we interpreted and used the data to design and apply both a quantitative and qualitative analysis. The core objective was to find meaningful relationships between POS data and customer ordering behavior to optimally adjust production planning and scheduling.

3.1 Data Collection

Two types of data were collected: Retailer data and Manufacturing data. Retailer data is provided by the retailer on a daily basis to our sponsor company under EDI format. This type of data provides all relevant sale and inventory information for each store and SKU. Manufacturing data is generated by our sponsor company and maintained on a daily or weekly basis depending on the type of data. This dataset provides all information regarding inventory positioning, customer orders and production scheduling for each SKU.

3.1.1 Retailer Data: Point of Sales (POS)

The Retailer data we decided to focus on came from a large customer of our sponsored company. In agreement with our sponsor, we focused on four key SKUs, which we label SKU1, SKU2, SKU3 and SKU4 and which are produced in one specific manufacturing platform. In agreement with our sponsor company, we chose those SKUs as the most representative sample of all products produced in the same platform. In fact, those items represent the largest share of retailer orders and for this reason were selected as the most suitable for our analysis. We filtered the data to have enough days to cover a significant period of sales. This resulted in collecting daily POS data points from January 1, 2013 through June 29, 2013. The POS data included:

- *Store ID*: A unique identifier for the retail store where POS originated.
- *Store Location*: The geographical location of the retail store
- *Universal Product Code (UPC)*: A unique identifier for the SKU according to the retailer product coding
- *Day of POS*: Date of POS transactions
- *POS Units*: The number of units sold for a given SKU in a given day
- *On-hand Store Inventory*: The daily inventory position of each SKU in each store
- *On-hand Warehouse Inventory*: The daily inventory position of each SKU in each retailer warehouse

3.1.2 Manufacturer Data: Production Planning, Inventory and Customer Orders

We were able to collect a dataset that covered the same period as the retailer data, from January 1, 2013 until June 29, 2013. Manufacturing data included:

- *Production Quantity*: The quantity produced per SKU per week per plant and measured in cases (equivalent to 12 units)
- *Inventory Quantity*: The total inventory on hand in our sponsor company's Distribution Centers (DCs) per SKU and per month
- *Customer Orders*: The orders placed by the retailer to our sponsored company on a weekly basis disaggregated by SKU

3.2 Data Visualization: Patterns Identification and Distribution Fitting

We merged the two datasets in order to visualize all key parameters

- Customer Orders (manufacturer data)
- Production Planning (manufacturer data)
- POS Sales (retailer data)
- Store Inventory (retailer data)
- Warehouse Inventory (retailer data)

We visualized the variables to identify any potential correlations between POS sales and Customer Orders, and between POS sale and inventory position of the retailer. The assumption behind our observations was that the retailer had a significantly stable periodic inventory policy that could be used to better predict the future Customer Orders when looking at the combination of the POS sales and their inventory level. We tested several approaches to develop an explanatory model that could better project the Customer Orders by determining the reorder point of the retailer and the ratio between the POS sales and its target inventory level. For those SKUs where we could find a stable relationship between POS sales and Customer Order we analyzed their corresponding distribution functions to better understand and predict their behavior. We then executed a normality test for both Customer Orders and POS sales datasets. Our hypothesis was that a normal distribution with a similar trend level could be applicable for both types of demand data; the only difference between the two distributions would therefore be the degree of volatility as we were expecting to see a bullwhip effect. With this hypothesis confirmed, we could then find a way to convert the POS sale into projected Customer Orders and finally solve for the adjusted production planning and scheduling. The projection of Customer Order was a necessary step in the

optimization problem as it allowed us to project the expected beginning and end of inventory for every week, thus determining the expected stock at the end of the production freeze period.

3.3 Production Planning Model: Converting, Projecting and Optimizing

We designed a multi-period production planning linear program to optimize production scheduling for a given set of weeks by minimizing the total relevant costs subject to capacity and inventory target constraints. The total relevant costs to minimize were the following:

- Holding costs: the inventory costs per unit per week calculated against the average inventory of the week (average between beginning and end of inventory)
- Changeover costs: the costs of converting the production line from running one product to another for a given week. In our model we are simplifying the sequence of the multi-product production scheduling, thus assuming a changeover cost anytime we decided to produce a specific SKU (similar to setup costs).

The production constraints were the following:

- Capacity constraints: less than the maximum capacity of the single production line
- Demand constraints: the end of the inventory for each week must be greater than the target days of supply (inventory target)

To simplify the model we assumed that all SKUs were being produced in the same plant so that the linear programming had to assign each SKU production quantity to each week for a unique factory location. To set up the model dynamically and to replicate what actually happened during the same period covered by the datasets, we first prepared a total of 26 periods (26 weeks) from the first week of January to June 29, 2013. For each week we set up the following objects:

- Beginning of inventory: inventory at the end of previous week
- Production planning: the quantity produced by our sponsor company for a given week
- Customer Orders: the orders received from the retailer
- End of inventory: beginning of the inventory plus the production quantity minus the Customer Order

Below is a table illustrating the logic of the production planning framework:

Table 1: Production Planning Framework

		Weeks			
		1	2	...	26
SKU1	<i>Beginning of Inventory</i>	A	D	...	XX
	<i>Production Planning</i>	B	E	...	YY
	<i>Customer Orders</i>	C	F	...	ZZ
	<i>End of Inventory</i>	$A+B-C=D$	$D+E-F=G$...	$XX+YY-ZZ$

We then included a new row for the new production planning that would constitute the decision variables for the linear programming. The new production planning would represent how much to produce for a total of four consecutive weeks as solved by the optimization problem. In agreement with our sponsor company, we established a freeze period of production planning for three consecutive weeks. This implied that if we were in week 5, we could only adjust from week 8 onwards, as the production scheduling for weeks 5, 6 and 7 could not be modified. We then projected the new adjusted planning over a four-week horizon to allow the optimization model to run the linear programming for a minimum significant number of periods. This would imply that if we were in week 5, we could only adjust production planning for weeks 8,9,10 and 11. Table 2 below shows an illustration of the model:

Table 2: Production Planning Rolling Schedule

Weeks		5	6	7	8	9	10	11
SKU1	<i>Beginning of Inventory</i>	347,95 3	298,70 5	268,03 3	241,68 1	207,121	336,34 0	329,97 7
	<i>Production Planning</i>	0	0	0	0	167,235	21,718	0
	<i>New Planning</i>	Freeze	Freeze	Freeze	0	0	46,607	0
	<i>Customer Orders</i>	49,248	30,672	26,352	34,560	38,016	28,080	30,240
	<i>End of Inventory</i>	298,70 5	268,03 3	241,68 1	207,12 1	336,340	329,97 7	299,73 7

The next step was to calculate a new set of expected Customer Orders from week 5 to week 11 (if we keep using the example period above). The new set of expected Customer Orders would trigger a new set of projected beginning and end of inventory which would in turn trigger a new set of production quantities for weeks 8-11 (as solved by the model). To reproduce such a set of expected Customer Orders, we converted the POS sales data into future retailer orders. In our example, where the current week is week 5, we therefore looked at the actual POS sales data for weeks 1 to 4 to develop a conversion formula that would translate the demand signals from the store into valuable information (expected Customer Orders) and anticipate the future behavior of the retailer. The conversion rate would result from the normal distribution test we described above.

Once we calculated the new expected Customer Orders for weeks 5 to 11, we were able to generate the new expected inventory at the end of week 7; thus we would be ready to run our new production scheduling for weeks 8-11.

3.3.1 Defining the Decision Variables

We set decision variables for quantities to be produced in four consecutive weeks and starting 3 weeks ahead of the present week. The linear programming solved simultaneously for all products involved and assigned a given quantity for each SKU in each of the four consecutive weeks. Below are the decision variables:

- X_{ij} : number of units of product i produced in week j
- Y_{ij} : binary variable which is equal to 1 if product i is produced in week j and equal to 0 if product i is not produced in week j

3.3.2 Defining the Objective Function

The objective is to minimize all relevant costs as per below notation:

$$\text{Minimize } \underbrace{\sum_{i=1}^n \sum_{j=1}^m S_{ij} * Y_{ij}}_{\text{Changeover Costs}} + \underbrace{\sum_{i=1}^n \sum_{j=1}^m H_{ij} * B_{ij}}_{\text{Holding Costs}} \quad (1)$$

where S_{ij} is the changeover costs for a product i in week j and H_{ij} is the holding cost for a product i in week j ; B_{ij} represents the average inventory (average between beginning and end of inventory) for product i in week j . The notation for B_{ij} is described in below formula:

$$B_{ij} = B_{ij-1} + X_{ij} - D_{ij} \quad (2)$$

D_{ij} is the expected demand of the retailer for product i in week j as derived by our projection from observing the POS sale of weeks $j-1, j-2, j-3, j-4$.

3.3.3 Defining the Constraints

The capacity constraint is given by below definition

(3)

$$\text{Subject to } \sum_{i=1}^n X_{ij} \leq C_j \quad \text{for } j = 1, 2, \dots, m \text{ and } i = 1, 2, \dots, n;$$

Where C_{ij} is the maximum capacity of production quantity for all products in week j .

The target inventory constraint is given by below definition

(4)

$$\text{Subject to } B_{ij} \geq T_{ij} \quad \text{for } j = 1, 2, \dots, m \text{ and } i = 1, 2, \dots, n;$$

where the target days of supply (T) of inventory is based on the following calculation:

(5)

$$T = (F_{L+R} + RMSE * k * \sqrt{L + R}) / (F_R) * 7$$

Where:

- F_{L+R} is the forecasted demand over period L (leadtime) and period R (review period).
- $RMSE$ is the squared root of the average of the forecast errors. In our model we used a value proportional to the standard deviation of the Customer Orders for each SKU
- k is the safety factor derived from a given service level. This is in turn derived from an Item Fill Rate of 98.5 %, which was kept constant across the model.

