Chapter 24
Supply Chain Analytics

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1 Introduction

Through examples and a case study, we shall learn how to apply data analytics to supply chain management with the intention to diagnose and optimize the value generation processes of goods and services, for significant business value.

A supply chain consists of all activities that create value in the form of goods and services by transforming inputs into outputs. From a firm's perspective, such activities include buying raw materials from suppliers (buy), converting raw materials into finished goods (make), and moving and delivering goods and services to customers (delivery).

The twin goals of supply chain management are to improve cost efficiency and customer satisfaction. Improved cost efficiency can lead to a lower price (increases market share) and/or a better margin (improves profitability). Better customer satisfaction, through improved service levels such as quicker delivery and/or higher stock availability, improves relationships with customers, which in turn may also lead to an increase in market share. However, these twin goals have the potential to affect each other conversely. Improving customer satisfaction often requires a higher cost; likewise, cost reduction may lower customer satisfaction. Thus, it is a challenge to achieve both goals simultaneously. Despite the challenge, however, those companies that were able to achieve them successfully (e.g., Walmart,

Electronic supplementary material The online version of this chapter (https://doi.org/10.1007/978-3-319-68837-4_24) contains supplementary material, which is available to authorized users.

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B. Pochiraju, S. Seshadri (eds.), *Essentials of Business Analytics*, International Series in Operations Research & Management Science 264,
https://doi.org/10.1007/978-3-319-68837-4_24

Amazon, Apple, and Samsung) enjoyed a sustainable and long-term advantage over their competition (Simchi-Levi et al. 2008; Sanders 2014; Rafique et al. 2014).

The twin goals are hard to achieve because supply chains are highly complex systems. We can attribute some of this complexity to the following:

1. Seasonality and uncertainty in supply and demand and internal processes make the future unpredictable.
2. Complex network of facilities and numerous product offerings make supply chains hard to diagnose and optimize.

Fortunately, supply chains are rich in data, such as point-of-sale (POS) data from sales outlets, inventory and shipping data from logistics and distribution systems, and production and quality data from factories and suppliers. These real-time, high-speed, large-volume data sets, if used effectively through supply chain analytics, can provide abundant opportunities for companies to track material flows, diagnose supply disruptions, predict market trends, and optimize business processes for cost reduction and service improvement. For instance, descriptive and diagnostic analytics can discover problems in current operations and provide insights on the root causes; predictive analytics can provide foresights on potential problems and opportunities not yet realized; and finally, prescriptive analytics can optimize the supply chains to balance the trade-offs between cost efficiency and customer service requirement.

Supply chain analytics is flourishing in all activities of a supply chain, from buy to make to delivery. The Deloitte Consulting survey (2014) shows that the top four supply chain capabilities are all analytics related. They are optimization tools, demand forecasting, integrated business planning and supplier collaboration, and risk analytics. The Accenture Global Operations Megatrends Study (2014) demonstrated the results that companies achieved by using analytics, including an improvement in customer service and demand fulfillment, faster and more effective reaction times to supply chain issues, and an increase in supply chain efficiency. This chapter shall first provide an overview of the applications of analytics in supply chain management and then showcase the methodology and power of supply chain analytics in a case study on delivery (viz., integrated distribution and logistics planning).

2 Methods of Supply Chain Analytics

Supply chain management involves the planning, scheduling, and control of the flow of material, information, and funds in an organization. The focus of this chapter will be on the applications and advances of data-driven decision-making in the supply chain. Several surveys (e.g., Baljko 2013; Columbus 2016) highlight the growing emphasis on the use of supply chain analytics in generating business value for manufacturing, logistics, and retailing companies. Typical gains include more accurate forecasting, improved inventory management, and better sourcing and transportation management.

It is relatively easy to see that better prediction, matching supply and demand at a more granular level, removing waste through assortment planning, and better category management can reduce inventory without affecting service levels. A simple thought exercise will show that if a retailer can plan hourly sales and get deliveries by the hour, then they can minimize their required inventory. One retailer actually managed to do that—"Rakuten" was featured in a television series on the most innovative firms in Japan (Ho 2015). The focus on sellers and exceptional customer service seems to have paid off. In 2017, Forbes listed Rakuten among the most innovative companies with sales in excess of $7 billion and market cap more than $15 billion.[1] Data analytics can achieve similar results, without the need for hourly planning and delivery, and it can do so not only in retail but also in global sourcing by detecting patterns and predicting shifts in commodity markets. Clearly, supply chain managers have to maintain and update a database for hundreds of suppliers around the globe on their available capacity, delivery schedule, quality and operations issues, etc. in order to procure from the best source. On transportation management, one does not have to look further beyond FedEx and UPS for the use of data and analytics to master supply chain logistics at every stage, from pickup to cross docking to last-mile delivery (Szwast 2014). In addition, there are vast movements of commodities to and from countries in Asia, such as China, Japan, and Korea, that involve long-term planning, sourcing, procurement, logistics, storage, etc., many involving regulations and compliance that simply cannot be carried out without the tools provided by supply chain analytics (G20 meeting 2014).

The supply chain is a great place to apply analytics for gaining competitive advantage because of the uncertainty, complexity, and significant role it plays in the overall cost structure and profitability for almost any firm. The following examples highlight some key areas of applications and useful tools.

2.1 Demand Forecasting

Demand forecasting is perhaps the most frequent application of analytics to supply chains. According to the Chief Supply Chain Officer Report (O'Marah et al. 2014), 80% of executives are concerned about the risks posed to their supply chain by excessive customer demand volatility. Demand volatility causes problems and waste in the entire supply chain from supply planning, production, and inventory control to shipping. In simple terms, demand forecasting is the science of predicting the future demand of products and services at every level of an organization, be it a store, a region, a country, or the world. Demand forecasting is essential in planning for sourcing, manufacturing, logistics, distribution, and sales. The sales and operations planning modules of ERP systems help to bring several disciplines together so that forecasts can be created and shared to coordinate different activities

[1] https://www.forbes.com/companies/rakuten/ (accessed on Mar 26, 2018).

in the supply chain. These include the obvious ones such as inventory levels, production schedules, and workforce planning (especially for service industries). The less obvious ones are setting sales targets, working capital planning, and supplier capacity planning (Chap. 4, Vollmann et al. 2010). Several techniques used for forecasting are covered in Chap. 12 on "Forecasting Analytics."

