The Impact of Out-of-Stocks and Supply Chain Design on Manufacturers: Insights from an Agent-Based Model
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The Impact of Out-of-Stocks and Supply Chain Design on Manufacturers: Insights from an Agent-Based Model

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Abstract

In today's competitive environment, consumers have high expectations regarding product availability. Out-of-stock (OOS) occurrences can have a detrimental impact to both retailers and manufacturers in terms of lost sales as well as reduced consumer loyalty. In this article, we investigate the impact of repeated OOS occurrences under different supply chain design scenarios, which mix the channel replenishment strategy with the inventory responsibility for in-store shelf management on the retailer versus on the manufacturer. We frame our agent-based simulation to examine the change in manufacturer's market share that results from OOS scenarios not only under different supply chain distribution scenarios (i.e., traditional versus direct store delivery or DSD), but also with different consumer preference characteristics (i.e., high and low brand loyalty) and varied levels of demand. The agent-based simulation allows us to examine the impact of consumer learning under repeated OOS situations. Our results provide new insights for manufacturers regarding repeated supply chain OOS situations.

Keywords

Supply chain design, out of stocks (OOS), direct store delivery (DSD), agent-based simulation

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Consumers have high expectations regarding product availability in today's competitive environment. Despite such expectations, out-of-stock (OOS) situations occur, and are reported to be in the 5–10 percentage range, but can exceed 10 percent for fast-moving and/or promoted items (Gruen, Corsten, and Bharadwaj 2002). Stockouts result from various causes. However, research has shown that the majority of OOS situations, at least in the consumer products/food industry, are caused by retailers' ordering and restocking practices (Gruen, Corsten, and Bharadwaj 2002). Retailers' poor ordering and restocking (or replenishment) practices not only reduce their store sales and service, but also negatively impact manufacturers. When consumers cannot find their preferred brands in a store, "brands may lose their value" (Tokman et al. 2012, 191), and retail OOS events often result in unexpected/unnecessary orders to the manufacturer, increasing costs (Kulp, Lee, and Ofek 2004). In many cases, manufacturers are reliant, to a large degree, on retailers properly managing manufacturers' products, including *ordering* and *replenishment*, in a retail setting.

Manufacturers can seek greater control over managing the *ordering* process for their products by adopting collaborative inventory management approaches, such as vendor-managed inventory (VMI). Williams and Tokar (2008) indicate that collaborative inventory approaches are designed to improve supply-and-demand coordination, while also controlling inventory more effectively. In VMI arrangements, the selling firm is responsible for managing inventory for the buying firm and, as such, buying firms "relinquish control of key resupply decisions" (e.g., order placement) to the selling firm (Waller, Johnson, and Davis 1999, 183). One of the key aspects of VMI is that the selling firm is responsible for monitoring the buying firm's inventory and resupplying product to a customer's designated location (Cottrill 1997).

In the retail industry, the designated delivery location is determined by the *replenishment* strategy whereby manufacturers may deliver to either the retailers' distribution centers or their stores (Pramatari and Miliotis 2008). When manufacturers manage replenishment to the retailers' distribution centers, even when managing that DC-level inventory through VMI, the potential for retailers to create OOS situations through poor in-store restocking practices still exists. Manufacturers can manage replenishment to the retailers' stores, delivering product directly to the store shelf, and manage the inventory (e.g., ordering) in what is called a direct store delivery (DSD) arrangement (Pramatari and Miliotis 2008). For the purposes of this article, we examine two distinct supply chain design scenarios; one that places the responsibility for store-level ordering and in-store replenishment from the retailers' distribution center(s) on the retailer (referred to here as traditional supply chain distribution channel) and the other that places the responsibility for ordering and in-store replenishment on the manufacturer (referred to here as DSD supply chain distribution channel).

While VMI arrangements, in general, have been discussed in the literature, research has not specifically examined the impact of the supply chain replenishment strategy (i.e., delivery location) on retail OOS situations. Williams and Tokar (2008, 224) suggest that research on collaborative inventory approaches needs to "model stockout phenomena more completely, particularly at the retail store echelon." Further, most research focused on OOS situations examines resulting consumer behavior or retailers' performance, not manufacturers' performance. Wu et al. (2013) call for research examining the upstream impact of OOS situations. Finally, Waller, Tangari, and Williams (2008) indicate that the negative impact of repeated stockouts can be significant. However, much of the OOS research in supply chain literature has only examined single stockout occurrences. To understand long-term supply chain implications, research needs to examine repeated OOS situations (Anderson, Fitzsimons, and Simester 2006).

The purpose of this article is to examine OOS situations under different supply chain design scenarios (i.e., traditional versus DSD) and with repeated OOS situations. Our primary focus is the impact of these OOS scenarios on manufacturers given the research by Gruen, Corsten, and Bharadwaj (2002) indicates retailers' practices are often responsible for stockouts in the first place. Since manufacturers have more control over shelf management under DSD arrangements, it is important to understand whether performance varies under different supply chain design scenarios and repeated OOS scenarios.

While used extensively in practice, DSD is not used to replenish all products. Certain product categories, such as salted snacks and soft drinks, tend to experience higher rates of DSD delivery/replenishment. This highlights the need to study different supply chain design scenarios, which may be used across different product types. In our analysis, we incorporate the impact of customer loyalty in the face of OOS conditions for different supply chain designs and analyze its impact on product sales under repeated stockouts.

In this article, we seek to answer the following questions: Does a DSD supply chain distribution channel provide significantly greater benefit to manufacturers than a traditional supply chain distribution channel?

Does high or low brand loyalty influence which supply chain distribution channel is better for manufacturers? What are the implications of repeated stockouts for manufacturers? We used agent-based simulation to model repeated OOS situations in a retail setting. Agent-based simulation has recently been applied in logistics/supply chain management research and offers a means to model dynamic and complex systems.

In the following sections, we review the relevant literature, describe the agent-based model and simulation parameters, and then analyze the simulation results. The results are discussed and implications to academics and practitioners are provided. Finally, we conclude with a research summary and directions for future research.