The big M method helps define the constraint for the changeover costs such that only when the solution is proposing to produce product i in week j we then charged those costs to product i in week j . Below the corresponding notation:

$$X_{ij} \leq M * Y_{ij} \quad \text{for } j = 1,2, \dots m \text{ and } i = 1,2, \dots n; \quad (6)$$

Finally we completed the linear programming by adding the non-negativity and binary constraint of the decision variables such that:

$$\begin{aligned} X_{ij} &\geq 0; \\ Y_{ij} &\in \{0,1\} \end{aligned} \quad (7)$$

3.4 Testing the Results: Our model vs Two Additional Scenarios

In order to test the results of our model, we designed two additional scenarios. One scenario simulated the current planning and scheduling process of our sponsor company: we can label this model as our baseline. This first test would emulate the same logic as our production planning model, with the exception that POS data would not be considered at all in the scheduling process. The objective of this test, called Orders-to-Orders test, is to isolate the effect of the POS sales into the optimization problem. By comparing our initial results with the Orders-to-Orders results, we could see if our model would produce any value and therefore validating or not the benefits of POS sales when planning for the bullwhip. The second test, labelled as POS-to-POS test, tested the value of POS sales without predicting future Customer Orders. This implied that the manufacturer could observe the POS sales and adjust the production planning without having to

consider any retail Customer Orders. The POS-to-POS scenario would in fact remove the planning layer of the retailer, thus removing the bullwhip produced by the retailer inventory policy. To reproduce such an environment, we used the same original model but we ignored the existence of the Customer Orders, and we planned for the demand of the final consumers. We then compared the results of this test with the results of our model and the Orders-to-Orders test to measure the added value of POS sales when the manufacturer could target a global optimal (that is considering the supply chain as one system). All three scenarios were run on a rolling basis. This implied a dynamic optimization model whereby the results of each week would be carried over to the following week's optimization run.

3.4.1 Test 1: Orders-to-Orders Scenario

In the Orders-to-Orders scenario, we used the same logic and rules described above for the design of the linear programming model. In order to emulate the current planning scenario of our sponsor company, we simply did not apply the POS conversion rate to generate projected Customer Orders. We only applied the moving average of the previous four weeks for any given current period we were going to analyze. We chose not to use the actual forecast values of our sponsor company as we deliberately simplified the forecasting approach to use the same simple method across all models. This would better isolate the effect of the POS integration in the model when compared with our baseline. The projected Customer Order was therefore derived from equation (8) below:

(8)

$$C_t = \text{Average} (C_{t-4}, C_{t-3}, C_{t-2}, C_{t-1},)$$

where C_t would be the projected Customer Order for the period t when the optimization was run. This projected value would be then applied for seven consecutive weeks to allow production

planning of four weeks beyond the freeze period of three weeks. All other parameters of the model were kept the same including the target DOS inventory level.

3.4.2 Test 2: POS-to-POS Scenario

Two changes in the logic of our original model were required to design the POS-to-POS scenario. The first was to modify the conversion rate used to project the future orders. As in this scenario, we removed the retailer orders; the only projection we made were the purchases made by the final consumers in the retail stores. Therefore the formula for the projected orders is as follows:

$$POS_t = Average (POS_{t-4}, POS_{t-3}, POS_{t-2}, POS_{t-1};) \quad (9)$$

where POS_t are the projected POS sales for the current period t that would be used to project final consumer demand over the following seven weeks. We therefore kept the observation of the POS sales for the previous four weeks but we did not use any conversion rate to inject the noise of the Customer Orders. This is why we just used the moving average of the four observations. The second change we had to implement from the original model was to modify the target DOS. As we described through formula (5) in chapter 3, the DOS target inventory is a function, among other things, of the RMSE. The RMSE in turn is a function of the standard deviation of the historical data used to generate the statistical forecast. Because we remove the Customer Orders of the retailer in this test we should expect an historical demand of POS sales that is less volatile than the historical demand of Customer Orders. This would require a revision of the DOS before running our optimization model. We first quantified the relationship between the RMSE and the bullwhip effect and then re-calculated the target DOS for each SKU based on the new expected RMSE while keeping the item fill rate at 98.5%.

4 Data Analysis and Results: Illustration and Discussion

In this section we present and discuss the analysis and results of our methodology, described in the previous chapter. We start by stating and proving our initial hypothesis of expecting a bullwhip effect between Customer Orders and POS sales. Then we plot the manufacturer and retailer datasets together for each of the four SKUs to illustrate any potential patterns and relationships between the two datasets that could confirm the bullwhip. This initial analysis will be therefore presented at SKU level. Once we identify the SKUs with significant relationships between POS sale and Customer Orders we then present the results of the multi-period production planning model using this relationship to adjust the master production scheduling. The results will show the differences in costs when comparing the model with the two test environments.

4.1 Simulating the Bullwhip Effect in a Periodic Review Inventory Policy

Our main hypothesis is that by plotting Customer Orders and POS sales data on the same chart we would be able to easily spot the bullwhip effect even before we could actually measure it and prove its existence statistical tests. In the long term, the trend of POS sales and Customer Orders should be aligned. This long-run equilibrium between the two datasets is what Williams, Waller, Ahire, and Ferrier label as “the inventory balance effect” (Williams, Waller, Ahire, & Ferrier, 2014). The main difference between the two datasets, however, is the standard deviation, with the Customer Orders having a larger level of volatility than the POS sales. Chen, Drezner, Ryan and Simchi Levi (Chen, Drezner, Ryan, & Simchi-Levi, March 2000) quantify the bullwhip effect as the variance of the Customer Orders (“sales in”) divided by the variance of the POS sales (“sales through”). The conclusion driven by the authors is that one of the drivers of the bullwhip effect is the demand

forecast itself. In fact, the number of periods observed to produce the forecast is inversely correlated with the increase in the bullwhip: the higher the number of periods, the closer the standard deviation of POS sales with the standard deviation of Customer Orders. Another important factor is the leadtime, the increase of which affects the calculation of the safety stock, thus amplifying the bullwhip. Before observing the real data from the retailer and from our sponsor company, we re-created a similar environment whereby a retailer would use a periodic review inventory policy to replenish its inventory. We assumed that the retailer was reviewing its inventory level every week and was facing a leadtime of one week. We assumed a service level of 98% and that the retailer was using a moving average forecasting technique with an RMSE being a tenth of the observed values. Using those assumptions we calculated the order-up-to point using below equation:

(10)

$$X = F_{L+R} + RMSE * k * \sqrt{L + R}$$

where:

- F_{L+R} is the forecasted demand over period L (leadtime) and period R (review period). In our scenario therefore we are forecasting demand over a total of two weeks (L=1, R=1);
- $RMSE$ is the forecast error
- k is the protecting factor corresponding to the normal Z value with probability of 98% (our service level target)
- $\sqrt{L + R}$ corresponds to the square root of the sum of leadtime and review period. In our case it is equal to the square root of 2.

We ran a Monte Carlo simulation of 10,000 iterations for a total of 52 weeks. The simulation was randomizing the demand for the products at retailer level assuming a normal distribution with a

level of volatility similar to the POS data we observed. We wanted to calculate the expected value of two parameters: the ratio of variance of Customer Orders over the variance of POS sales and the ratio of the average of Customer Orders over the average of POS sales. We observed the following bullwhip effect:

- Variance of Customer Orders/Variance of POS sales = 1.78 units on average
- Standard deviation of Customer Order/Standard Deviation of POS sales = 1.33 units on average
- Mean of Customer Orders/mean of POS sales = 1.00 unit on average

Figure 1 below shows that the 90% of the time the bullwhip was between 1.4 and 2.2 when measured in terms of variance of sales in over variance of sales through. The figure is plotting the normal distribution function of the bullwhip effect as resulted from the simulation runs.

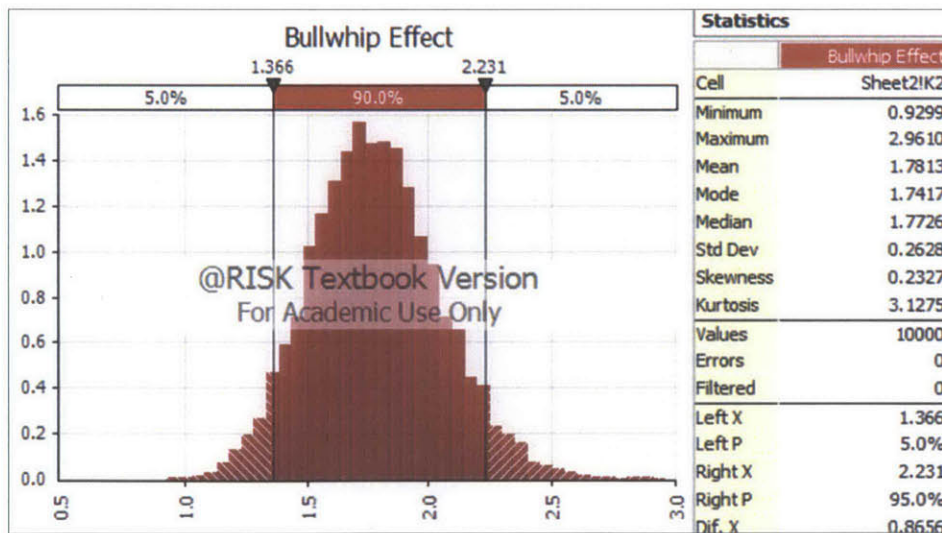


Figure 1: Normal Distribution Function of Bullwhip Effect

Figure 2 below plots the 52 weeks period where we can observe the differences in amplifications of the Customer Orders versus the POS sales.