One notable example of the use of forecasting is provided by Rue La La, a US-based flash-sales fashion retailer (Ferreira et al. 2015) that has most of its revenues coming from new items through numerous short-term sales events. One key observation made by managers at Rue La La was that some of the new items were sold out before the sales period was over, while others had a surplus of leftover inventory. One of their biggest challenges was to predict demand for items that were never sold and to estimate the lost sales due to stock-outs. Analytics came in handy to overcome these challenges. They developed models using which demand trends and patterns over different styles and price ranges were analyzed and classified, and key factors that had an impact on sales were identified. Based on the demand and lost sales estimated, inventory and pricing are jointly optimized to maximize profit. Chapter 18 on retail analytics has more details about their approach to forecasting and inventory management.

Going forward, firms have started to predict demand at an individual customer level. In fact, personalized prediction is becoming increasingly popular in e-commerce with notable examples of Amazon and Netflix, both of which predict future demand and make recommendations for individual customers based on their purchasing history. Several mobile applications can now help track demand at the user level (Pontius 2016). An example of the development, deployment, and use of such an application can be found in remote India (Gopalakrishnan 2016). As part of the prime minister's Swachha Bharat (Clean India) program, the Indian government sanctioned subsidies toward constructing toilets in villages. A volunteer organization called Samarthan has built a mobile app which helps track the progress of the demand for construction of toilet through various agencies and stages. The app has helped debottleneck the provision of toilets.

2.2 Inventory Optimization

Inventory planning and control in its simplest form involves deciding when and how much to order to balance the trade-off between inventory investment and service levels. Service levels can be defined in many ways, for example, fill rate measures the percentage of demand satisfied within the promised time window. Inventory investment is often measured by inventory turnover, which is the ratio between annual cost of goods sold (COGS) and average inventory investment. Studies have shown that there is a significant correlation between overall manufacturing profitability and inventory turnover (Sangam 2010).

Inventory management often involves the planning and coordination of activities across different parts of the supply chain. The lack of coordination can lead to excessive cost and poor service levels. For example, the bullwhip effect (Lee et al. 1997) is used to describe the upstream amplification and variability in demand of a supply chain due to reactive orders placed by wholesalers, distributors, and factory planners. There are modern tools that can help reduce the effect of such actions by increasing demand visibility and sharing of information (Bisk 2016).

A study by IDC Manufacturing Insights found that many organizations that utilized inventory optimization tools reduced inventory levels significantly in 1 year (Bodenstab 2015). Inventory optimization plays a critical role in the high-tech industry where most products and components become obsolete quickly but demand fluctuates significantly. The ability to predict demand and optimize inventory or safety stock is essential for survival because excess inventory may have to be written off and incur a direct loss. For instance, during the tech bubble burst in 2001, the network giant Cisco wrote off $2.1 billion of inventory (Gilmore 2008).

Inventory management can be improved through acquiring better information and real-time decision-making. For example, an American supermarket chain headquartered in Arkansas had a challenge to improve customer engagement within several of their brick-and-mortar locations. Managers were spending hours in getting the inventory of products in position instead of spending time on customer engagement. The R&D division developed a mobile app that fed real-time information to concerned employees. This mobile app provided a holistic view of sales, replenishment, and other required data that were residing in multiple data sources. They also developed an app for the suppliers to help them gain a better understanding of how their products were moving. Likewise, one of the leading retail chains of entertainment electronics and household appliances in Russia was able to process POS data in real time, which helped in avoiding shortages and excessive stock (Winckelmann 2013). The processing of inventory data of over 9000 items in 370 stores and four distribution centers is complex and time consuming. Their use of the SAP HANA[2] solution with in-memory real-time processing and database compression was a significant asset in improving the results.

2.3 Supply Chain Disruption

One of the biggest challenges to supply chain managers is managing disruption. It is important to predict potential disruptions and respond to them quickly to minimize their impact. Supply chain disruption can have a significant impact on corporate performance. At a very high level, firms impacted by supply chain disruptions have 33–40% lower stock returns relative to their benchmark and suffer a 13.5% higher volatility in share prices as compared to a previous year where there was no

[2] SAP HANA is an in-memory RDBMS of SAP, Inc.

disruption. Disruptions can have a significant negative impact on profitability—a typical disruption could result in a 107% drop in operating income, 7% lower sales growth, and 11% higher cost (Hendricks and Singhal 2015).

Supply chain disruptions can be caused by either uncontrollable events such as natural disasters or controllable events such as man-made errors. Better information and analytics can help predict and avoid man-made errors. For example, one shipping company that was facing challenges of incomplete network visibility deployed a supply chain technology that gave them a seamless view of the system. The technology enabled managers to get shipping details and take preventive or corrective actions in real time. In this example, prescriptive analytics could have also provided better decision support for the managers to assess and compare various options and actions. The benefits of improved efficiency, more reliable operations, and better customer satisfaction could have aided in the expansion of their customer base and business growth (Hicks 2012).

Connected Cows is a widely reported example of technology being used to aid farmers in better monitoring their livestock (Heikell 2015). The cows are monitored for well-being 24 h a day. This technology not only helps in taking better care of the livestock but also in reducing the disruptions in the production of dairy houses. Connected Cows helps farmers to determine which cows are sick and take timely action to nurse them back to good health with minimal effect on production. A similar concept can be applied to other assets of an organization where creating connected assets can draw valuable insights and provide needed preventive or corrective actions that minimize supply chain disruptions.