Literature Review

Empty shelves at retail stores are a frequent occurrence (Papakiriakopoulos and Doukidis 2011). In a retail environment, OOS situations happen at relatively high rates—5–10 percent for standard items and above 10 percent for fast-moving/promoted items in the consumer products/food industry (Gruen, Corsten, and Bharadwaj 2002). It is estimated that one in three customers, shopping in consumer electronic stores, leave without buying at least one item they came into the store to purchase (IHL Group 2015). Similarly, Anderson, Fitzsimons, and Simester (2006) studied the impact of stockouts on a mail-order catalog company selling bedding and home accessories and found 21.9 percent of items ordered during the five-week treatment period were stocked out and 31.6 percent of orders placed included at least one OOS item.

While a stockout can negatively impact customer service and loyalty, it also has a significant impact on profitability for the supply chain. Retailers, for example, lose nearly half of potential purchases when a stockout occurs, resulting in an estimated 4 percent annual sales loss (Gruen, Corsten, and Bharadwaj 2002). A recent study by Battista et al. (2011) estimated OOS situations at an Italian apparel retailer represented 28.7 percent lost revenue growth. The impact of a stockout expands beyond lost sales, however. Out-of-stock situations can reduce customer satisfaction and retail store loyalty, and, when consumers substitute products, true demand patterns are distorted (Ehrenthal and Stölzle 2013). Corsten and Gruen (2003, 608) indicated that OOS scenarios "not only disappoint customers, but perpetuate themselves and drive up costs throughout the supply chain."

When faced with an OOS situation, consumers can take one of five actions: (a) decide not to purchase; (b) delay purchase; (c) buy a competing manufacturer's product at the original retail store; (d) buy a substitute product within the same original brand at the original retail store (e.g., different size or configuration); or (e) buy the desired, original manufacturer's product at a different retail store (Emmelhainz, Emmelhainz, and Stock 1991; Gruen, Corsten, and Bharadwaj 2002). Consumer reactions can vary by product type. For example, consumers are more brand loyal to cosmetics and, thus, are more likely to delay purchase, buy the desired product at a different store, or buy a substitute product within the same original brand (e.g., smaller size), but consumers' reactions to paper towels are quite different as consumers are more likely to buy a substitute product (Gruen and Corsten 2002). To exacerbate this situation, consumer reactions may change when faced with repeated OOS situations. A recent study found that the likelihood that a consumer would switch retail stores more than doubled from the first stockout to the third stockout (ECR Europe and RolandBerger Strategy Consultants 2003).

Ehrenthal and Stölzle (2013) classified stockouts by where in the supply chain they occur: either pre-store (e.g., related to manufacturers having fulfillment/delivery issues to retailers and/or retailers having fulfillment/delivery issues to their stores); or in-store (e.g., retailer ordering problems, store inventory/replenishment problems, and/or promotion-driven stockouts). In-store issues can be significant. Up to 10 percent of the time when product is not available on the shelf, store employees cannot find the inventory in the backroom (Waller, Tangari, and Williams 2008). Phantom inventory (i.e., inventory in store, but not where customers can find it) is common in retailing and can result in a significant amount of lost sales (Ton and Raman 2010).

Research has shown that 70–75 percent of stockouts are due to the retailer's ordering and/or replenishment practices resulting in ordering too few products, placing orders too late to meet demand, or failing to restock shelves in a timely manner (Gruen, Corsten, and Bharadwaj 2002). Many of these OOS scenarios occur in-store. As such, the supply chain design strategy (traditional versus DSD) can potentially have a significant impact on stockouts by affecting in-store fulfillment. Under traditional channels, the manufacturer ships product to the retailer's distribution center and the retailer maintains control of replenishment to the store. Alternatively, products can bypass the retailer's distribution center and be delivered directly to the store. This form of replenishment, called direct to store or direct store delivery (DSD), can be facilitated by the manufacturer (e.g., Coke or Pepsi managing individual retail store delivery) or by a specialty distributor (e.g., produce or greeting cards); regardless, in-store fulfillment, including order and shelf management, is no longer under the control of the retailer. Under DSD, manufacturers are required to meet specific performance goals, such as in-stock percentages (Waller, Johnson, and Davis 1999).

DSD is often used for various food product categories, such as beverages and bread, and sometimes general merchandise categories, such as apparel/footwear, prescription medications, and greeting cards/magazines. Fast-moving and/or perishable items often use DSD channels as they move product to the store faster, in part because a step in the supply chain is removed, and, thus, lead-time to shelf is shorter (GMA Direct Store Delivery Committee and Willard Bishop 2011). While DSD may not make sense for all products, DSD is the preferred channel option for some of the highest selling product categories, accounting for 52 percent of store profits in the grocery/mass merchant industry despite DSD being used for only 24 percent of product volume (GMA Direct Store Delivery Committee, AMR Research, and Clarkston Consulting 2008).

DSD offers many benefits to manufacturers. Not only is lead-time reduced when the retailer's distribution center is bypassed, but also overall system inventory may be reduced. Having the manufacturer manage store shelf inventory has the added benefit of removing inventory from the retailer's backroom and, thus, eliminates inventory "vanishing." Further, since the manufacturer is now managing inventory at the retailer's store shelf, the manufacturer has greater visibility to store-level sales, improving demand management and gaining faster insight into sales with respect to promotional lift, price changes, and new product launches (GMA Direct Store Delivery Committee, AMR Research, and Clarkston Consulting 2008). This visibility helps to reduce demand volatility (Waller, Johnson, and Davis 1999). Shorter lead-times and faster turns also affect cash flow. Direct-store-delivery payment cycles are shorter since the average replenishment cycle is five times faster for DSD than traditional delivery (GMA Direct Store Delivery Committee, AMR Research, and Clarkston Consulting 2008). A well-performing DSD manufacturer provides retailers with value-added services, which may lead to more shelf-space and/or additional promotional opportunities by becoming the supplier of choice. Direct store delivery also provides benefits to the retailer, such as a reduction in labor needed for order management and in-store merchandising. Retailers typically do not own inventory until it arrives to the store shelf, which improves the retailers' cash flow as well (GMA Direct Store Delivery Committee, AMR Research, and Clarkston Consulting 2008).

These benefits do not come to the manufacturer without cost, however. Transportation costs likely increase for the manufacturer due to smaller, more frequent shipments to individual stores rather than large shipments to distribution centers. This generates more sales transactions, which can add costs for both the manufacturer and the retailer. By taking on responsibility for store-shelf management, manufacturers need additional labor with DSD and need to develop different distribution capabilities. If the manufacturer is not replenishing stock frequently enough, OOS events may actually increase. However, DSD in-stock rates are generally higher than traditional delivery options (GMA Direct Store Delivery Committee and Willard Bishop 2011).