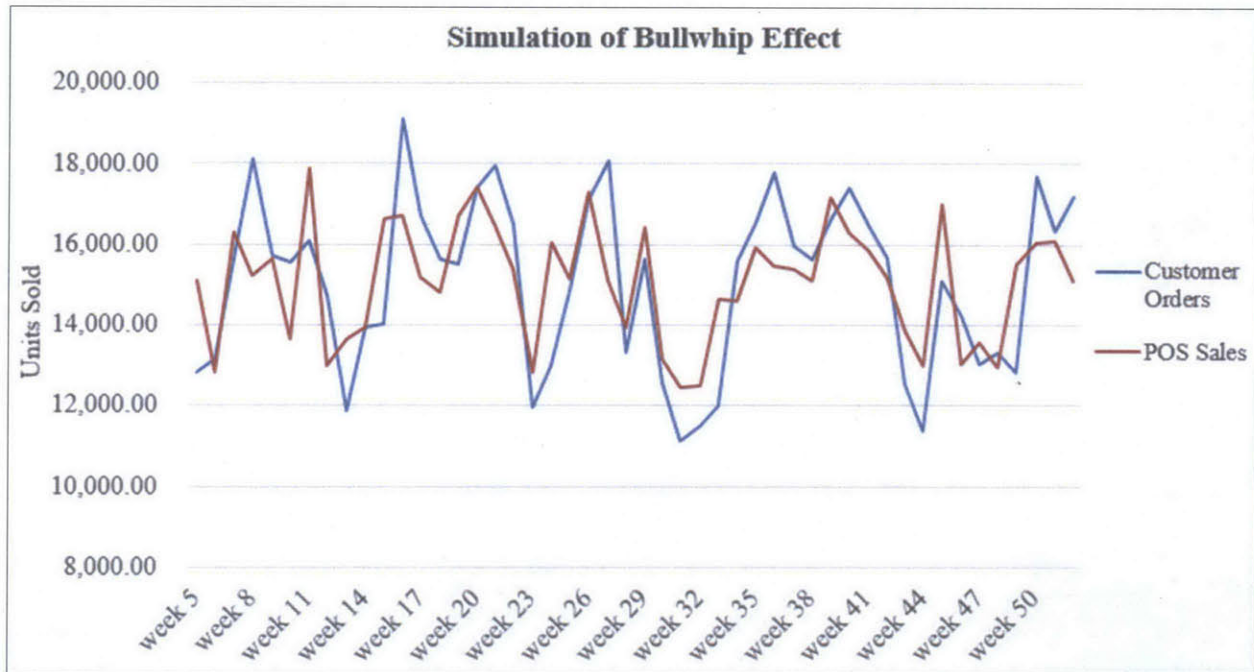


Figure 2: Customer Orders vs POS Sales in a Simulated Bullwhip Effect

The bullwhip effect measured above would be even larger if we increased the following parameters:

- leadtime
- service level
- forecast error (inversely related to the number of observed periods used in the moving average)

The results confirm the existence of a bullwhip effect, based on our assumption on the existence of a periodic review policy, as well as the alignment of mean values between the two datasets. Now we are ready to explore the real data from the retailer and our sponsor company to see if we can observe the above behavior and use it to better predict the Customer Orders and eventually adjust the production planning. We start by analyzing SKU 1.

4.2 Analyzing SKU1

Figure 3 below illustrates the 26 weeks pattern of SKU1 by plotting POS sale, Customer Orders and average customer inventory.

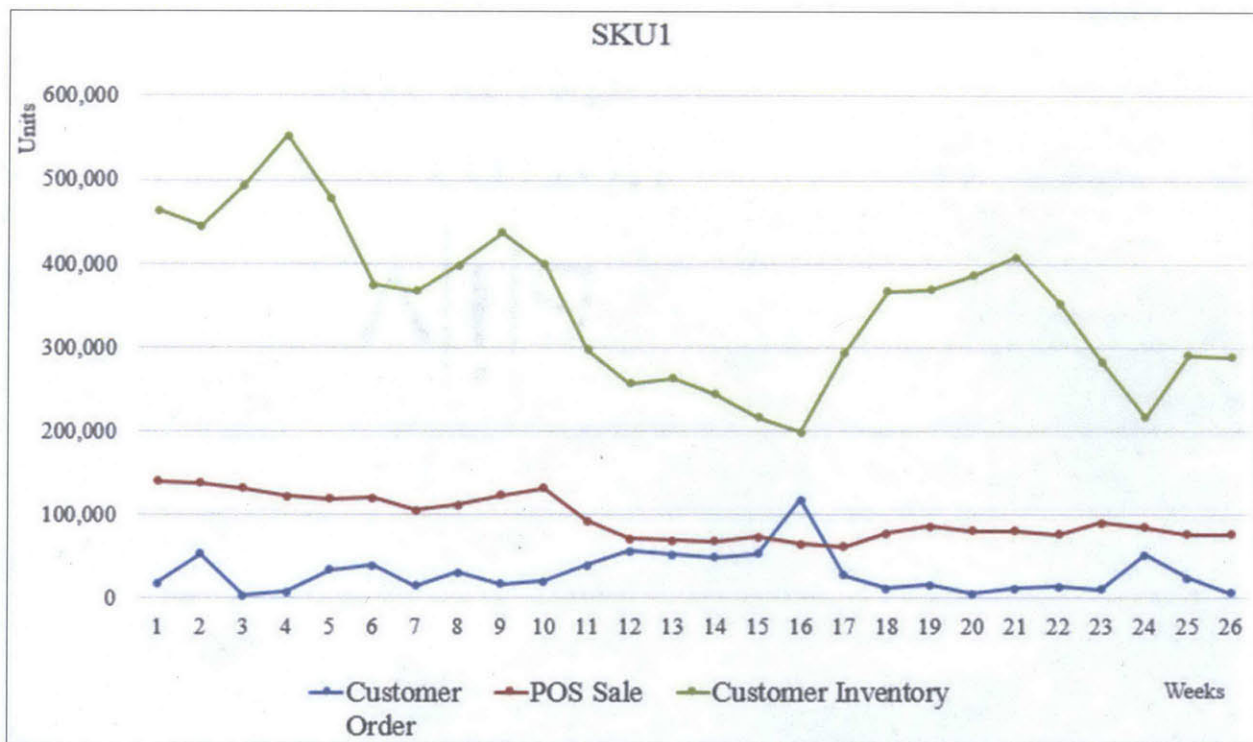


Figure 3: SKU1 Retailer and Manufacturer Data

At a first glance we can see that during the 26 week period the Customer Orders are not aligned with the POS sales as they are not following the same expected value in the long run. In other words, the mean values for the two datasets differ from each other. In fact, the average value for Customer Orders stands at 30,440 units while the mean of POS sales is 95,325 units. We also note

that the customer inventory average is 351,464 units. If we calculate the ratio of customer inventory over the POS sales, we can observe that the retailer is keeping a stock 3.7 times larger than the weekly POS sales units with a coefficient of variation of 18%. This low level of volatility suggests that the retailer is keeping a relatively stable order-up-to point in its periodic review policy. However, we are not in a position to accept our hypothesis of the expected relationship between POS sales and Customer Orders, primarily because both datasets are not sharing the same expected level of mean demand. Therefore we cannot use SKU 1 data to better predict the Customer Orders and build on the new production planning model. There could be many reasons why we do not observe the expected pattern; any of those potential explanations could only be detected by engaging in a direct dialogue with the customer to understand its inventory policy. The fact that the retailer has been ordering on average a third of what was actually sold in the stores indicates that the retailer may have had a significantly high inventory level at the beginning of the observed period. This high level of stock may have been reviewed downward by the retailer to effectively mirror the actual sales in stores. This is why eventually the retailer ordered less than what was actually sold in the stores to reset its inventory level to a more accurate and lower target. It is difficult however to be sure of what actually happened by just looking at the data and laying out the key statistics. This sort of behavior illustrated by SKU1 should trigger our sponsor company to engage with the retailer in a more collaborative approach when it comes to understand the reasons behind the Customer Orders pattern. The alert for the sponsor company should be a misalignment between the trend of the POS data and the Customer Orders.

4.3 Analyzing SKU2

Figure 4 below illustrates the 26 weeks pattern of SKU2 by plotting POS sale, Customer Orders and average customer inventory.

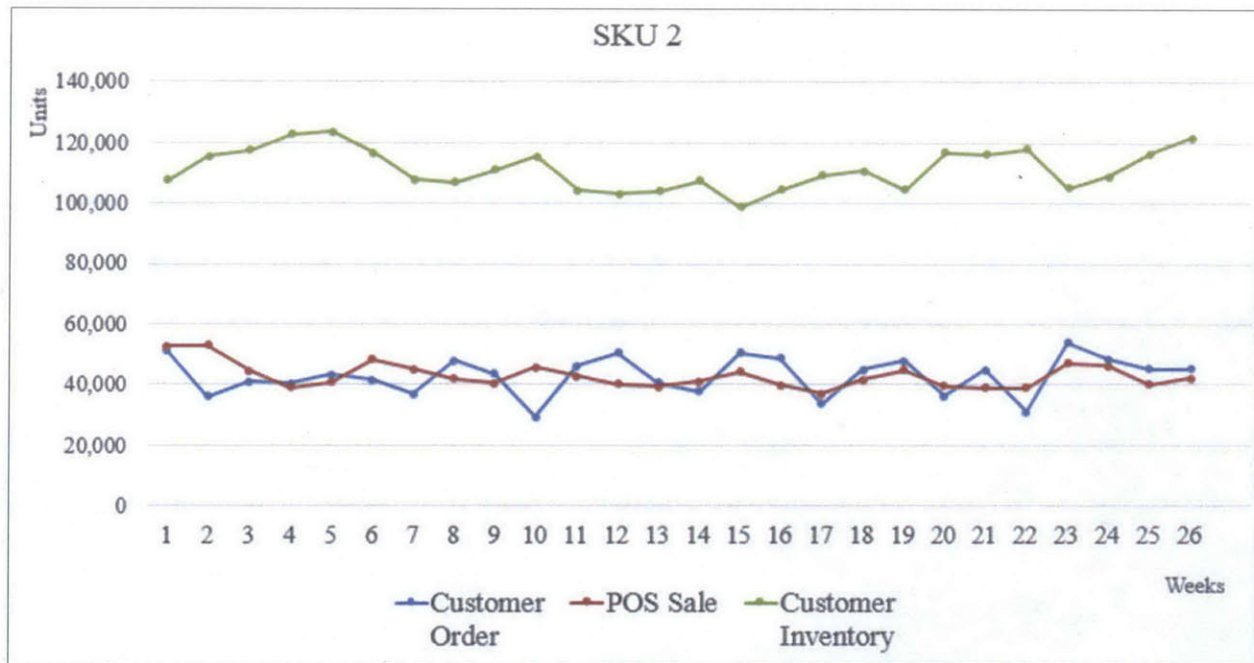


Figure 4: SKU2 Retailer and Manufacturer Data

The inventory level for the retailer is distributed with an average of 111,351 units. When we calculate the ratio of the retailer vis-à-vis the POS sales, we can observe that the inventory level stands at 2.6 weeks of equivalent POS sales with a coefficient of variation of 12%. We can therefore conclude that as with SKU 1 the inventory policy of the retailer for SKU 2 presents a relatively stable order-up-to point.

Contrary to what we observed with SKU 1, however, SKU 2 does present the behavior we expected to see when plotting Customer Orders with POS sales. In fact, we can observe how both Customer

Orders and POS sales align with each other in the long run, with the Customer Orders fluctuating more than the POS sales do. If we isolate the two datasets in the chart, the expected behavior of the same trend and bullwhip effect are even more visible.