All of the aforementioned examples have had considerable historical data that helped in identifying supply chain disruptions and risk assessment. At times, this is not the case, and rare events such as Hurricane Katrina, epidemics, and major outages due to fire accidents may occur. Such events have high impact but low probability without much historical data, and hence the traditional approach cannot be used. The HBR review paper (Simchi-Levi et al. 2014) has addressed this issue by developing a model that assesses the impact of such events rather than their cause. In these extreme cases, the mitigation strategy takes center stage. They visualize the entire supply chain as a network diagram with nodes for the supplier, transportation center, distribution center, etc. where the central feature is the time to recovery (TTR)—"the time it would take for a particular node to be fully restored to functionality after a disruption." Using linear optimization, the model removes one node at a time to determine the optimal response time, and it generates the performance index (PI) for each node. There are many benefits for this approach; most importantly, managers gain a thorough understanding on the risk exposure of each node. The risk can subsequently be categorized as high, medium, and low, and corresponding prescriptive actions can be initiated. This model also depicts some of the dependencies among the nodes and the bottlenecks. There are certain cases where the total spending is low but the overall impact of disruption is significant—a carmaker's (Ford) spending on valves is low; however, the supply disruption of these components would cause production line to be shut down. This methodology was used by the Ford Motor Company to assess its exposure to supply chain disruptions.

2.4 Commodity Procurement

The price and supply of commodity can fluctuate significantly over time. Because of this uncertainty, it becomes difficult for many companies that rely on commodity as raw materials to ensure business continuity and offer a constant price to their customers. The organizations that use analytics to identify macroeconomic and internal indicators can do a more effective job in predicting which way prices might go. Hence, they can insulate themselves through inventory investment and purchases of future and long-term contracts. For example, a sugar manufacturer can hedge itself from supply and demand shocks by multiple actions, such as contracting out production on a long-term basis, buying futures on the commodity markets, and forward buying before prices upswing.

Another example is the procurement of ethanol that is used in medicines or drugs. Ethanol can be produced petrochemically or from sugar or corn. Prices of ethanol are a function of its demand and supply in the market, for which there is good degree of volatility. The price of ethanol is also affected by the supply of similar products in the market. As such, there are numerous variables that can impact the price of ethanol. Data analytics can help uncover these relationships to plan the procurement of ethanol. The same analytics tools and models can be extended to other commodity-based raw materials and components (Chandrasekaran 2014).

The last example is the spike in crop price due to changing climate. Climate change is likely to affect food and hunger in the future due to its impact on temperature, precipitation, and CO_2 levels on crop yields (Willenbockel 2012). Understanding the impact of climate change on food price volatility in the long run would be useful for countries to take necessary preventive and corrective actions. Computable general equilibrium (CGE) is used by researchers to model the impact of climate change, which has the capability to assess the effects external factors such as climate can have on an economy. The baseline estimation of production, consumption, trade, and prices by region and commodity group takes into account the temperature and precipitation (climate changes), population growth, labor force growth, and total factor productivity growth in agricultural and nonagricultural sectors. The advanced stage simulates various extreme weather conditions and estimates crop productivity and prices subsequently.

The examples provided barely touch upon the many different possible applications in supply chain management. The idea of the survey is to provide guidance regarding main areas of applications. The references at the end of the chapter contain more examples and descriptions of methods. In the next section, we describe in detail an example that illustrates inventory optimization and distribution strategies at a major wireless carrier.

3 VASTA: Wireless Service Carrier—A Case Study

Our case study was set in 2010 where VASTA was one of the largest wireless service carriers in the USA and well known for its reliable national network and superior customer service. In the fiscal year of 2009, VASTA suffered a significant inventory write-off due to the obsolescence of handsets (cell phones). At the time, VASTA carried about $2 billion worth of handset inventory in its US distribution network with a majority held at 2000+ retail stores. To address this challenge, the company was thinking to change its current "push" inventory strategy, in which inventory was primarily held at stores, toward a "pull" strategy, where the handset inventory would be pulled back from the stores to three distribution centers (DCs) and stores would alternatively serve as showrooms. Customers visiting stores would be able to experience the latest technology and place orders, while their phones would be delivered to their homes overnight from the DCs free of charge. The pull strategy had been used in consumer electronics before (e.g., Apple), but it had not been attempted by VASTA and other US wireless carriers as of yet (Zhao 2014a, b).

As of 2010, the US wireless service market had 280 million subscribers with a revenue of $194 billion. With a population of about 300 million in the USA, the growth of the market and revenue were slowing down as the market became increasingly saturated. As a result, the industry was transitioning from the "growth" business model that chased revenue growth to an "efficiency" model that maximized operational efficiency and profitability.

The US wireless service industry was dominated by a few large players. They offered similar technology and products (handsets) from the same manufacturers, but competed for new subscribers on the basis of price, quality of services, reliability, network speeds, and geographic coverage. VASTA was a major player with the following strengths:

- Comprehensive national coverage
- Superior service quality and reliable network
- High inventory availability and customer satisfaction

These strengths also led to some weaknesses:

- Lower inventory turnover and higher operating cost when compared to competitors.
- Services and products priced higher than industry averages due to the higher operating costs

The main challenge faced by VASTA was its cost efficiency, especially in inventory costs. VASTA's inventory turnover was 28.5 per year, which was very low compared to what Verizon and Sprint Nextel achieved (around 50–60 turns per year). Handsets have a short life cycle of about 6 months. A $2 billion inventory investment in its distribution system posed a significant liability and cost for VASTA due to the risk of obsolescence. In the following sections, we will analyze VASTA's proposition for change using sample data and metrics.

3.1 Problem Statement

To maintain its status as a market leader, VASTA must improve its cost efficiency without sacrificing customer satisfaction. VASTA had been using the "push" strategy, which fully stocked its 2000+ retail stocked to meet customer demand. The stores carried about 60% of the $2 billion inventory, while distribution centers carried about 40%.

The company was thinking to change the distribution model from "push" to "pull" which pulled inventory back to DCs. Stores would be converted to showrooms, and customers' orders would be transmitted to a DC which then filled the orders via express overnight shipping. Figures 24.1 and 24.2 depict the two strategies. In these charts, a circle represents a store and a triangle represents inventory storage.

The "push" and "pull" strategies represent two extreme solutions to a typical business problem in integrated distribution and logistics planning, that is, the strategic positioning of inventory. The key questions are as follows: Where to place inventory in the distribution system? And how does it affect all aspects of the system, from inventory to transportation and fulfillment to customer satisfaction?

Clearly, the strategies will have a significant impact not only on inventory but also on shipping, warehouse fulfillment, new product introduction, and, most importantly, consumer satisfaction. The trade-off is summarized in Table 24.1.