Methodology

We consider a supply chain comprised of two manufacturers, A and B, delivering products to two different retailers, 1 and 2. Manufacturers A and B deliver products using two different supply chain distribution channels (i.e., traditional and DSD). When traditional supply chain distribution channels are used (as shown in fig. 1), products are sent from the manufacturer to the retailer's distribution center (DC) and may be temporarily stored before being sent by the retailer to its own individual stores. In contrast, when DSD supply chain distribution channels are used (fig. 2), the manufacturer delivers products directly to the retailer's individual stores, bypassing the retailer's DC. Manufacturer A produces product A, which is sold by Retailer 1 and Retailer 2. Both retailers also sell competing product B produced by Manufacturer B. Retailers 1 and 2 serve consumers that are characterized as either high brand or low brand loyal. Therefore, we model the overall supply chain system as having (a) two competing manufacturers each with its own product brand, (b) two competing retailers, (c) two different supply chain distribution channels (i.e., traditional and DSD), and (d) two types of consumers (i.e., high and low brand loyalty).

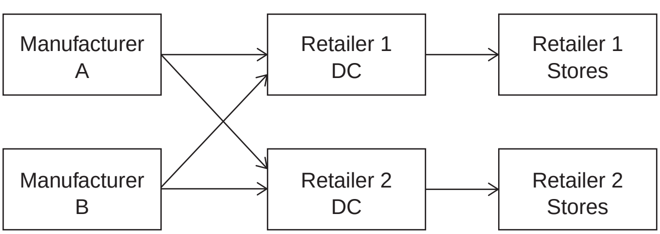

Figure 1 Traditional Supply Chain Distribution Channel

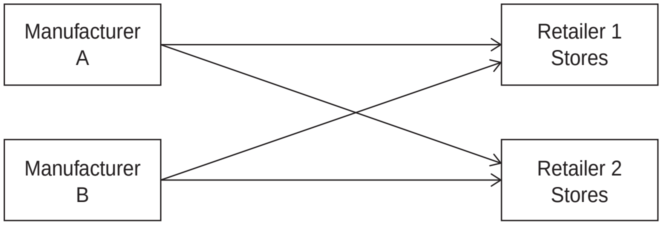

Figure 2 DSD Supply Chain Distribution Channel

Given the complexity of the supply chain under study, we use a simulation approach to test the impact of different supply chain distribution channels (traditional versus DSD) and different consumer preferences (high and low brand loyalty) on manufacturers in the presence of repeated product OOS situations. While simulation models have been widely used in supply chain research, most simulation studies have used discrete event simulation (Evers and Wan 2012). In contrast, we use an agent-based simulation approach to understand consumer learning associated with repeated OOS events.

Agent-based simulation is a simulation modeling approach that uses autonomous and interacting agents that can be programmed to exhibit certain behaviors. Agent-based simulation allows the dynamics of complex and interactive systems, such as supply chains, to be modeled. An overview of agent-based simulation can be found in Macal and North (2010). Recently, agent-based models have been applied to understanding supply chain problems, such as supply chain risk (Basole and Bellamy 2014; Wu et al. 2013). In a supply chain context, agent-based simulation allows agents (who may represent entities or even consumers at the individual level) to interact, negotiate, learn, and adapt behaviors (Wu et al. 2013). We developed an agent-based simulation model using NetLogo (Railsback, Lytinen, and Jackson 2006) to simulate the supply chains depicted in figures 1 and 2.

Figure 3 shows how our agent-based simulation models were built. We first built a basic simulation framework including interactions between customers, competing products, and competing brands. The basic model is then enhanced by incorporating brand loyalty behavior resulting in two separate simulation models. Finally, the different distribution channels are incorporated resulting in four different agent-based simulation models (fig. 3). Each component of the four simulation models developed is discussed below.

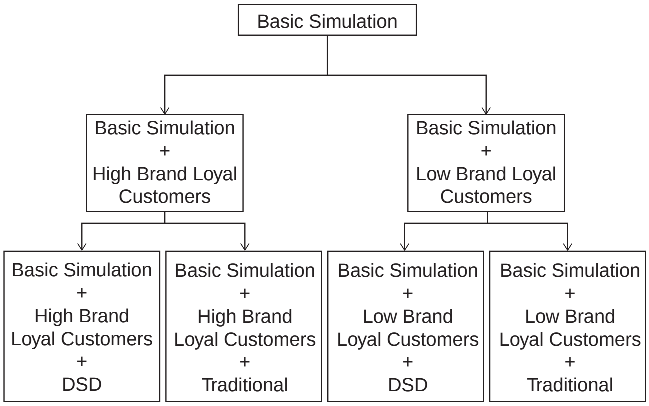

Figure 3 Agent-Based Simulation Models Developed

Basic Simulation

Manufacturers, retailers, and consumers are represented as agents in the basic simulation. The manufacturer agents deliver product to retailers. In addition to supplying its main product (Product A or Product B depending on the manufacturer), we assume that each manufacturer offers additional alternative or substitutable "within brand" products, such as different size presentations, which are also delivered to the retailers. Following the procedures used by Wu et al. (2013), we assume that the manufacturer composition is fixed, and, therefore, manufacturers A and B hold a fixed percentage of the overall market. In other words, if market share for Manufacturer A decreases, Manufacturer B picks up market share. We assume that retailers 1 and 2 also have a fixed percentage of overall market across all retailers whereby if Retailer 1 loses market share, Retailer 2 gains market share (similar to procedures used by Wu et al. 2013).