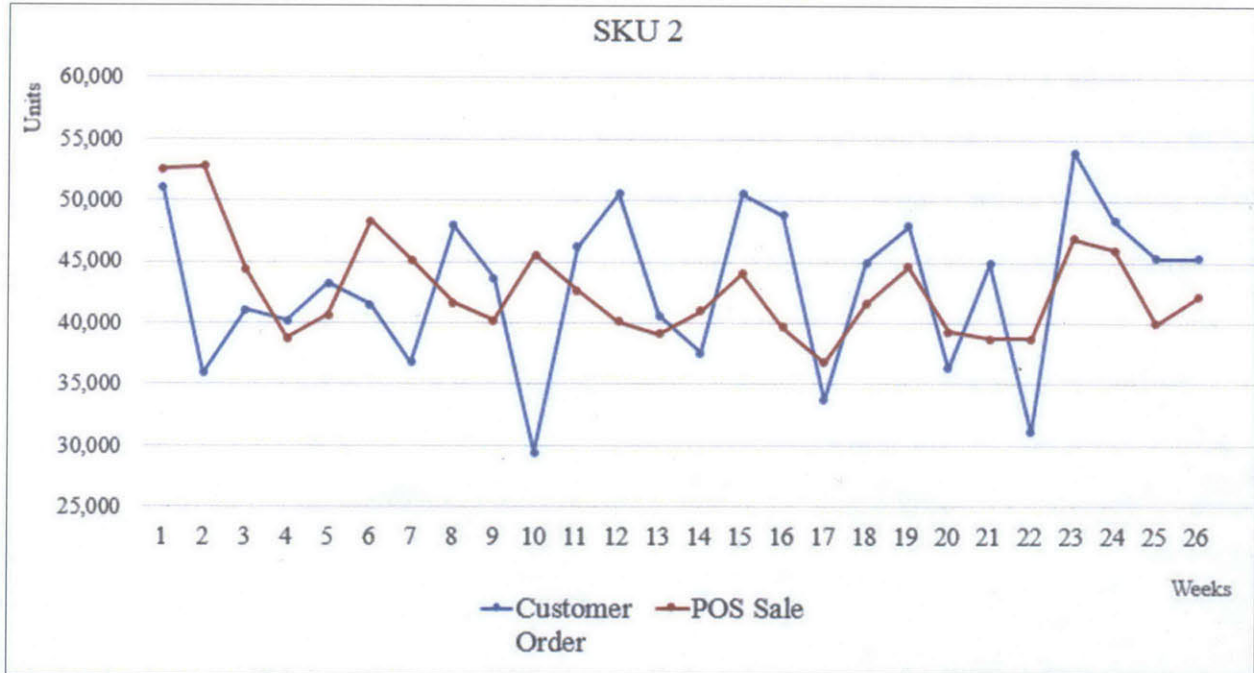


Figure 5: Bullwhip Effect on SKU2

The results confirm our observations. In fact, the average of Customer Orders stands at 42,952 units while the average of POS sales stands at 42,210 units. The two values are extremely close to each other, pointing towards the same direction of the results of our simulation where the two means align each other throughout the year. In addition, the data confirm the bullwhip effect. The ratio between the variance of the Customer Order with the variance of the POS sales stands at 3.1, while the ratio of the standard deviations stands at 1.76. Both ratios are therefore higher than our simulation results which were 1.78 and 1.33 respectively, thus suggesting the presence of a bullwhip effect. To rule out the possibility that the ratio is randomly greater than 1, we run a F test statistics to compare the variances of the two data samples. The null hypothesis is that the variance

of Customer Orders is equal to the variance of the POS sale (the ratio is equal to 1) while the alternative hypothesis is that the variation of Customer Orders is greater than the variation of POS sales (one-tail test). Table 3 below shows the result of the F-test for SKU2.

Table 3: F Test Statistic for Differences in Variances_SKU2

	<i>Customer Orders</i>	<i>POS Sales</i>
Mean	42951.69	42210.35
Variance	41519967	13425728
Observations	26	26
Df	25	25
F	3.092567	
P(F<=f) one-tail	0.003207	

The P value is 0.003, suggesting that there is only a 0.3% chance that the variance of Customer Orders is larger than the variance of POS sales by chance. Therefore we reject the null hypothesis. We can therefore consider SKU 2 as a valid candidate for the design and implementation of the production planning model.

4.4 Analyzing SKU3

Next we analyzed the patterns for SKU 3. Figure 6 below plots the customer inventory, the Customer Orders and POS sales.

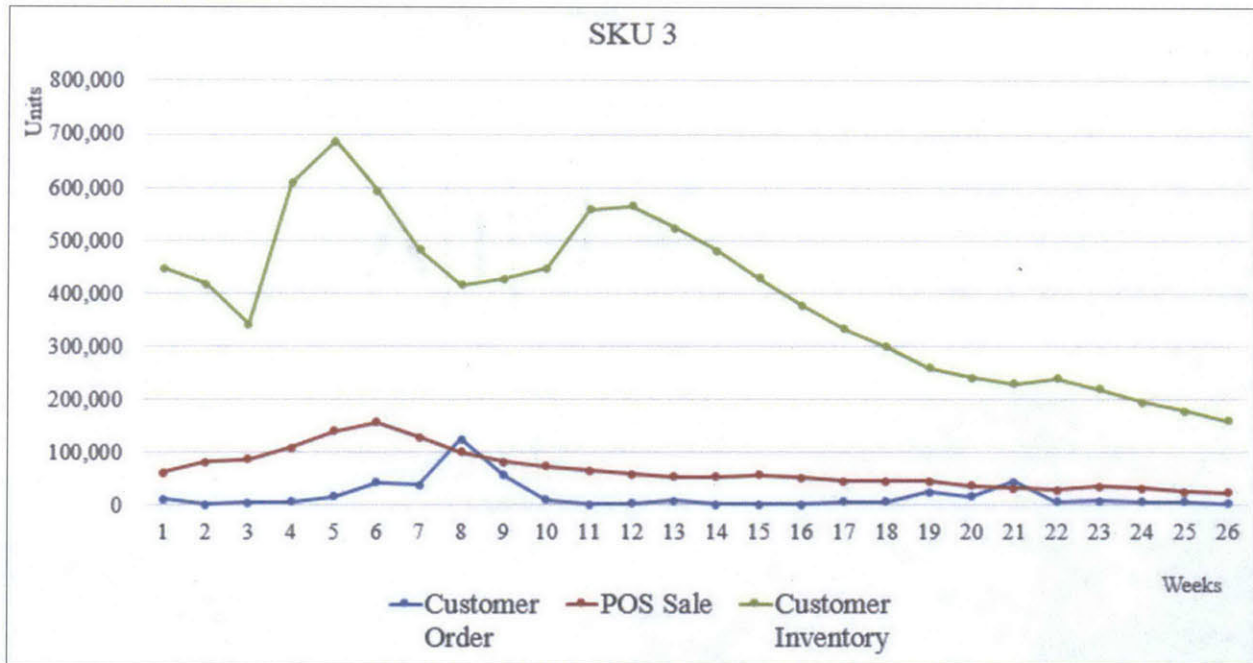


Figure 6: SKU3 Retailer and Manufacturer Data

At a first glance, the POS sales and Customer Orders align with each other only at the very end of the 26 weeks period while for a large portion of the dataset they seem to have a different level of trend. In fact, the mean value for POS sales is 64,664 units while the mean of Customer Orders stands at 16,897. The average customer inventory is 389,785 units, which correspond to 6.7 weeks of POS sales. The coefficient of variation for the target inventory is 26%, suggesting a less stable inventory policy than the ones observed with the previous SKUs. Those results are affected among other things by the two visible peaks in week 6 and 8, for POS sales and Customer Orders respectively. The peak of POS sales in this case is suggesting the presence of an outlier likely

produced by a promotional event. We could split the POS sales dataset in two segments: one from week 1 to week 10 and the other covering week 11 to week 26. If we proceed with this split, we can observe that the average of POS sales of the first segment (the outlier) stands at 101,128 units which corresponds to 2.4 times the average of the second segment of the dataset. This indicates the presence of a promotional effect on the product. Even with the split of data, however, the POS sales and Customer Orders still present significant differences between each other when comparing the respective mean values. For those reasons we are not considering SKU 3 as a valid candidate for our production planning model. As explained above for SKU1, SKU3 visualization should be a flag for our sponsor company to further investigate the inventory policy of the retailer. In this case we also observe a significant peak that would suggest a promotional event. However it is not easy to detect a defined relationship between POS sales and retailer orders as the retailer built up inventory prior the start of the promotion and eventually reacted after two weeks of the POS peak with a corresponding peak of orders. This is an isolated element of relationship between POS and Customer Orders and there is therefore not enough evidence to detect a pattern between the two sets. Like for SKU1, a lack of a clear relationship between POS and Customer Orders should invite our sponsor company in discussing with the customer and understand the reasons behind such inventory policy.

4.5 Analyzing SKU4

We now look at the last SKU of our dataset: SKU4. Figure 7 below illustrates the POS sales, Customer Orders and customer inventory.