While the push strategy allowed VASTA to better attract customers, the pull strategy had the significant advantage of reducing inventory and facilitating the fast introduction of new handsets, which in turn reduced the cost and risk of inventory obsolescence. However, the pull strategy did require a higher shipping and warehouse fulfillment cost than the push strategy. In addition, VASTA had to renovate stores to showrooms and retrain its store workforce to adapt to the change.

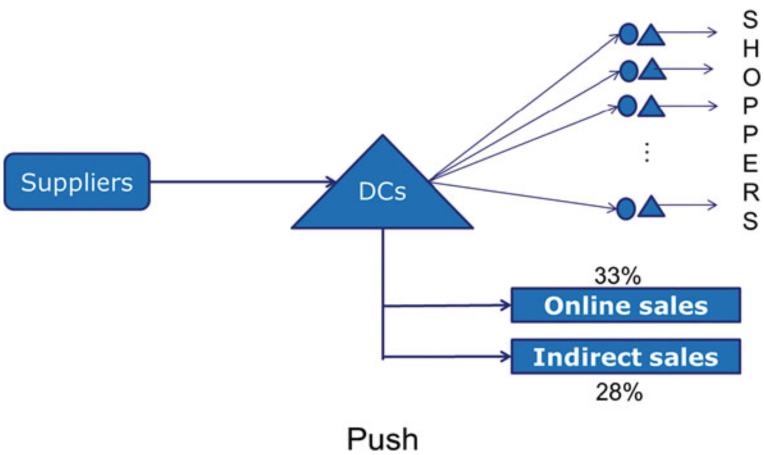

Fig. 24.1 VASTA's old distribution model. Source: Lecture notes, "VASTA Wireless—Push vs. Pull Distribution Strategies," by Zhao (2014b)

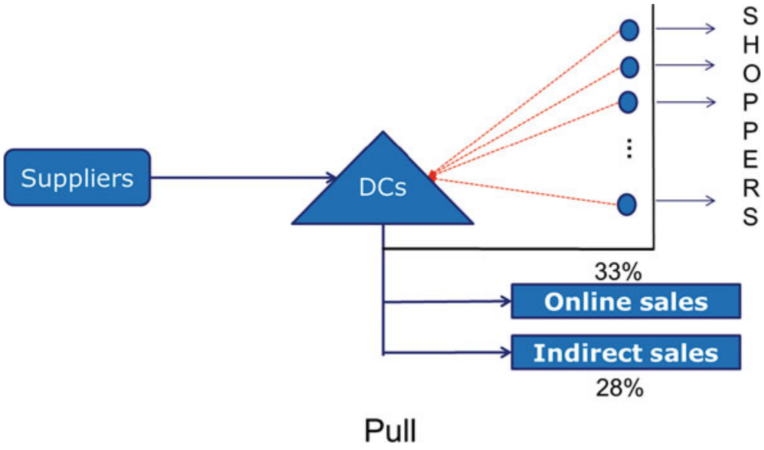

Fig. 24.2 VASTA's proposed new distribution model. Source: Lecture notes, "VASTA Wireless—Push vs. Pull Distribution Strategies," by Zhao (2014b)

Table 24.1 Pros and cons of the two distribution models

	Pros	Cons
Push	• Customer satisfaction • Batch picking at DCs • Batch, 2-day shipping to stores	• Significant inventory investment • Risk of obsolescence
Pull	• Significant inventory reduction • Faster switch to new handsets	• Customers have to wait for delivery • Unit picking at DCs • Unit, express overnight shipping to individual customers

Intuitively, the choice of pull versus push strategies should be product specific. For instance, the pull strategy may be ideal for low-volume (high uncertainty) and expensive products due to its relatively small shipping and fulfillment cost but high inventory cost. Conversely, the push strategy may be ideal for high-volume (low uncertainty) and inexpensive products. However, without a quantitative (supply chain) analysis, we cannot be sure of which strategy to use for the high-volume and expensive products and the low-volume and inexpensive products; nor can we be sure of the resulting financial impact.

3.2 Basic Model and Methodology

We shall evaluate the push and pull strategies for each product at each store to determine which strategy works better for the product–store combination from a cost perspective. For this purpose, we shall consider the total landed cost for product

i at store j, C_{ij}, which is the summation of store inventory cost, IC_{ij}; shipping cost, SC_{ij}; and DC fulfillment cost, FC_{ij}:

$$C_{ij} = IC_{ij} + SC_{ij} + FC_{ij} \tag{24.1}$$

The store inventory cost is represented by

$$IC_{ij} = h_i \times I_{ij} \tag{24.2}$$

where h_i is the inventory holding cost rate for product i (per unit inventory per unit of time) and I_{ij} is the average inventory level of product i at store j.

The shipping cost is represented by

$$SC_{ij} = s_j \times V_{ij} \tag{24.3}$$

where s_j is the shipping cost rate (per unit) incurred for demand generated by store j and V_{ij} is the sales volume per unit of time for product i at store j. Under the push strategy, s_j is the unit shipping cost to replenish inventory at store j by the DCs; under the pull strategy, s_j is the unit shipping cost to deliver the handsets to individual customers from the DCs.

Finally, the DC fulfillment cost is represented by

$$FC_{ij} = f\left(V_{ij}\right) \tag{24.4}$$

where f is an increasing and concave function representing economies of scale in picking and packing.

We shall ignore the difference in DC inventory levels between push and pull because under both strategies, the DCs face the same aggregated demand and must provide the same inventory availability. We summarize the calculation in Table 24.2.

We need to estimate all cost parameters and sales (demand) and inventory level statistics for each product–store combination from the data.

Table 24.2 Basic model of costs

For product ***i*** at store ***j***	Costs (per unit of time)
Average inventory level	I_{ij}
Inventory cost	$IC_{ij} = h_i \times I_{ij}$
Weekly sales volume	V_{ij}
Shipping cost	$SC_{ij} = s_j \times V_{ij}$
Fulfillment cost	$FC_{ij} = f(V_{ij})$
Total cost	$IC_{ij}+SC_{ij}+FC_{ij}$

3.3 Cost Parameter Estimates

To calculate the costs, such as store inventory, shipping, and DC fulfillment (e.g., picking and packing) cost for each product–store combination, we need to estimate the inventory holding cost rate, h_i; the shipping cost rate, s_j; and the fulfillment cost function, $f(V_{ij})$. We will use a previously collected data set of sales (or demand, equivalently) and inventory data at all layers of the VASTA's distribution system for 60 weeks. One period will equal 1 week because inventory at both the stores and DCs is reviewed on a weekly basis.