Demand originates from a population of 1,000 consumer agents. When a consumer agent intends to purchase a product, the consumer agent first decides which store to visit (i.e., Retailer 1 or 2). Once in the store, the consumer agent decides which product to purchase (i.e., Product A, produced by Manufacturer A, or Product B, produced by Manufacturer B). At the start of the simulation, consumer agents are randomly assigned retailer and manufacturer preferences. To obtain 70 percent market share between manufacturers A and B, we randomly assign 70 percent of the agents to have a strong preference for a manufacturer (either A or B). The remaining 30 percent will be manufacturer indifferent or neutral. Similarly, we randomly assign 70 percent of agents to have a strong preference for a retailer (either 1 or 2), while the remaining 30 percent will be retailer indifferent. Since preferences are randomly assigned, agents may (a) have a strong preference for both a manufacturer and a retailer, (b) have a strong preference for a manufacturer (retailer) but be retailer (manufacturer) indifferent, or (c) be indifferent to manufacturer and retailer. Whenever consumer agents prefer a manufacturer or retailer, the agents will choose the preferred manufacturer brand or retailer with a high probability. Initially, the probability of choosing a preferred manufacturer brand or retailer is 1.0, while the probability of choosing a manufacturer brand or retailer when an agent is indifferent is 0.5.

The basic simulation framework allows Retailer 1 to experience stockouts for Product A. When an agent encounters a stockout, several responses are possible. Based on the Gruen, Corsten, and Bharadwaj (2002) study, consumer agents may decide to not purchase the product at all; delay the purchase; substitute by buying Manufacturer B's product; buy a substitute product made by Manufacturer A; or buy Manufacturer A's product at Retailer 2. The likelihood of selecting the different responses in the face of a stockout depends on the brand loyalty of the customer. Retailer 2 and Manufacturer B's Product B do not experience any OOS situations, allowing us to capture the effect of multiple OOS situations on Product A and Retailer 1 without the confounding effects of OOS events from competing entities in the supply chain. Thus, Retailer 2 and Product B represent the numerous substitutions/options typically available to consumers facing an OOS condition.

Incorporating Consumer Loyalty

When facing a stockout for Product A, the likelihood that a consumer decides to either delay the purchase, substitute with Product B, substitute within Brand A, buy Product A at Retailer 2, or simply not purchase the product at all is affected by the level of loyalty the consumer has for Manufacturer A's product brand. While consumers typically experience high levels of brand loyalty for products, such as cosmetics, feminine hygiene, and diapers, other products, such as toilet tissue, paper towels, and salted snacks, tend to provoke low brand loyalty behavior (Gruen, Corsten, and Bharadwaj 2002). In the face of an OOS event, high brand-loyal consumers are more likely to switch stores in order to purchase Manufacturer A's product. In contrast, low brand-loyal consumers are more likely to substitute the product rather than switch to Retailer 2. We use the response parameters reported by Gruen, Corsten, and Bharadwaj (2002) to determine the

Table 1/Different Responses to Product OOS situations and Action Probability Depending on Consumer Type

Action	**Loyal Consumer**	
	High Brand	**Low Brand**
Substitute within brand	0.26	0.20
Substitute with different brand	0.19	0.25
Delay purchase	0.11	0.09
Do not purchase	0.06	0.25
Buy at another store	0.38	0.21

Note: Parameters based on Gruen, Corsten, and Bharadwaj 2002.

likelihood of each potential decision and resulting action (i.e., substitute product, switch stores, or delay purchase) that high and low brand loyal consumers may take when faced with a stockout (see table 1).

The probability of preferring a particular product diminishes whenever the consumer agent encounters an OOS situation. As stated in Tokman et al. (2012), empty shelves can impact consumers' loyalty to the brand. We incorporate this aspect of consumer learning in our simulations by reducing the likelihood that a consumer agent will prefer to purchase Manufacturer A's Product A in the future after experiencing a stockout when a different brand is purchased or the consumer decides to not purchase at all.[1] In other words, when a stockout occurs and the consumer agent decides to either purchase Product B or to not purchase at all, the likelihood that the consumer agent will choose to purchase Product A in the future will be reduced by 2 percent and 5 percent for high and low brand loyal consumers respectively. When faced with OOS situations, an indifferent agent's preference for Product A is reduced by 5 percent. Note that if enough OOS situations are encountered the probability of an agent selecting Product A can diminish to zero (but will never be negative) whereby the agent will not attempt to purchase Product A again.

Incorporating the Distribution Channel

According to Gruen, Corsten, and Bharadwaj (2002), traditional and DSD supply chain distribution channels result in approximately 93 percent and 98 percent in-stock levels respectively. The typical duration (or recovery time) for OOS situations is as follows: 20 percent of OOS situations are replenished in eight hours or less; 25 percent take between eight hours up to one day to be replenished; 36 percent take one to three days to be replenished; and 19 percent take three or more days to be replenished (Gruen, Corsten, and Bharadwaj 2002).

We simulate one full year of retail operations. During the year, 12 random OOS situations are modeled. We model the same number of OOS situations under both traditional and DSD supply chain distribution channels. While OOS events start at the same time under both supply chain distribution channels, OOS events may end at different times. The duration of each OOS event is randomly generated such that its distribution fits the typical duration for OOS situations (20, 25, 36, and 19% of OOS situations taking respectively less than 8 hours, between 8 and 24 hours, one to three days, or over three days) and achieves 93 and 98 percent in-stock levels for traditional and DSD channels respectively.

Simulation Model Testing

Given the nature of the system under study, a nonterminating simulation better reflects the conditions typically encountered in a retail setting where stores remain open for long periods of time, customers continuously visit stores, shelves are replenished on a regular basis and OOS conditions may occur at any time. In addition, a nonterminating simulation allows us to capture the effect of multiple OOS events on product sales. As previously mentioned, we simulate one full year of retail operations.

As is typically the case with nonterminating simulations, for each simulation run we delete the initial data obtained, a.k.a. warm up the model, to avoid the initial transient problem. Using Welch's (1983) method, we determined that in order to obtain stable performance measures, the first 10 days of simulated time as well as the first 10 days after each OOS event had to be discarded. Note that each OOS event can create a significant momentary impact on performance measures, such as daily sales. As a result, it is necessary to delete the first 10 days of simulated time after each OOS event to collect performance measures under steady state. After the warm-up period, we collect performance measures for 14 consecutive days. Using the data collected after the warm-up period we use the batch means method (Law and Kelton 1999; Law and Carson 1979) to obtain confidence intervals for performance measures resulting in interval half-lengths of less than 1 percent of the mean (i.e., 95% confidence intervals for performance measures that are within +/− 1% of the mean).