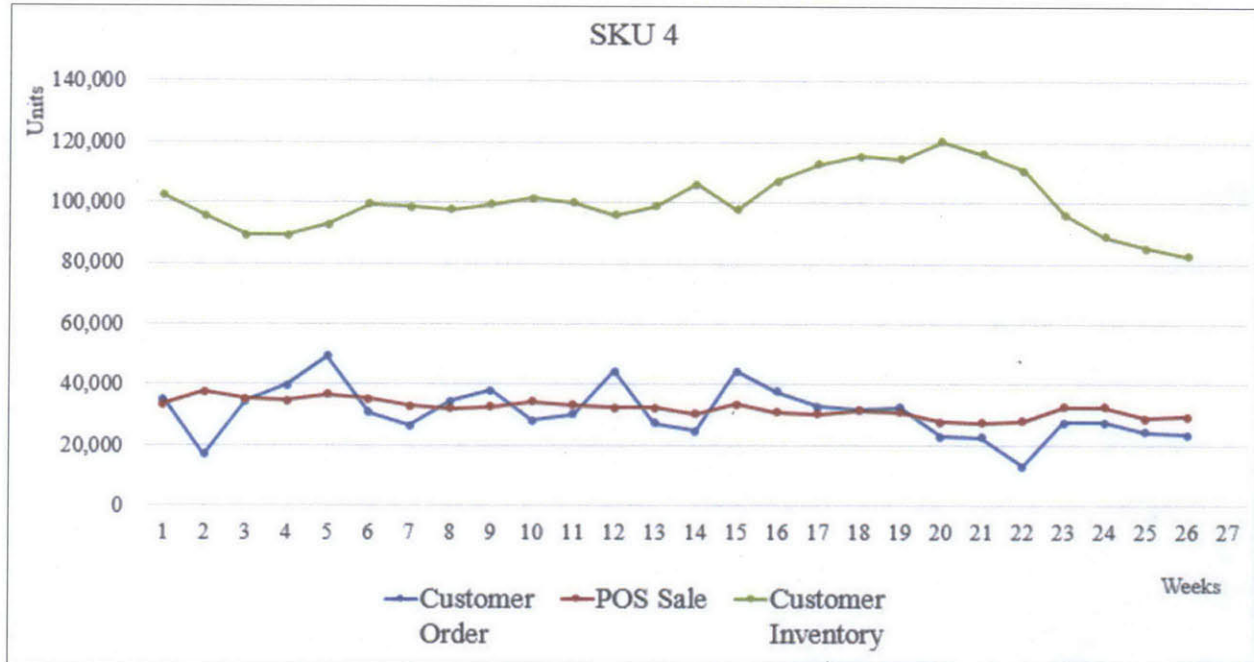


Figure 7: SKU4 Retailer and Manufacturer Data

The customer inventory average stands at 100,511 units, which correspond to 3.2 weeks of POS sales with a standard deviation of 16%. This shows that the inventory policy is relatively stable. The chart seems to suggest, as we observed for SKU 2, that we have the expected relationship between POS sales and Customer Orders. The average value of POS sales is 31,710 units while the mean of Customer Orders is 30,753 units. The two values are close enough to support our hypothesis that the two datasets share the same trend. When it comes to the ratio between the two variances, we do observe the expected bullwhip effect. In fact, the variance of Customer Orders over the variance of POS sales stands at 8.4, while the ratio between the standard deviations stands

at 2.9. The bullwhip effect for SKU 4 is therefore more evident than the one observed for SKU 2.

The effect is even more visible when we isolate the two datasets as per figure 8 below.



Figure 8: Bullwhip Effect on SKU4

To rule out the possibility that the difference in variances is random, we again performed the F test as we did for SKU2. Table 4 below show the results of the test.

Table 4: F Test Statistic for Differences in Variances_SKU4

	<i>Customer Orders</i>	<i>POS sales</i>
Mean	30752.77	31710.19
Variance	71583489	8546360
Observations	26	26
df	25	25
F	8.375904	
P(F<=f) one-tail	5.7E-07	

We reject the null hypothesis as the P value is close to 0 and therefore confirms that the variance of Customer Orders is significantly larger than the variance of the POS sales. The results shown above confirm that SKU 4 follows the behavior we have simulated with a periodic review policy. It is therefore the second valid candidate together with SKU 2 to introduce and develop the production planning model. Before proceeding with a description of the results of the production planning model when incorporating POS sales we first want to verify if we can assume that both POS sales and Customer Orders are normally distributed. The distribution fitting exercise will determine if we can accept the hypothesis of using normal distribution for both POS sales and Customer Orders so that we can find a quick and simple approach to convert the observed POS sales into projected future Customer Orders. This is in fact the preliminary step before jumping into the optimization model run which will adjust the production scheduling.

4.6 Distribution Fitting: Testing for Normality for SKU2 and SKU4

For each of the candidate SKUs of our production planning model, we would like to assume a normal distribution for both POS sales and Customer Orders datasets. We used the Lilliefors test to confirm our hypothesis that both POS sales and Customer Orders were normally distributed. We chose this test as it represents the normality test with the most statistical power. This test compares the cumulative distribution function of the empirical data with a normal distribution. The null hypothesis is that the distribution is normal. To reject such hypothesis, the test is measuring the maximum vertical distance between the two cumulative distribution functions (CDFs) and comparing the result against a list of t values per each percentage of significance level. If the t value is higher than the significant value chosen, then the null hypothesis of normality can be rejected and therefore we can't assume a normal distribution. Table 5 below shows the results

of the Lilliefors test for SKU2 for Customer Orders while figure 9 is plotting the corresponding test charts.

Table 5: SKU2_Customer Orders Normality Test Results

<i>Lilliefors Test Results</i>	Customer Order Data Set #1
Sample Size	26
Sample Mean	42951.69
Sample Std Dev	6443.60
Test Statistic	0.1205
CVal (15% Sig. Level)	0.1475
CVal (10% Sig. Level)	0.1558
CVal (5% Sig. Level)	0.1703
CVal (2.5% Sig. Level)	0.1817
CVal (1% Sig. Level)	0.2489

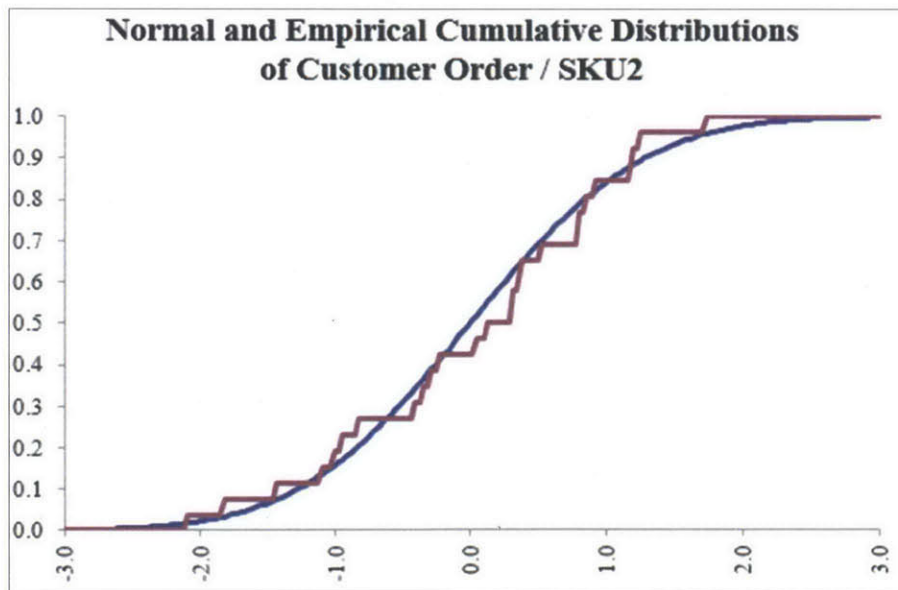


Figure 9: SKU2_Customer Orders Normality Test CDF chart

The test statistic value is equal to 0.1205 and is smaller than any of the comparable values corresponding to the different significance levels. This implies that we cannot reject the null

hypothesis and therefore it is correct to assume that Customer Orders for SKU2 are normally distributed. The results for SKU2 for POS sales are illustrated below.

Table 6: SKU2_POS Sales Normality Test Results

<i>Lilliefors Test Results</i>	POS Sale Data Set #1
Sample Size	26
Sample Mean	42210.35
Sample Std Dev	3664.11
Test Statistic	0.1403
CVal (15% Sig. Level)	0.1475
CVal (10% Sig. Level)	0.1558
CVal (5% Sig. Level)	0.1703
CVal (2.5% Sig. Level)	0.1817
CVal (1% Sig. Level)	0.2489

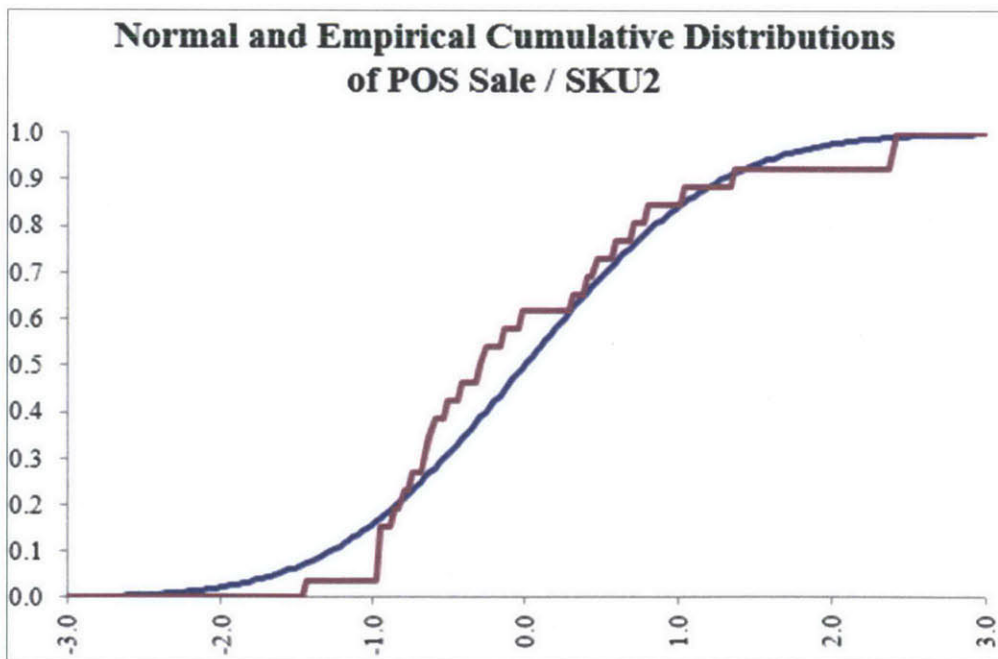


Figure 10: SKU2_POS Sales Normality Test CDF Chart

As observed for Customer Orders, the test value of POS sales data is lower than any comparable value for each corresponding significance level. Therefore we do not reject the null hypothesis of

normality. We can therefore continue with our assumption that POS sales for SKU2 are normally distributed.

Table 8 and figure 11 show the same results for SKU4, with both datasets in the same table and cdf chart.