Inventory cost rate:

Inventory holding cost per week = capital cost per week + depreciation cost per week

Capital cost per week = Annual capital cost/Number of weeks in a year

Depreciation cost per week = [Product value − Salvage value]/Product life cycle

VASTA carried two types of handsets: smartphones and less expensive feature phones with parameters and inventory holding cost per week, h_i, as in Table 24.3.

Shipping cost rate: Clearly, the shipping rates are distance and volume dependent. Here, we provide an average estimate for simplicity. The pull strategy requires shipping each unit from DCs to individual customers by express overnight freight. Quotation from multiple carriers returned the lowest flat rate of $12/unit. The push strategy, however, requires weekly batch shipping from DCs to stores by standard 2-day freight. Overnight express rate is typically 2.5 times the 2-day shipping rate; with a volume discount of 40%, we arrive at an average of $2.88/unit. Table 24.4 summarizes the shipping rates.

DC fulfillment cost: Distribution centers incur different costs for batch picking and packing relative to unit picking and packing due the economies of scale. For VASTA's DCs, the pick of the first unit of a product costs on average $1.50. If more than one unit of the product is picked at the same time (batch picking), then the cost of picking any additional unit is $0.1. We shall ignore the packing cost as it is negligible relative to the picking cost.

Table 24.3 Features of phones sold by VASTA

Smartphones (expensive)	Feature (inexpensive) phones
• Average product value: $500	• Average product value: $200
• Salvage value at store: 0%	• Salvage value at store: 0%
• Annual capital cost: 7%	• Annual capital cost: 7%
• Inventory cost/week: $19.90	• Inventory cost/week: $7.96

Table 24.4 Shipping costs of phones

	Pull	Push
Shipping method	Overnight express to customers	2-day batch to stores
Shipping cost rate s_j	$12/unit	$2.88/unit

Under the push strategy, the stores are replenished on a weekly basis. Let V_{ij} be the weekly sales volume. Because of batch picking, the weekly fulfillment cost for product *i* and store *j* is

$$f\left(V_{ij}\right) = \$1.50 + \left(V_{ij} - 1\right) \times \$0.1 \quad for\ V_{ij} > 0. \tag{24.5}$$

Under the pull strategy, each demand generated by a store must be fulfilled (picked) individually. Thus, the fulfillment cost for product *i* and store *j* is

$$f\left(V_{ij}\right) = V_{ij} \times \$1.50 \quad for\ V_{ij} > 0. \tag{24.6}$$

3.4 Analysis, Solution, and Results

To simplify the analysis, we shall group products with similar features together based on their sales volume and cost. There are essentially two types of phones: smartphones and feature phones. The average cost for a smartphone is \$500, and the average cost of a feature phone is \$200. Thus, we shall classify products into four categories as follows:

- High-volume and expensive products, that is, hot-selling smartphones
- High-volume and inexpensive products, that is, hot-selling feature phones
- Low-volume and expensive products, that is, cold-selling smartphones
- Low-volume and inexpensive products, that is, cold-selling feature phones

Using the data of a representative store and a representative product from each category (Table 24.5), we shall showcase the solution, analysis, and results.

In the pull model for high-volume products, we assume a per-store inventory level of five phones—these are used for demonstration and enhancing customer experience. Table 24.6 compares the total cost and cost breakdown between the push and pull strategies for the representative high-volume and expensive product.

The calculation shows that we can save 46.51% of the total landed cost for this high-volume and expensive product if we replace the push strategy by the pull strategy. This is true because the savings on inventory cost far exceeds the additional cost incurred for shipping and DC fulfillment.

Table 24.5 Representative sales of types of phone

	Average Weekly sales volume (unit)	Average On-hand inventory (unit)
High volume and expensive (hot-smart)	99	120
High volume and inexpensive (hot-feature)	102	110
Low volume and expensive (cold-smart)	2.5	15
Low volume and inexpensive (cold-feature)	7.3	25

Table 24.6 Savings for “hot-smart” phones between pull and push strategies

High volume and expensive (hot-smart)	Pull	Push
Inventory level	**5** *(I_{ij})*	**120** *(I_{ij})*
Inventory cost	**\$99.52** *($I_{ij} \times h_{ij} = 5 \times \$19.90$)*	**\$2388.46** *($I_{ij} \times h_{ij} = 120 \times \$19.90$)*
Weekly sales volume	**99** *(V_{ij})*	**99** *(V_{ij})*
Shipping cost	**\$1188** *($V_{ij} \times s_{ij} = 99 \times \$12/unit$)*	**\$285.12** *($V_{ij} \times s_{ij} = 99 \times \$2.88/unit$)*
Fulfillment cost	**\$148.50** *($V_{ij} \times \$1.50 = 99 \times \$1.50$)*	**\$11.30** *($\$1.50 + (V_{ij} - 1)*0.1 = \$1.50 + 98*0.1$)*
Total cost	**\$1436.02**	**\$2684.88**
Savings	–	**46.51%**

Table 24.7 Savings for “hot-feature” phones between pull and push strategies

High volume and inexpensive (hot-feature)	Pull	Push
Inventory level	**5** *(I_{ij})*	**110** *(I_{ij})*
Inventory cost	**\$39.81** *($I_{ij} \times h_{ij} = 5 \times \$7.96$)*	**\$875.77** *($I_{ij} \times h_{ij} = 110 \times \$7.96$)*
Weekly sales volume	**102** *(V_{ij})*	**102** *(V_{ij})*
Shipping cost	**\$1224** *($V_{ij} \times s_{ij} = 102 \times \$12/unit$)*	**\$293.76** *($V_{ij} \times s_{ij} = 102 \times \$2.88/unit$)*
Fulfillment cost	**\$153.00** *($V_{ij} \times \$1.50 = 102 \times \$1.50$)*	**\$11.60** *($\$1.50 + (V_{ij} - 1)*0.1 = \$1.50 + 101*0.1$)*
Total cost	**\$1416.81**	**\$1181.13**
Savings	–	**−19.95%**

Next, we consider the high-volume and inexpensive product. As shown in Table 24.7, the pull strategy does not bring any savings but incurs a loss of about 20% relative to the push strategy. Clearly, the saving on the inventory cost in this case is outweighed by the additional spending on shipping and DC fulfillment.