The simulation models were verified performing extensive testing of each model under extreme conditions to ensure simulation outputs behave as expected. As part of the testing performed, we corroborated that the randomly generated OOS events resulted in typical measures of in-stock percentages. In addition, the randomly generated OOS events also followed typical OOS distribution lengths reported in the literature (see Gruen, Corsten, and Bharadwaj 2002).

As depicted in figure 3 (above) and previously described, four different simulation models were developed. In order to compare performance metrics across the different models, we use common random numbers as a variance reduction technique. Using common random numbers allows each simulation to start with the same population mix. Using the same population mix allows us to run each simulation model with the same initial system conditions. In addition, whenever performance metric comparisons are made, paired-t tests are performed to determine if the differences obtained are statistically significant (Law and Kelton 1999). Only statistically significant differences are reported in our Results and Discussion section.

Performance Metrics

Several performance metrics are collected throughout the simulation. For each manufacturer agent, we record the total number of sales for its product brand. In addition, Manufacturer A's lost sales are recorded. Manufacturer A faces a lost sale during a stockout whenever consumer agents decide to substitute with Manufacturer B's product or to not purchase at all.

While our focus is on the manufacturer, we also collected metrics on the retailer agent for comparison purposes. Total sales for products A and B are used to compute retailer market share. When experiencing a stockout, Retailer 1 faces a product lost sale for Product A only when consumer agents fail to buy Product A, buy Product A from Retailer 2, or delay purchase but, due to randomness in the simulation, do not return to make the purchase before the end of the simulation.[2] Retailer 1 does not lose a sale if the consumer decides to buy a substitute product from Manufacturer A or B. We also record the number of times an OOS situation is encountered for each consumer agent throughout the simulation.

To compute manufacturer and store market share, we use absolute market share computed as the ratio of total product sales to total market sales (Szymanski, Bharadwaj, and Bayrakdarian 1993). At the end of the simulation, we use the last 14 days of Manufacturer A and Manufacturer B sales to compute *Final Manufacturer A market share*. We define *Final Manufacturer A market share* = Total Product A sales / (Total Product A sales + Total Product B sales). Similarly, we use the last 14 days of Store 1 and Store 2 sales to compute *Final Retailer 1 market share*. We define *Final Retailer 1 market share* = Total Retailer 1 sales / (Total Retailer 1 sales + Total Retailer 2 sales).

While final manufacturer and retailer market share are important performance measures in our simulation, we are particularly interested in studying the difference between initial manufacturer (retailer) market share and final manufacturer (retailer) market share after repeated OOS events. We focus on computing the difference in manufacturer (retailer) market share as we test scenarios with varying levels of initial market share for both manufacturers (retailers). We define *Manufacturer A MS Difference* = Initial Manufacturer A market share – *Final Manufacturer A market share*. For comparison purposes, we define *Retailer 1 MS Difference* = Initial Store 1 market share – *Final Store 1 market share*.

Experimental Design, Results and Discussion

Given that DSD in-stock percentages are generally better than traditional supply chain distribution channels (Gruen, Corsten, and Bharadwaj 2002), we expect that DSD would result in lower manufacturer and retailer lost sales when compared to traditional supply chain distribution channels. However, it is not clear the impact that the other system conditions, such as initial retailer or manufacturer market share, consumer loyalty, or demand level, will have on DSD's ability to produce significant performance benefits reflected in lower *Manufacturer A MS Difference* as well as lower *Retailer 1 MS Difference*. In our study, the dependent variables are *Manufacturer A MS Difference* and *Retailer 1 MS Difference*. Independent variables are Initial Manufacturer A market share, Initial Manufacturer B market share, Initial Retailer 1 market share and Initial Retailer 2 Market Share, Demand, and Customer Brand Loyalty.

To understand the impact that the independent variables can have on *Manufacturer A MS Difference* and *Retailer 1 MS Difference*, we design a series of experiments in which we vary the values of the independent variables. We use these experiments to statistically validate whether or not the different combinations affect consumer decisions over time and/or impact performance for traditional and/or DSD supply chain distribution channels (e.g., would the performance under traditional distribution come close to the performance of DSD under different variable values).

Our experiments are run with three levels of Initial Manufacturer A market share: 20, 35, and 50 percent, indicating that 20, 35, and 50 percent of customers experience an initial high preference for Manufacturer's A brand product. Recall that 30 percent of customers are indifferent to either manufacturer, meaning they have a 50 percent chance of selecting either product A or B. Therefore, initial overall preference for Product A is 35, 50, and 65 percent once both high preference and indifferent customers are considered. Initial Manufacturer market share values for Product A and Product B vary in each experiment in such a way that their combined manufacturer market share remains fixed at 70 percent. Therefore, in each experiment 30 percent of the population is indifferent to either manufacturer.

Similarly, our experiments are run with three levels of Initial Retailer 1 and 2 market share. Values for Initial Retailer 1 market share are: 20, 35, and 50 percent, indicating that 20, 35, and 50 percent of customers experience an initial high preference for Retailer 1. Recall that 30 percent of customers are retailer indifferent meaning they have a 50 percent chance of visiting either store. Therefore, initial overall preference for Retailer 1 is 35, 50, and 65 percent once both high preference and indifferent customers are considered. Initial Retailer 1 and Retailer 2 market share values vary in each experiment, such that their combined market share remains fixed at 70 percent. In each experiment, 30 percent of the population is indifferent to either retailer.

Based on our interactions with retail store managers, we set daily Demand for the entire system at 240, 600, and 960 for our experiments. The three different values chosen for Initial Retailer 1 market share and Initial Manufacturer A market share, as well as the three values of Demand, result in 27 different scenarios. Each of the 27 scenarios is run in each of the four simulation models depicted in figure 3, resulting in 108 experiments.