Table 7: SKU4_ Normality Test Results for Both POS and Customer Orders

	Customer Order	POS Sale
<i>Lilliefors Test Results</i>	SKU4	SKU4
Sample Size	26	26
Sample Mean	30752.77	31710.19
Sample Std Dev	8460.70	2923.42
Test Statistic	0.0863	0.1069
CVal (15% Sig. Level)	0.1475	0.1475
CVal (10% Sig. Level)	0.1558	0.1558
CVal (5% Sig. Level)	0.1703	0.1703
CVal (2.5% Sig. Level)	0.1817	0.1817
CVal (1% Sig. Level)	0.2489	0.2489

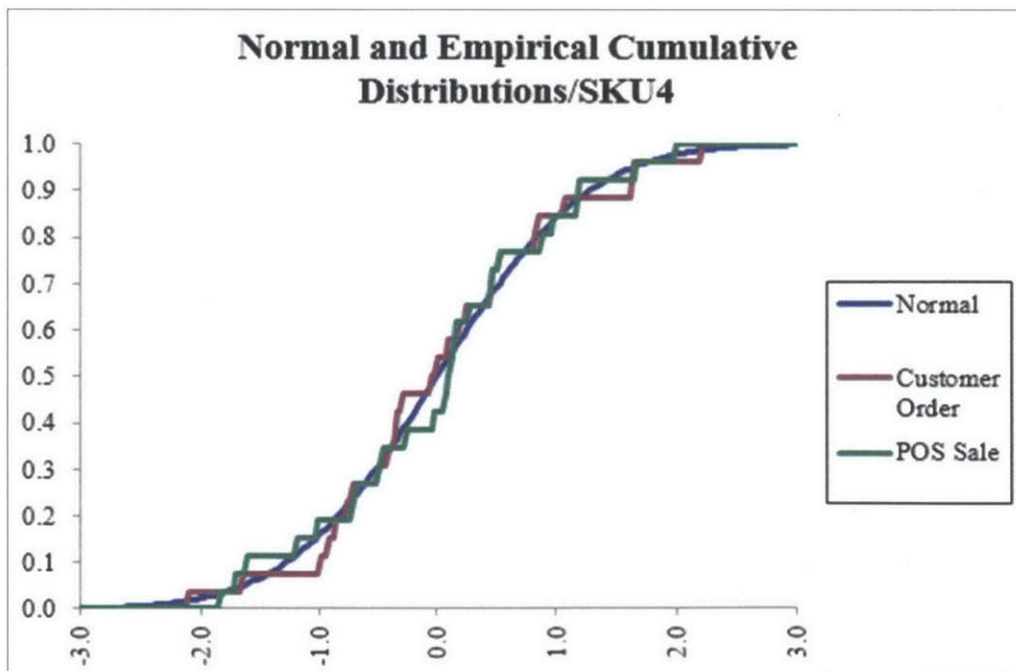


Figure 11: SKU4_Customer Orders and POS Sales Normality Test CDF Chart

As we can see from the test values for both POS sales and Customer Orders, we can fairly assume a normal distribution for both datasets also for SKU4. The test value for POS sales and Customer Orders are indeed sufficiently small that we are not in a position to reject the null hypothesis.

To summarize, we have the following results for SKU2 and SKU4:

- The ratio of variances between Customer Orders and POS sales is greater than the ratio measured through our simulation thus indicating the presence of a bullwhip effect
- The mean values of POS sales and Customer Orders tend to be close to each other in the long run as resulted from our simulation; this indicates that the customer is using a stable periodic review policy where the average order is the average weekly forecast demand times the length of the review period
- Both POS sales and Customer Orders can be assumed to have a normal distribution

4.7 Conversion Rate: From Observed POS Sales to Projected Customer Orders

Now that we have verified our assumptions and hypothesis on the distribution and relationship between POS sales and Customer Orders, we can use this relationship to project Customer Orders after observing the most recent POS sales. As we have seen from our initial result that both POS sales and Customer Orders do resemble each other in the long run, the key element of differentiation in the short term is the ratio of variances and standard deviations between the two datasets. Our conversion rate therefore inflates the observed POS sales to produce the most likely future Customer Orders. In other words, the conversion rate is simply injecting the noise of the bullwhip effect into the most recent POS sales to come up with a short term projection of Customer Orders. We are therefore planning for the bullwhip.

To illustrate the methodology of the conversion rate we are going to plot the CDF of two datasets: one with standard deviation of 10 (representing POS sales) and one with standard deviation of 16 (representing Customer Orders). The bullwhip effect for this illustration is therefore 1.6. Both datasets have the same mean of 100. A given data point taken from the normal distribution of POS sales will be therefore converted into a Customer Order data point corresponding to the equivalent cumulative distribution value. The figure below illustrates such conversion.

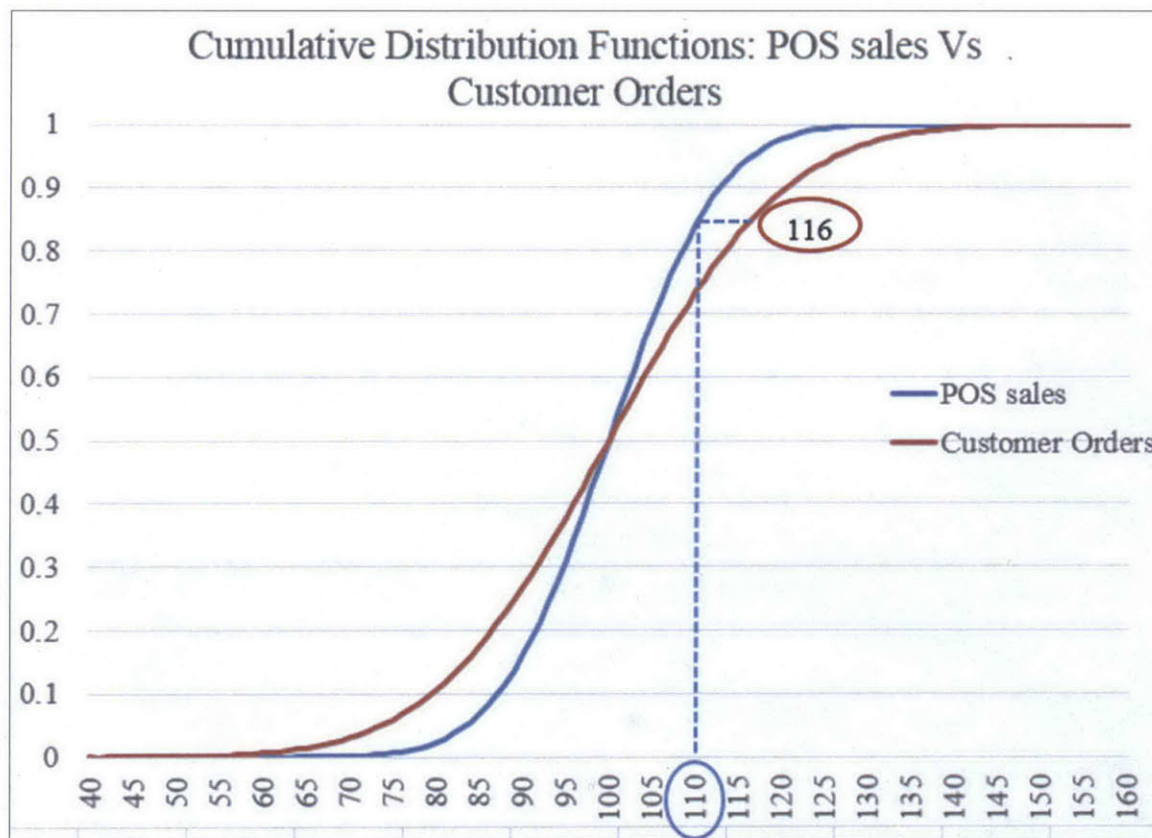


Figure 12: Conversion Rate Illustration

As we can see from the graph above, we selected a value from the POS sales equivalent to 110 and found its corresponding cumulative probability in the POS sales CDF curve. Then we moved to the right to identify the Customer Order value that corresponds to the same cumulative

probability. In our example above the Customer Order value is 116. We can conceptualize the conversion rate with below equation:

(11)

$$x_C = \frac{x_{POS} - \mu_{POS}}{\sigma_{POS}} * \sigma_C + \mu_C$$

where

- $x_C, \sigma_C,$ and μ_C are respectively the Customer Order value, the standard deviation of Customer Order distribution and the mean value
- $x_{POS}, \sigma_{POS},$ and μ_{POS} are respectively the POS sales value, the standard deviation of POS sales distribution and the mean value

In the production planning model that follows we are going to use the conversion rate above to find a projected set of Customer Order values from the observation of a set of POS sales. In particular, we are going to observe the last four weeks of POS sales to project the next seven Customer Orders. This is our initial step before running the optimization problem and solving for the adjusted production planning schedule. The conversion formula for the production planning model is as follows:

(12)

$$x_{C,t} = \frac{\frac{\sum_{i=t-4}^{t-1} x_{POS,i}}{4} - \mu_{POS}}{\sigma_{POS}} * \sigma_C + \mu_C$$

Where $\sum_{i=t-4}^{t-1} x_{POS,i} / 4$ is the moving average of the observed periods of POS sales which in our model is equivalent to the last four weeks. The weekly X_C will be then projected along the following seven weeks to generate the basis for the optimization model.

4.8 Actual Production and Inventory

Error! Reference source not found.8 and Table 9 show the actual production and inventory positions for SKU 1 – 4. This thesis does not emphasize the comparison of any of the models to the actual data because the number of constraints in the actual production planning optimization algorithm is considerably more than that of any of the models described in this model. This difference between the actual environment and our model results in an unfair comparison because with fewer constraints our models can only produce more optimized results.

Table 8: Actual Manufacturer Production and Inventory for SKU2, 4

Actual	SKU 2	SKU4
DOS	25	33
Item Fill Rate	100%	100%
Changeover	\$ 7,500	\$ 4,500
Holding	\$ 81,872	\$ 22,976
Total Cost	\$ 116,848	

Table 9: Actual Manufacturer Production and Inventory for SKU1, 3

Actual	SKU1	SKU3
DOS	34	44
Item Fill Rate	100%	73%
Changeover	\$ 7,500	\$ 3,000
Holding	\$ 87,804	\$ 6,187
Total Cost	\$ 104,490	

4.9 Multi-Period Production Planning: POS-to-Orders Model Results

The POS-to-Orders Model is shown below in Table 10 and Table 11 for all 4 SKUS. As stated previously, this model uses the POS data to improve the production planning to fulfill the Customer Orders.

Table 10: POS-to-Orders Model for SKU 2, 4

POS2Orders	SKU 2	SKU 4
DOS	25	33
Item Fill Rate	100%	100%
Changeover	\$ 6,000	\$ 4,500
Holding	\$ 19,249	\$ 20,427
Total Cost	\$ 50,176	

Table 11: POS-to-Orders Model for SKU 1, 3

POS2Orders	SKU 1	SKU 3
DOS	34	44
Item Fill Rate	100%	100%
Changeover	\$ 1,500	\$ 2,500
Holding	\$ 24,482	\$ 57,949
Total Cost	\$ 86,431	

4.10 Multi-Period Production Planning: Orders-to-Orders Model Results

The Orders to Orders model ignores the POS data and only adjusts the production plan by using historical Customer Orders data. The purpose of doing so is to mimic the manufacturer's forecasting model so that this model can be used as a baseline to compare all other models against. Table 12 and 13 show the results of the Orders-to-Orders model for all SKUs.