Now, we consider the low-volume products and assume two store copies for demonstration in the pull method’s showroom. Table 24.8 shows the calculation for the low-volume and expensive product.

For the low-volume and inexpensive product, refer to Table 24.9.

Table 24.8 Savings for "cold-smart" phones between pull and push strategies

Low volume and expensive (cold-smart)	Pull	Push
Inventory level	**2** *(I_{ij})*	**15** *(I_{ij})*
Inventory cost	**\$38.81** ($I_{ij} \times h_{ij} = 2 \times \$19.90$)	**\$298.56** ($I_{ij} \times h_{ij} = 15 \times \$19.90$)
Weekly sales volume	**2.5** (V_{ij})	**2.5** (V_{ij})
Shipping cost	**\$30.00** ($V_{ij} \times s_{ij} = 2.5 \times \$12/unit$)	**\$7.20** ($V_{ij} \times s_{ij} = 2.5 \times \$2.88/unit$)
Fulfillment cost	**\$3.75** ($V_{ij} \times \$1.50 = 1.5 \times \$1.50$)	**\$1.65** ($\$1.50 + (V_{ij} - 1)*0.1$ $= \$1.50 + 1.5*0.1$)
Total cost	**\$73.56**	**\$307.41**
Savings	–	**76.07%**

Table 24.9 Savings for "cold-feature" phones between pull and push strategies

Low volume and inexpensive (cold-feature)	Pull	Push
Inventory level	**2** (I_{ij})	**25** (I_{ij})
Inventory cost	**\$15.92** ($I_{ij} \times h_{ij} = 2 \times \$7.96$)	**\$199.04** ($I_{ij} \times h_{ij} = 120 \times \$7.96$)
Weekly sales volume	**7.3** (V_{ij})	**7.3** (V_{ij})
Shipping cost	**\$87.60** ($V_{ij} \times s_{ij} = 7.3 \times \$12/unit$)	**\$21.02** ($V_{ij} \times s_{ij} = 7.3 \times \$2.88/unit$)
Fulfillment cost	**\$10.95** ($V_{ij} \times \$1.50 = 7.3 \times \$1.50$)	**\$2.13** ($\$1.50 + (V_{ij} - 1)*0.1$ $= \$1.50 + 6.3*0.1$)
Total cost	**\$114.47**	**\$222.19**
Savings	–	**48.48%**

Table 24.10 Savings for all types of phones between pull and push strategies

	Cold-smart	Cold-feature	Hot-smart	Hot-feature
% Savings	76.07%	48.48%	46.51%	–19.95%

Table 24.10 summarizes the percentage savings as we move from "push" to "pull" for the representative store and representative products of all four categories.

Consistent to our intuition, the pull strategy brings the highest savings for the low-volume and expensive product (cold-smart), and the lowest savings (even a loss) for the high-volume and inexpensive product (hot-feature). In general, the pull strategy tends to bring less savings for products with a higher volume and/or a less cost.

To assess the impact of the pull strategy on store inventory, we quantify the reduction of inventory investment per store. For the representative store, Table 24.11 shows the number of products in each category and their corresponding inventory level reduction. Specifically, there are 22 products in the hot-smart category, 20 in the hot-feature category, 15 in the cold-smart category, and 11 in the cold-feature category. The store inventory investment can be calculated for both the pull and push strategies.

From this table, we can see that inventory investment per store under the pull strategy is only about 5% of that under the push strategy. Thus, the pull strategy can reduce the store-level inventory by about 95%. Given that store inventory accounts for 60% of the $2 billion total inventory investment, the pull strategy will bring a reduction of at least $1 billion in inventory investment as compared to the push strategy.

Despite the significant savings in inventory, the pull strategy can increase the shipping and DC fulfillment costs substantially. To assess the net impact of the pull strategy, we shall aggregate the costs over all products for each cost type (inventory, shipping, and fulfillment) in the representative store and present them in Table 24.12.

The table shows that the inventory cost reduction outweighs the shipping/picking cost inflation and thus the pull strategy results in a net savings per store of about 31% relative to the push strategy.

Table 24.11 Store inventory investment for pull and push strategies

		Pull		Push	
Category	# of products	Inventory level	Inventory investment	Inventory level	Inventory investment
Hot-smart	22	5	$5 \cdot \$500 \cdot 22 = \$55{,}000$	120	$120 \cdot \$500 \cdot 22 = \$1{,}320{,}000$
Hot-feature	20	5	$5 \cdot \$200 \cdot 20 = \$20{,}000$	110	$110 \cdot \$200 \cdot 20 = \$440{,}000$
Cold-smart	15	2	$5 \cdot \$200 \cdot 20 = \$15{,}000$	15	$110 \cdot \$200 \cdot 20 = \$112{,}500$
Cold-feature	11	2	$2 \cdot \$200 \cdot 11 = \$4{,}400$	25	$25 \cdot \$200 \cdot 11 = \$55{,}000$
Total	68	–	$94,400	–	$1,927,500

Table 24.12 Total costs for pull and push strategies

Per store per week	Pull	Push
Total inventory cost	$3757.85	$76,729.33
Total shipping cost	$52,029.60	$12,487.10
Total picking cost	$6,503.70	$528.78
Total cost	$62,291.15	$89,745.21

3.5 Advanced Model and Solution

As shown by our prior analysis, the pull strategy does not outperform the push strategy for all products. In fact, for high-volume and inexpensive products (hot-feature phones), it is better to satisfy a portion of demand at stores. Thus, the ideal strategy may be hybrid, that is, the store should carry some inventory so that a fraction of demand will be met in-store, while the rest will be met by overnight express shipping from a DC. The question is how to set the store inventory level to achieve the optimal balance between push and pull.