Results and Discussion

Impact of Brand Loyalty

Over all scenarios tested, traditional distribution channels had over three times higher Manufacturer A lost sales compared to DSD distribution channels regardless of brand loyalty. *Manufacturer A MS Difference* had an average value of 6.7 percent for low brand-loyal consumers and 1.6 percent for high brand-loyal consumers under traditional distribution channels, but only 1.6 percent for low brand-loyal consumers and 0.2 percent for high brand-loyal consumers under DSD distribution channels. Despite that some consumers are motivated to purchase an OOS product at Retailer 2 or fail to make a purchase, *Final Retailer 1 market share* was not statistically different from Initial Retailer 1 market share over the scenarios tested, therefore *Retailer 1 MS Difference* = 0. While OOS situations generated lost sales for the retailer, overall retailer preference was not significantly affected at the 95 percent confidence level. Figure 4 shows manufacturer average daily lost sales for high and low brand-loyal consumers using different values of Initial Retailer 1 market share. Figure 4 illustrates that traditional distribution results in significantly higher levels of average daily lost sales compared to DSD. In addition, average daily lost sales increase as Initial Retailer 1 market share increases. Brand loyalty also had a significant impact on the average daily lost sales experienced by Manufacturer A (see fig. 5). In summary, manufacturers pay the price for stockouts, regardless of brand loyalty and/or distribution channel strategy, but manufacturers' lost sales are even higher for low brand-loyal products using traditional distribution under repeated OOS conditions.

This is a significant finding for manufacturers. While manufacturers may be focusing on using DSD for products that have high brand-loyal consumers (e.g., due to the higher cost of DSD to the manufacturer), our findings suggest there is potentially a greater opportunity to achieve positive results from DSD by focusing on products that are purchased by low brand-loyal customers. This is particularly important in light of work by

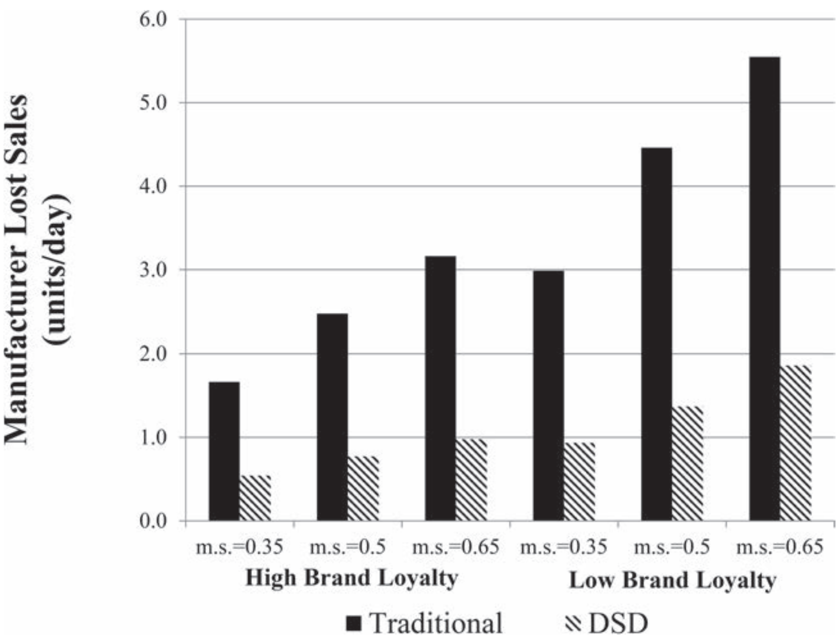

Figure 4 Manufacturer A Average Daily Lost Sales for High Brand-Loyal and Low Brand-Loyal Consumers for Different Levels of Initial Store 1 Market Share
Note: Initial Store 2 market share = 0.35, Demand = 600

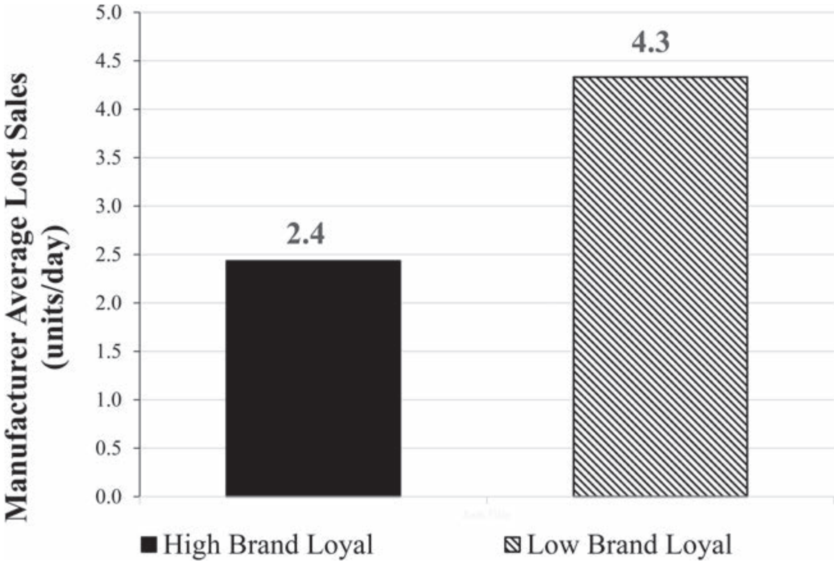

Figure 5 Manufacturer A Average Daily Lost Sales by Consumer Type under Traditional Distribution for All Values of Initial Store 1 Market Share
Note: Initial Store 2 market share = 0.35, Demand = 600

Trautrims et al. (2009) who found that more profitable products tend to be stocked out more often than less profitable counterparts. As such, manufacturers should consider using DSD not only when consumer brand loyalty is low (given an OOS event is more likely to prompt a consumer to switch to a competitor's product), but also when profit margin is high. Direct store delivery offers the manufacturer the chance to avoid a lost sale and, thus, retain the attractive profit margin.

Direct store delivery provides the most direct benefits to the manufacturer with respect to lost sales/market share. When a manufacturer faces higher costs to provide DSD as a supply chain distribution option, it should be used only when the expected gains in manufacturer market share exceed the costs associated with DSD distribution. Although retailers may not perceive a significant benefit from DSD in terms of enhanced market share when compared to traditional supply chain distribution channels, retailers do receive additional benefits from DSD, including reduced labor costs from bypassing the retailer's DC and from the manufacturer taking responsibility for managing shelf inventory and merchandising product. Manufacturers often have better insight on how their products and marketing plans can be enhanced in the markets they serve (Pramatari and Miliotis 2008), enabling increased sales. When products are delivered using DSD, retailers do not have backroom inventory of those products and thus reduce phantom inventory. Further, with higher levels of product availability, DSD should lead to greater customer satisfaction for both the retailer and the manufacturer.