Table 12: Orders to Orders Model for SKU 2, 4

Orders2Orders	SKU2	SKU4
DOS	25	33
Item Fill Rate	100%	100%
Changeover	\$ 6,000	\$ 5,500
Holding	\$ 19,385	\$ 21,985
Total Cost	\$ 52,870	

Table 13: Orders to Orders Model for SKU 1, 3

Orders2Orders	SKU1	SKU3
DOS	34	44
Item Fill Rate	95%	86%
Changeover	\$ 4,500	\$ 3,000
Holding	\$ 29,505	\$ 53,377
Total Cost	\$ 90,382	

4.11 Multi-Period Production Planning: POS-to-POS Model Results

As mentioned in our methodology section, before running the rolling plan for the POS-to-POS scenario we had to first calculate the new target DOS inventory for both SKU2 and SKU4. In order to adjust the DOS, we had to first calculate the new RMSE that resulted from a different base of historical data. We ran a simulation where to prove that the ratio of the RMSE for Customer Orders over the RMSE for POS sales was equal to the ratio of standard deviations of both datasets. In other words, we wanted to verify that the initially measured bullwhip effect would have the same value when comparing the two RMSEs. To run the simulation we used the average and standard deviations from SKU2. The RMSE was calculated at the end of 52 weeks against a four-week moving average forecast. The simulation ran for 10,000 iterations. Figure 13 below shows the results for the RMSE expected value:

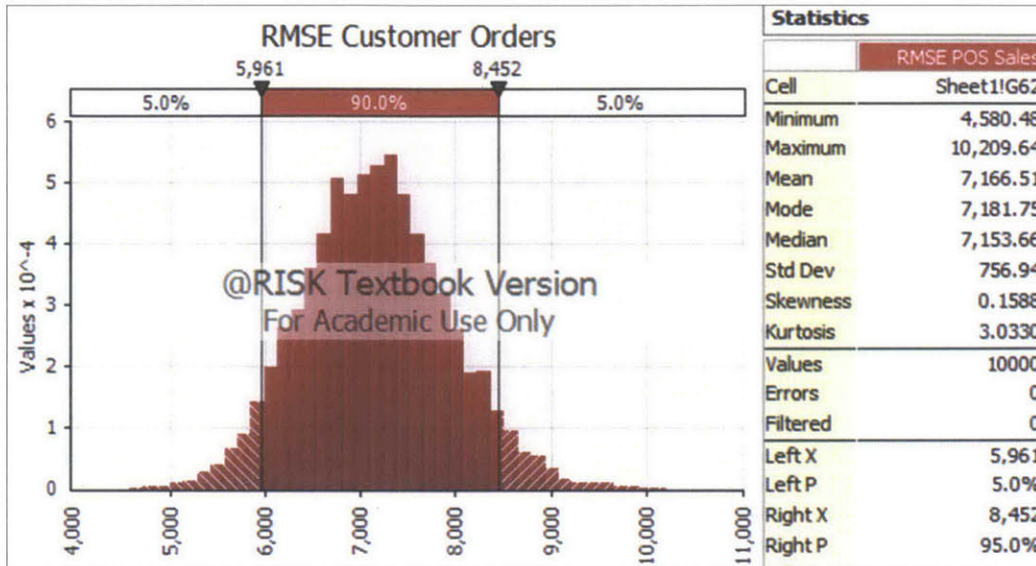


Figure 13: RMSE for Customer Orders after 10,000 iterations

On average, the RMSE for Customer Orders for SKU2 would stand at 7,166.51. The RMSE for the POS Sales should be less as the historical data of POS present a lower volatility rate. We then ran a similar simulation for SKU2 using the mean and standard deviation of the history of POS sales. We expected an RMSE value that would be proportionally lower than the RMSE for Customer Orders. Figure 14 below shows the results of 10,000 iterations.

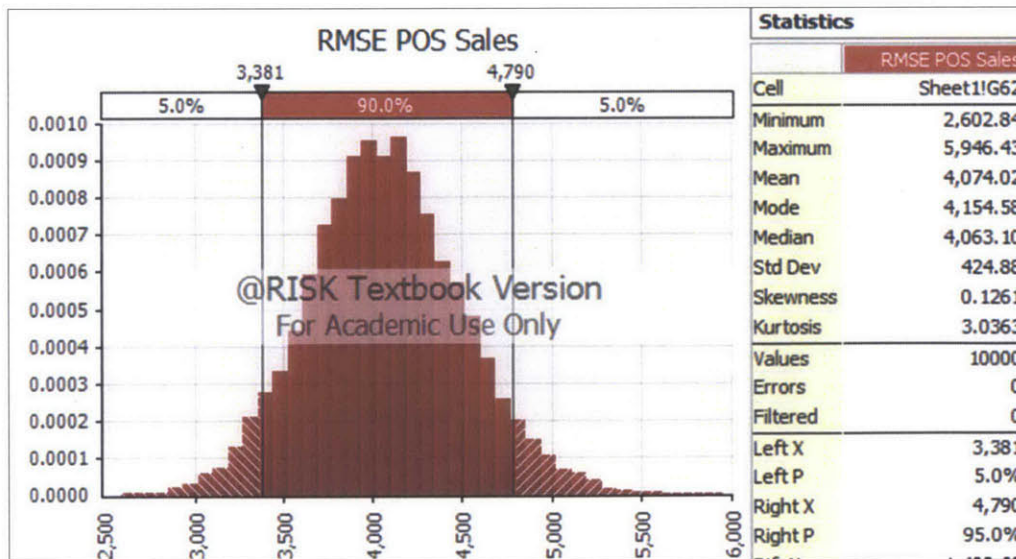


Figure 14: RMSE POS sales after 10,000 iterations

The average value for the RMSE when using POS sales as historical data was 4,074.02. The ratio of the two RMSEs was therefore 7,166.51 divided by 4,074.02 which gives us 1.76. This was exactly the same ratio that resulted from standard deviation of Customer Orders over standard deviation of POS sales. The simulation confirmed that the bullwhip effect has the same value when comparing the RMSEs of the two datasets. We can therefore assume that whenever we apply the same forecast technique using POS history instead of Customer Order history, the new RMSE will be equal to the following equation:

(13)

$$RMSE_{POS} = \frac{RMSE_{CO}}{\sigma_{CO}} * \sigma_{POS}$$

Where σ_{CO} is the standard deviation of Customer Orders and σ_{POS} is the standard deviation of POS data.

The equation above can now be used to calculate the new DOS supply for the POS-to-POS test scenario. By using the DOS formula (5) mentioned in our Methodology section, we found the new DOS shown in table 14, below, when updating the RMSE and fixing the Item Fill Rate at 98.5%.

Table 14: DOS Comparison between original model and POS-to-POS test

Product	DOS Original Model	DOS POS-to-POS test
SKU2	25	20
SKU4	33	19

The results above show that by using POS sales as demand history instead of using Customer Orders, the manufacturer can keep the same item fill rate with a lower target DOS inventory. This

is possible, as we have seen, mainly because of a reduction of the RMSE: it is now lower when forecasting POS sales. This initial reduction of the target inventory level suggests a reduction of the average inventory for the manufacturer even before we run the optimization problem and solve for the new production planning. Before observing the results of the test, we created an inventory target frontier to illustrate the linear relationship between the bullwhip effect and the reduction of the DOS value, as shown in figure 15 below.

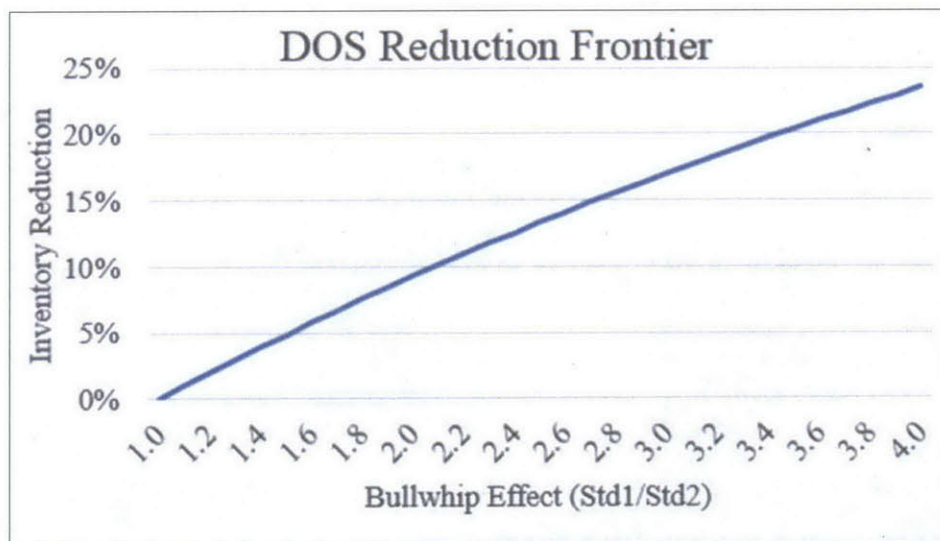


Figure 15: DOS Reduction Frontier

The above frontier shows that with higher levels of the bullwhip effect, there is higher inventory reduction when planning using POS history instead of Customer Order History. This is possible because the RMSE of POS forecasts is lower than the RMSE of Customer Orders, and the gap between the two values increases as the ratio of the standard deviations goes up. This explains why we observed a higher reduction of DOS for SKU4 than for SKU2: the bullwhip effect for the former product is higher.

Table 15 and Table 16 show the POS-to-POS model for SKU1 – 4.