To answer this question, we shall introduce more advanced inventory models (Zipkin 2000). Consider the representative store and a representative product. Store inventory is reviewed and replenished once a week. The following notation is useful:

- T: the review period
- $D(T)$: the demand during the review period:
- $E[D(t)] = \mu$: the mean of the demand during the review period
- $STDEV[D(t)] = \sigma$: the standard deviation of the demand during the review period

The store uses a base-stock inventory policy that orders enough units to raise the inventory (on-hand plus on order) to a target level S at the beginning of each period. The probability of satisfying all the demand in this period via store inventory alone is α (α is called the Type 1 service level). Assuming that $D(t)$ follows a normal distribution, $Normal(\mu, \sigma)$, and lead time is negligible (as it is true in the VASTA case), then

$$S = \mu + z_\alpha \sigma, \tag{24.7}$$

where z_α is the normal distribution standard score of α. Clearly, if $\alpha = 0$, we return to the pull strategy where all demand is met by the DCs, only. If $\alpha = 100\%$, then we return to the push strategy where all demand is met by the stores, only. A hybrid strategy will set α such that $0 < \alpha < 1$.

The expected store demand met by the DCs via overnight express shipping can be written as

$$E\left[D_1\right] = E\left[\max\left\{0, D(T) - S\right\}\right] = \sigma\left[\phi\left(z_\alpha\right) - z_\alpha\left(1 - \alpha\right)\right], \tag{24.8}$$

where $\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$ is the standard normal probability density function.

The expected store demand met by store inventory is

$$E\left[D_2\right] = E\left[\min\left\{D(T), S\right\}\right] = E\left[D(T)\right] - E\left[D_1\right]. \tag{24.9}$$

At the end of the period, the expected inventory level is

$$EI = E\left[\max\left\{0, S - D(T)\right\}\right] = S - \mu + E\left[D_1\right]. \tag{24.10}$$

Because the inventory level at the beginning of the period is S, the average on-hand inventory during the period can be approximated by

$$I = \frac{S + EI}{2}. \tag{24.11}$$

Using α as the decision variable, we can calculate the total landed cost by Eq. (24.1),

$$C_{ij} = IC_{ij} + SC_{ij} + FC_{ij},$$

where $IC_{ij} = h_i \times I_{ij}$ and I_{ij} come from Eq. (24.11).

SC_{ij} is the sum of two parts:

1. Batch and 2-day shipping of the quantity $E[D_2]$ from DCs to the store
2. Express overnight shipping of the quantity $E[D_1]$ from DCs to customers

FC_{ij} is also the sum of two parts:

1. Batch picking at DCs for the quantity of $E[D_2]$
2. Individual picking at DCs for the quantity of $E[D_1]$

To identify the optimal strategy, we shall solve the following nonlinear optimization problem for product i at store j. That is, we shall find the α_{ij} ($0 \leq \alpha_{ij} \leq 1$) such that the total cost C_{ij} is minimized

$$\text{Min}_{0 \leq \alpha_{ij} \leq 1} C_{ij}.$$

To solve this problem, we shall need demand variability (or uncertainty) information in addition to averages, such as the standard deviation of demand per unit of time. Table 24.13 provides the estimates of the representative products at the representative store.

The results for the representative hot-smartphone are plotted in Fig. 24.3. It shows how the total cost varies with α (store type 1 service level). Clearly, a hybrid strategy is best for the representative hot-feature phone (better than both the pull and push strategies). However, the pull strategy is still the best for the representative hot-smartphone.

Similarly, the results for the low-volume products are plotted in Fig. 24.4. The pull strategy works the best for the cold-smartphone, while a hybrid strategy is the best for the cold-feature phone.

Table 24.13 Estimates of representative phones at a representative store

	Weekly sales average	Weekly sales standard deviation	On-hand inventory
High volume and expensive (hot-smart)	99	40	120
High volume and inexpensive (hot-feature)	102	53	110
Low volume and expensive (cold-smart)	2.5	2.3	15
Low volume and inexpensive (cold-feature)	7.3	9.1	25

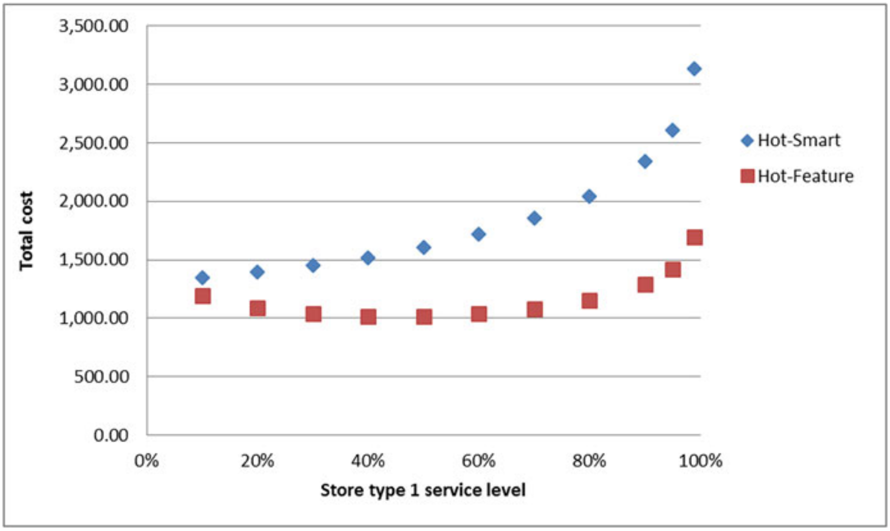

Fig. 24.3 Comparison between push and pull strategies for hot phones

Table 24.14 Savings from moving to pull strategy

	Hot-feature	Cold-feature
The best Type 1 service (α)	50%	50%
% demand met by store	79%	50%
Saving from pull	28%	8.4%

We can draw the following conclusions from these results:

- The pull strategy is best for both the hot- and cold-smartphones.
- For feature phones, it is best to use a hybrid strategy (refer to Table 24.14).

From the store perspective, the savings gained from switching from pull to hybrid is 13.4% (or $8081.90) per store per week.