Impact of Variables Affecting Manufacturer A Market Share

To analyze the effect of variables used in the simulation model on *Manufacturer A MS Difference*, we ran a linear regression using the experiment results. The regression model allows us to understand the impact of variables, such as Demand level, Initial Manufacturer A market share, Initial Retailer 1 market share, supply chain distribution channel used (i.e., traditional versus DSD), as well as brand loyalty (i.e., high or low brand loyal), on *Manufacturer A MS Difference* (dependent variable). The linear regression model used is shown as:

$$\textit{Manufacturer A MS Difference} = \beta_0 + \text{Demand}^* \beta_1 + \text{Initial Manufacturer A market share}^* \beta_2 + \text{Initial Retailer 1 market share}^* \beta_3 + \text{distribution channel}^* \beta_4 + \text{brand loyalty}^* \beta_5$$

The last two variables, distribution channel and brand loyalty, are qualitative so we use indicator variables in the regression model. The distribution channel variable takes a value of 0 if the supply chain distribution channel used is DSD and 1 if traditional. The brand loyalty variable takes a value of 0 if the consumer is high brand loyal and 1 if low brand loyal.

Table 2 shows the results obtained for the linear regression model. The regression model has an R-square of 0.70, and all coefficients are significant. It is interesting to note that all coefficients obtained (with the exception of the intercept) are positive; therefore, an increase in any of the independent variables will produce greater *Manufacturer A MS Difference*. In other words, *Final Manufacturer A market share* will decrease when (a) product Demand, Initial Manufacturer A market share, and/or Initial Retailer 1 market share are higher, (b) a traditional supply chain distribution channel is used, and (c) consumer brand loyalty is low.

It can be observed from table 2 that the change in *Manufacturer A MS Difference* for different supply chain distribution channels (3.22%) is similar to the change obtained for different brand loyalties (3.26%). This highlights the importance of considering the supply chain distribution channel as well

Table 2/Linear Regression Results for Scenarios Tested

	Value	p-value
β_0 (Intercept)	−7.91	< .0001
β_1 (Demand)	0.0046	< .0001
β_2 (Initial manufacturer A market share)	6.70	< .0001
β_3 (Initial retailer 1 market share)	6.05	0.0001
β_4 (Distribution channel)	3.22	< .0001
β_5 (Brand loyalty)	3.26	< .0001

as brand loyalty for the product when determining the best supply chain strategy. This result was unexpected as manufacturers often consider brand loyalty as an important investment that must be maintained via advertising and promotions (e.g., temporary price markdowns, coupons). However, our results suggest that improvements to supply chain practices (e.g., DSD in the case of our research) can have the same "payoff" as high consumer loyalty with respect to *Manufacturer A MS Difference* in OOS scenarios.

From the results presented in table 2, when a product with high brand loyal consumers is moved from a traditional to a DSD supply chain distribution channel, the manufacturer will obtain on average a 3.22 percent increase in final manufacturer market share. While brand loyalty is intrinsic to the type of product, and therefore it is hard to significantly affect customer loyalty; our simulation results suggest that the impact of changing distribution channel in the face of multiple OOS events is almost as high as the impact of changing customer loyalty.

The impact of Initial Manufacturer A and Retailer 1 market share on Manufacturer A MS Difference can also be obtained from the regression analysis. From table 2, we can observe that a unit change in Initial Manufacturer A market share produces a higher impact on Manufacturer A MS Difference (therefore producing a lower *Final Manufacturer A market share*) than a unit change in Initial Retailer 1 market share (6.70 > 6.05). This result supports the use of DSD for any retail stores, not just those with high levels of market share. The coefficient for demand is also positive, but its impact, relative to Initial Retailer 1 and Manufacturer A market share, is difficult to assess given the different scales used for Demand. Nevertheless, we can infer from the regression results that manufacturers will obtain greater benefits from implementing DSD in retail stores with higher levels of demand.

Impact of Repeated OOS Events

While previous research studies often focus on the effect of one stockout and its impact on retailers only, our research studies the effect of repeated OOS events and includes the impact to both retailers and manufacturers. Recently, Peinkofer et al. (2015, 268) called for research to consider repeated OOS events in order to "provide a more complete picture" of the effects of multiple OOS events over time on consumer behavior. We find that multiple OOS situations significantly reduce Final Manufacturer A market share, particularly under high Demand and Initial Manufacturer A market-share conditions. Figure 6 shows the effect of multiple OOS events on Manufacturer A market share for low brand-loyal consumers under traditional and DSD supply chain distribution channels.

From figure 6, we observe that Manufacturer A market share tends to decline after every OOS event. From figure 6a, we can also observe that the decline in Manufacturer A market share is more pronounced under traditional distribution channels compared to DSD shown in figure 6b. Products delivered using DSD channels are less affected by repeated OOS scenarios, nevertheless conditions of high demand, high Initial Manufacturer A market share, and high Initial Retailer 1 market share can decrease Final Manufacturer A market share under the DSD option. This result illustrates the importance of studying repeated stockouts. Research examining only a single instance of a stockout is not likely providing a comprehensive view of the impacts of OOS situations from a longitudinal perspective. Without a more accurate depiction of the impacts of repeated stockouts, research may offer misleading suggestions to managers regarding distribution channels and inventory management.

Impact of Consumer Loyalty Given Traditional and DSD Supply Chain Distribution Channels

While loyal consumers are less likely to switch products, low loyalty consumers may be more easily swayed to buy a competitor's product under OOS conditions. Over all experiments tested, we observed that under a DSD supply chain distribution channel, 21 percent of consumers experienced at least one OOS event. Those customers who experienced at least one stockout experienced on average 1.37 OOS events throughout the one year of simulated time. In comparison, under a traditional supply chain distribution channel, 36 percent of consumers experienced at least one OOS event. Those customers who experienced at least one stockout experienced on average 2.39 OOS events during one year of simulated time. OOS situations