Table 15: POS-to-POS Model for SKU 2, 4

POS2POS	SKU2	SKU4
DOS	20	19
Item Fill Rate	100%	100%
Changeover	\$ 6,000	\$ 5,500
Holding	\$ 16,114	\$ 12,679
Total Cost	\$ 40,293	

Table 16: POS-to-POS Model for SKU 1, 3

POS-to-POS	SKU1	SKU3
DOS	23	31
Item Fill Rate	100%	100%
Changeover	\$ 6,000	\$ 3,000
Holding	\$ 39,371	\$ 57,103
Total Cost	\$ 105,474	

4.12 Results Discussion SKU2 and SKU4

Table 17 shows a summary of the different models for SKU 2 and 4. The results show a decrease in cost as the role of POS increases. This is a promising trend, as it validates the usefulness of POS data. SKUS 2 and 4 are excellent examples of the bullwhip effect in which the Customer Orders was a consistent multiple of the changes in the POS data. The standard deviation of the ratio of SKU 2 and SKU 4's retailer on-hand inventory to POS is quite moderate, ranging from 12% to 30%, and the difference between the POS and Order quantity is less than 3%.

The nature of the relationship between Customer Orders and POS sales show a consistent retailer inventory policy and confirmed our initial hypothesis of long term inventory balance and bullwhip effect. Table 17, below, summarizes the results of the 3 models to evaluate the usefulness of POS. We did not include any comparison with the actual costs as this would not have provided valid results.

Table 17: Summary of SKU2, 4

SKU2 + SKU4	Total Cost	Vs. Orders2Orders	Vs. POS2Orders
Orders2Orders	\$ 52,870	NA	NA
POS2Orders	\$ 50,176	5.10%	NA
POS2POS	\$ 40,293	19.70%	23.79%

The Orders-to-Orders model and the POS-to-Orders model share several similarities. Both predict Customer Orders resulting in sharing the same variability and bullwhip effect. The difference between the two models is that the latter uses POS to improve the Customer Orders forecast. The resulting savings represent the improved accuracy of the production planning with respect to Customer Orders. This improved accuracy allows production to better match Customer Orders to reduce inventory costs. But because the inherent variability exists, and that the POS is only used to improve the accuracy of the Customer Orders, the difference in total cost is only 5.1%.

The POS-to-POS model shows a much larger cost reduction when compared to the other models because the variation in the POS data is approximately 0.5 to 0.3 of the Customer Orders. This improvement in the variation reflects the removal of the bullwhip effect. In order to implement the POS-to-POS model, the manufacturer and the retailer must develop a relationship that shares POS in real time and agree on the inventory policy that is based on the POS data.

In all 3 modeled situations, the item fill rate for SKU1 and SKU 3 was 100% for the entire duration of the analysis.

4.13 Results Discussion SKU 1 and SKU 3

Table 18 shows the summary of SKU1, and 3. The results of SKU 1 and 3 were not in line with those of 2 and 4 because of dynamics of the inventory policy that were not clearly visible in the POS data. Although the POS still weakly dictates the Customer Orders, the standard deviation of the ratio of retailer on-hand inventory to POS ranges considerably from 65% to 121%, and the ratio of POS to order quantity is 3:1.

Table 18: Summary of SKU1, 3

SKU2 + SKU4	Total Cost	Vs. Orders2Orders	Vs. POS2Orders
Orders2Orders	\$ 90,382	NA	NA
POS2Orders	\$ 86,431	4.37%	NA
POS2POS	\$ 105,474	-22.03%	-16.70%

The difference in POS and quantity ordered is the primary cause for the higher cost in the POS-to-POS model when compared to the other 2 models. This results because the POS-to-POS does not aim to fulfill Customer Orders but as the name implies, aims to fulfill POS. Although the POS to POS model is quantitatively ineffective for SKU 1 and 3, qualitatively it can alert the manufacturer to engage in discussions with the retailer to understand the dynamics of its inventory policy to best prepare production planning.

Despite high variation in ratio of inventory to POS, we still see cost savings in using the POS data to adjust the production plan compared to only using historical data. All SKUs examined showed this cost savings because the retailer must replenish its stock based on POS.

4.14 Sensitivity Analysis: “What If” Scenarios with Different Bullwhip Effects

We ran two sensitivity analysis to verify the effect of changes in the bullwhip effect on the benefits of using POS data in both models, POS-to-Order and POS-to-POS. For the latter, we were expecting higher benefits with higher levels of the bullwhip effect. For the former, we were not expecting any linear relationship between the gains and the bullwhip effect as the POS-to-Order model simply reproduces the noise rather than removing it.

4.14.1 Changing the Bullwhip in the POS-to-POS model

As we showed above in the Results section, the POS-to-POS model produces the best outcome as it significantly reduces the bullwhip effect of the Customer Orders. In fact, by focusing only on the POS data, we are reducing the volatility of the historical dataset and therefore targeting a lower number of DOS. This in turn relaxes the target inventory constraints of the model for every week, thus producing lower costs for the optimal solution (the target inventory constraint is binding for several periods of the rolling model). The DOS inventory reduction frontier illustrated in Figure 15 shows a linear relationship between the bullwhip effect and the potential savings when it comes to using POS data to project future POS sales. The larger the bullwhip effect, the lower the target inventory level, and therefore the lower the inventory costs in our production planning model. By updating our production planning model with the changes in the bullwhip, we found the following results as shown in Table 19:

Table 19: Sensitivity Analysis of POS-to-POS

Bullwhip	Order to Order	POS-to-POS	Savings
1.5	\$47,988	\$40,293	16%
2.0	\$50,829	\$40,293	21%
2.5	\$53,582	\$40,293	25%
3.0	\$57,102	\$40,293	29%
3.5	\$59,500	\$40,293	32%
4.0	\$64,020	\$40,293	37%

As we can see from the table above, with a bullwhip effect of 1.5 for both SKUs, we reach a total level of savings of 16%. If we then have two products with a higher bullwhip effect of 4.0 each, we reach a total level of savings of 37%. This sensitivity analysis shows the great potential in using POS data to project POS sales and therefore influence the ordering decision process of the retailer. As the added value of the POS-to-POS model is the elimination of the bullwhip effect, the higher the initial level of noise, the higher the savings if POS data are integrated in a collaborative planning environment between the manufacturer and the retailer.

4.14.2 Changing the Bullwhip Effect in the POS-to-Order Model

When it comes to the POS-to-Order model we should not expect any significant changes when products had different levels of the bullwhip effect. In fact, the model reproduces the noise of the retailer inventory policy without removing such volatility from the planning process. We wanted to see whether the model could still register some savings even when the level of bullwhip for the two SKUs was changed. Below are the results of the sensitivity analysis for POS-to-Order model:

Table 20: Sensitivity Analysis of POS-to-Order

Bullwhip	Order to Order	POS-to-Order	Savings
1.5	\$47,988	\$45,761	5%
2.0	\$50,829	\$49,095	3%
2.5	\$53,582	\$51,987	3%
3.0	\$57,102	\$54,946	4%
3.5	\$59,500	\$57,292	4%
4.0	\$64,020	\$60,776	5%

As we can see from the table above, the POS-to-Order model produces gains irrespective of the value of the bullwhip effect. However, the relationship between the savings and the bullwhip effect is not linear as both 1.5 and 4.0 levels of the bullwhip effect show the same 5% total savings. This confirms that our sponsor company could benefit from the POS-to-Order model even with a relative lower level of the bullwhip effect, 1.5, and that a manufacturer should not expect significantly higher gains with this model as the bullwhip goes up.

5 Conclusion: the Value of POS data

We showed evidence that collecting POS data from the retailer and integrating them into the planning process of a manufacturing CPG company can generate business value. By studying the relationship between POS sales and Customer Orders at each SKU level, a manufacturing company can leverage such a relationship and better plan for the bullwhip effect to come. This in turn would improve the accuracy of the overall supply planning process as the company could use POS sales to adjust the production planning schedule by better projecting Customer Orders. As a result, savings in relevant supply chain costs, such as holding and change over costs, may materialize.

At the same time, our thesis show a higher degree of value in using POS data when it comes to using historical POS to better predict future POS sales and adjust the production planning accordingly. In fact, in a business environment where the manufacturer could collaborate with the retailer, the bullwhip effect could be significantly reduced from the equation. The manufacturer could observe the POS data and leverage them to influence the ordering process of the retailer in order to reduce the bullwhip effect generated by the additional inventory planning layer. In the case of using POS to better project future POS, the lion's share of the gains originates from a reduction of the safety stock, thus a reduction of the overall target inventory level. This in turn would relax the production planning schedule constraints and meet the same item fill rate with fewer relevant costs.

To capitalize on those benefits a manufacturer would need to both invest in collecting POS data from all its retailers and also engage in a constant dialogue with them. Analyzing each SKU is a necessary step to leverage the power of POS data, but it is not enough. A manufacturer should use

the POS data to investigate and question the ordering behavior of the retailers and eventually involve them in a joint collaborative supply chain planning process.

As this thesis has shown, reconciling the Customer Orders with the POS sales could help the manufacturer visualize and quantify the bullwhip effect. After this initial step, it will be clearer for the company which SKUs to use in integrating POS data into the planning process with or without the retailer. The higher the bullwhip effect, the higher the value of integrating POS data in the supply planning process. The more misaligned the Customer Orders with POS sales, the higher the need for the manufacturer to understand the inventory policy of the retailer and eventually influence it. The manufacturer can therefore use the insights of our model to prompt a segmentation of its products based on the degree of bullwhip effect and the level of misalignment between POS sales and Customer Orders. This segmentation would help the company identify the products where POS data could bring the highest value and therefore push for a deeper investigation and understanding of the customer demand behavior.

There are, however, limitations to our model. The limited number of observed SKUs, as well as the limited number of observed days of POS data, require a further research on all other key products and retailers. Our model also takes as a main assumption that the manufacturing process only allows an adjustment of the production schedule after three weeks. It would therefore be relevant to analyze the effect of using POS data in our model when removing the three week freeze period. In other words, it would be worthwhile investigating the power of POS data when a manufacturing company can adjust the production planning immediately the week after instead of waiting for two additional weeks. This further research could then evaluate if the costs incurred in designing a more flexible manufacturing and production schedule process would be offset by the savings produced by the POS data integration in the planning process.

Finally, the power of POS data can be leveraged to improve the planning and monitoring of promotional events, thereby involving other key stakeholders in the manufacturing company such as marketing and sales. This, along with the benefits for the production planning process, could trigger enormous benefits throughout the entire company's value chain.

POS data has still yet to show all of its potential value but the methodology and approach described in the thesis as well as further suggested researches would help companies in unleashing the benefits hidden behind them. Companies who are able to integrate POS data into their demand and supply planning process could design more flexible and demand driven supply chains. Collecting, interpreting and integrating POS data is a must for any companies in the CPG industry: it is the secret ingredient for a supply chain that meets the real demand and adapts quickly to customer behaviors changes.

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