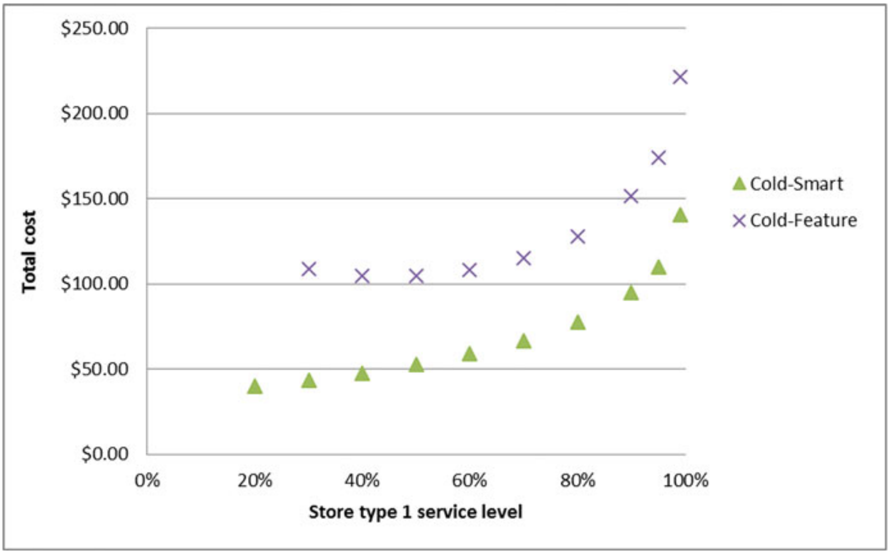

Fig. 24.4 Comparison between push and pull strategies for cold phones

3.6 Customer Satisfaction and Implementation

So far, our analysis focuses on the total landed cost, which is smaller under the pull strategy than the push strategy. Despite this cost efficiency, a fundamental issue remains: Will customers accept the pull strategy? More specifically, will customers be willing to wait for their favorite cell phones to be delivered to their doorstep overnight from a DC?

An analysis of the online sales data shows that in the year 2010, one out of three customers purchased cell phones online. While this fact implies that a large portion of customers may be willing to wait for delivery, it is not clear how the rest two-thirds of customers may respond to the pull strategy. It is also unclear how to structure the delivery to minimize shipping cost while still keeping it acceptable to most customers. The available delivery options include the following:

1. Overnight free of charge
2. Overnight with a fee of $12
3. Free of charge but 2 days
4. Free of charge but store pickup

Different options have significantly different costs and customer satisfaction implications; they must be tested in different market segments and geographic regions. To ensure customer satisfaction, VASTA had decided to start with option 1 for all customers.

Table 24.15 Implementation plan of pull strategy

Phase I	• Implement the pull strategy for one DC and some target stores • Negotiate shipping contracts with carriers • Review savings, service levels, and impact on customers
Phase II	• Implement the pull strategy to all stores served by the DC • Experiment the options of store pickup and 2-day free home shipping
Phase III	• Full-scale implementation of the pull strategy to all three DCs • Review savings, service levels, and impact on customers

Implementation of the pull strategy requires three major changes in the distribution system:

1. Converting retail stores to showrooms and retraining sales workforce
2. Negotiating with carriers on the rate and service of the express shipping
3. A massive transformation of the DCs that will transition from handling about 33% individual customer orders to nearly 72% individual customer orders (the indirect sales, through third-party retail stores such as Walmart, can be fulfilled by batch picking and account for 28% of total sales)

Despite the renovation costs and training expenses, showrooms may enjoy multiple advantages over stores from a sales perspective. For instance, removing inventory can save space for product display and thus enhance customers' shopping experiences. Showrooms can increase the breadth of the product assortment and facilitate faster adoption to newer handsets and thus increase sales. Finally, they can also help to reduce store-level inventory damage and theft, thereby minimizing reverse logistics.

Negotiation with carriers needs to balance the shipping rate and the geographic areas covered as a comprehensive national coverage may require a much higher shipping rate than a regional coverage. Important issues such as shipping damages and insurance coverage should also be included in the contract. The hardest part of implementation is the DC transformation, especially given the unknown market response to the pull strategy. Thus, a three-phase implementation plan (see Table 24.15) had been carried out to slowly roll out the pull strategy in order to maximize learning and avoid major mistakes.

3.7 Epilogue

In 2011, VASTA implemented the pull strategy in its US distribution system. FedEx overnight was used. System inventory reduced from \$2 billion to \$1 billion. Soon after, other US wireless carriers followed suit, and the customer shopping experience of cell phones completely changed in the USA from buying in stores to ordering in stores and receiving delivery at home. In the years after, VASTA continued to fine-tune the pull strategy into the hybrid strategy and explored multiple options of express shipping depending on customers' preferences. VASTA remains as one of the market leaders today.

4 Summary: Business Insights and Impact

In this chapter, we showcase the power of supply chain analytics in integrated distribution and logistics planning via a business case in the US wireless services industry. The company, VASTA, suffered a significant cost inefficiency despite its superior customer service. We provide models, methodology, and decision support for VASTA to transform its distribution strategy from "push" to "pull" and eventually to "hybrid" in order to improve its cost efficiency without sacrificing customer satisfaction. The transformation resulted in $1 billion savings in inventory investment and helped the company to maintain its leadership role in an increasingly saturated marketplace.

Supply chains are complex systems and data rich. We have shown that by creatively combining such data with simple analytics, we can achieve the twin goals of cost efficiency and customer satisfaction while making a significant financial impact. This chapter also reveals three business insights that one should be aware of when employing supply chain analytics:

- *The conflicting goals* of cost efficiency and customer satisfaction are hard to sort out qualitatively. Quantitative supply chain analysis is necessary to strike the balance.
- *System thinking*: Distribution strategies can have a significant impact on all aspects of a system: inventory, shipping, customer satisfaction, as well as in-store and warehouse operations. We must evaluate all aspects of the system and assess the net impact.
- *One size does not fit all*: We should customize the strategies to fit the specific needs of different products and outlets (e.g., stores).

Electronic Supplementary Material

All the datasets, code, and other material referred in this section are available in www.allaboutanalytics.net.

- Data 24.1: Vasta_data.xls

Exercises

Ex. 24.1 Reproduce the basic model and analysis on the representative store for the comparison between push and pull strategies.
Ex. 24.2 Reproduce the advanced model and analysis on the hybrid strategy for the representative store.
Ex. 24.3 For NYC and LA stores, use the basic and advanced models to find out which strategy to use for each type of product, and calculate the cost impact relative to the push strategy.

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