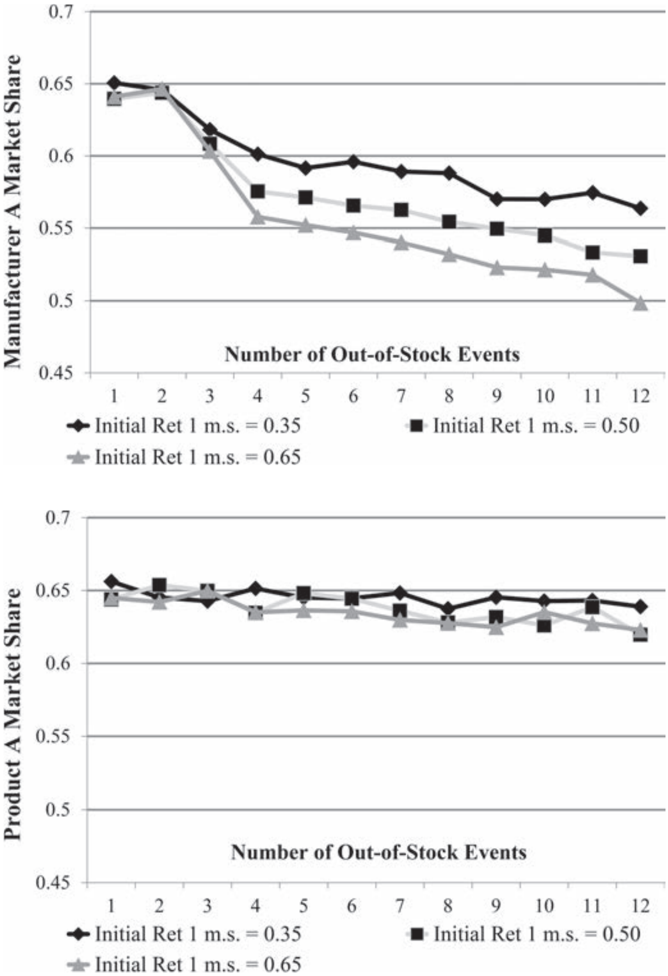

Figure 6 Effect of Multiple OOS Events on *Manufacturer A Market Share*

Note: Results shown for low brand-loyal consumers with Initial Manufacturer A market share = 0.65, Demand = 600, and varying levels of Initial Retailer 1 market share

are not uncommon in practice, as recent research illustrated that one in 13 items that a consumer is intending to purchase is out of stock at the store (Ehrenthal, Gruen, and Hofstetter 2014).

The reduction observed in Final Manufacturer A market share is due not only to lost product sales, but also due to a reduction in consumer loyalty in response to multiple stockouts, even when the reduction in loyalty is low (2% and 5% for high and low loyalty consumers). This illustrates that consumer learning after repeated stockouts can have a significant effect on manufacturer market share. In developing our agent-based simulation, we coded the consumer agents to remember the OOS event had occurred. To the best of our knowledge, this research is the first to explore the impact of consumer learning due to stockouts on manufacturers' operations. Recent research has noted that as consumers become accustomed to omni-channel shopping, expectations increase and consumers are becoming even more frustrated with OOS scenarios in stores (Rigby 2011). As such, reducing OOS scenarios will become increasingly important for manufacturers and retailers, alike.

In summary, we have four key observations. First, both the distribution channel strategy and brand-loyalty levels significantly impacted manufacturer market share—but neither had a significant impact on retailer market share. For manufacturers, DSD improves final manufacturer market share for both high and low brand-loyalty products, but the improvement is more substantial in cases of low brand loyalty. Low brand-loyal items, particularly those with high profit margins, may offer manufacturers important DSD opportunities. Our results also suggest that manufacturers should consider taking a stronger voice in the design of a supply chain distribution channel, where possible, and should consider DSD opportunities, if they have such capabilities, particularly when OOS situations are high. Second, all the system parameters we considered (e.g., product demand, Initial Manufacturer A and Retailer 1 market share) increase *Manufacturer A MS Difference* (reduce *Final Manufacturer A market share*) in the presence of repeated stockouts. Third, we quantify the impact of repeated OOS conditions on market share. Multiple OOS situations have a negative impact on manufacturers. While we find that products under DSD are less affected by repeated OOS events, high demand, high initial brand loyalty, and high retailer market share lead to an increase in *Manufacturer A MS Difference* regardless of the supply chain distribution channel. Finally, we see that consumer learning and adaptation of response can have a negative impact on final manufacturer market share.

Conclusions and Future Work

The insights from this article can be used to guide academics studying OOS considerations as well as provide managerial implications. We show that research should incorporate repeated OOS situations, not just one-time occurrences, to more accurately understand the long-term implications of repeated stockouts. As competition for the consumer increases, it is important to understand the strategic implications of supply chain distribution channels and repeated OOS situations. Offering various distribution services is a means for differentiation in the marketplace (Holcomb, Liao-Troth, and Manrodt 2014). Further, it is important that managers in both retailing and manufacturing firms understand how repeated OOS events reduce store and product loyalty and profitability. In particular, managers should compare the costs associated with supply chain distribution channels (i.e., traditional versus DSD) with the costs of lost sales/market share to make better supply chain distribution decisions, when possible.

A number of interesting extensions may be developed from this article. First, Zinn and Liu (2008) note that loyalty to the retailer will dissuade consumers from visiting a competing retailer even after a stockout. Therefore, retailer loyalty is an important factor that could be manipulated to consider the impact of OOS situations under both supply chain distribution channels. Further, with the advent of retailers creating their own store-brand products, which are generally fulfilled via traditional supply chain distribution channels, there is potential for retailer-manufacturer conflict (Groznik and Heese 2010). Future research could examine whether retailers ensure better in-stock performance on their store brand products compared to manufacturers' brands. Next, we note that in our model, consumers remember the OOS experience and reduce their brand loyalty after each OOS situation. An interesting extension of this article would be to see if consumers "forgive" manufacturers and/or retailers for OOS situations over time. In other words, does a consumer's memory of the stockout fade over time when product is in stock at the next purchase or next series of purchases, potentially lowering the negative impact of OOS events? Finally, given that it is generally agreed to that serving existing customers is less expensive than finding new customers, reducing repeated OOS situations is even more critical. Future work could examine the impact of repeated stockouts on customer retention.

Notes

1. Note: OOS situations only reduce the likelihood of future purchases on Manufacturer A's Product A – not Manufacturer B's Product B or the likelihood of repeat purchases from either Retailer 1 or Retailer 2 in order to isolate the impact of OOS situations on the target manufacturer.
2. Note: if consumers delay purchase but do not return to make the purchase before the simulation ends, then Manufacturer B (or Product B) will not gain the additional market share. In this case, the combined market share for Manufacturer A and Manufacturer B and Product A and Product B may be under 70 percent.

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