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A Petri net based simulation to study the impact of customer response to stock-out on supply chain performance

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Abstract: Based on a Petri-net based simulation model, we investigate the effect of different customer response to stock-out on both the stock-out supply chain and the competing supply chain. Five types of customer stock-out responses are incorporated in the model to quantitatively assess the correlation between customer response and supply chain performance including bullwhip effect (BWE), on-hand inventory, and backlog level. After presenting the results of a series of Petri-net based simulation experiments, we discuss opportunities for both manufacturers and retailers to work better together to mitigate supply chain disruption. We also discuss the value of information sharing on mitigating BWE.

Subjects: Engineering Management; Logistics; Marketing Management; Risk Management; Supply Chain Management

Keywords: supply chain management; customer response; bullwhip effect; stock-out; information sharing

1. Introduction

Although supply chain management has long emphasized on better managing product inventory through advanced information systems and inventory tracking technology, out-of-stocks (OOSs) are still prevalent in retail markets. Using data from 661 outlets and more than 71,000 consumers,

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PUBLIC INTEREST STATEMENT

Out-of-Stocks (OOS) are still prevalent in retail markets, and the worldwide OOS rate remains a surprisingly high at 8.3%. Stock-outs can entail substantial losses, from a brand sales perspective and a category sales perspective. Using data from 661 outlets and more than 71,000 consumers, people found that there were five different kinds of customer responses to OOS. This perspective article describes some of the effects of customer response to OOS to the whole supply chain, including the retailers and the manufacturers, based on the data gathered via Petri-net model. The article discusses opportunities for both manufacturers and retailers to work better together to mitigate supply chain disruption. The value of information sharing for different products varies depending on the segments of the customer responses. As a result, the supply chain managers may focus on sharing product (having different customer responses) specific information for effective mitigation strategies.

Gruen, Corsten, and Bharadwaj (2002) conclude that the worldwide OOS rate remains a surprisingly high at 8.3%. Studies indicate that stock-outs can entail substantial losses, from a brand sales perspective (Schary & Christopher, 1979) and a category sales perspective (Fitzsimons, 2000). Both the stock-out brand and the competing brand may suffer indirect losses in the form of supply chain inefficiencies (Gruen et al., 2002). This motivates empirical analyzes of consumer behavior after experiencing stock-outs and study on how to manage stock-outs to improve customer retention (e.g. Anderson, Fitzsimons, & Simester, 2006; Dong, Yao, & Xu, 2008). Understanding customer purchasing behaviors has been a major research theme in the marketing domain where survey and field experiments are two commonly used methods for data collection. Incorporating the purchasing behavior into a supply network to "bridge" customer responses to stock-out (a marketing phenomenon) with supply network performance (a supply chain phenomenon) requires more quantitative modeling which is currently lacking. Indeed, customer behavior (return) has systematically impact on bullwhip effect (BWE) (Chatfield & Pritchard, 2013). However, most supply chain modeling takes the end customer as a passive recipient of products/services provided by upstream elements and treats any unfilled demands as backlog, meaning that customers experiencing stock-outs would remain attached to the store until the products are available again (Lee, Padmanabhan, & Whang, 1997; Sterman, 1989; Wright & Yuan, 2008). The fact is that with more information at the fingertips and more available outlets and channels for purchasing, consumers are becoming less tolerated for stock-out situations, especially for online shopping. With worldwide consistency, consumers increasingly shop at alternate outlets to find the items they need (Gruen et al., 2002), which has significant impact on the performance of stock-out brand and competing brand, and even the overall supply network. Thus to effectively identify supply chain mitigation strategies, it is necessary to model responses from different customers experiencing stock-outs.

In this research, we seek to understand how customer response to stock-out impact the BWE of the supply chains through creation of a Petri-net based simulation model. We focus not only on the stock-out supply chain, but also on the competing supply chain. A Petri-net based model including five customer stock-out responses collected from marketing literature was developed to study the supply chain performance. Our model is framed in a supply chain network of two competitive manufactures each delivering their own brand of product to two retailers where consumers may choose from two brands of the same product at two different retailers. When one brand of product encounters stock-out, the Petri-net based simulation analyzes the impact of customer response on the supply chain performance of both the stock-out brand and the competing brand. The supply network performance is measured by three metrics (Wan & Evers, 2011): BWE, on-hand inventory and backlog level. It is well accepted that BWE, an amplification effect of demand variation, is symptomatic of a poorly performing supply chain (Jones & Simons, 2000). Two related consequences from bullwhip effect are high level of on-hand inventory and backlog. The efficacy of mitigation strategies with information sharing (IS) and customer relationship management can also be evaluated.

This has implications for how supply chain managers choose risk mitigation strategies: different products may require different risk mitigation strategies and different supply chain may feel a difference in the impact to IS. We contend that understanding the impact of a consumer response in the face of a stock-out disruption at both the stock-out supply chain and the competing supply chain is an important step towards developing better methods for supply chain risk management and resilience. This may be used to develop more effective supply chain management strategies for both the stock-out supply chain and the competing supply chain when facing stock-out disruptions.

The remained of the paper is organized as follows: Section 2 reviews literature related to supply chain stock-out, and customer response to retailer OOS. Section 3 presents a Petri-net simulation model developed for the research question. Experimental designs and result analysis are provided in Section 4, followed by Section 5—conclusion and limitation.

2. Literature review

In this section, we review the literature on supply chain stock-out disruption, customer response to retailer OOS and BWE as the foundation of the Petri-net based simulation model.

2.1. Supply chain disruption, BWE and stock-out

Drawing upon Contingency Theory, Talluri et al. (2013) posit that the appropriateness and effectiveness of risk mitigation strategies are contingent on the internal and external environments and that there is no one-size-fits-all strategy. A recent Deloitte study of 600 Supply Chain and C-Level executives revealed that 45% felt that their supply chain risk management programs were only somewhat effective or not effective at all, while a mere 33% used risk management approaches to proactively and strategically manage supply chain risk based on conditions in their operating environment (Manuj, Esper, & Stank, 2014). Supply chain disruption can cause lots of problem in the whole supply chain, such as stock-out, lead to consumer dissatisfaction (Kim & Lennon, 2011; Pizzi & Scarpi, 2013).

While there recently emerges activate research in stock-out research, stock-out remains a critical problem for retailers, distributors, and manufacturers in the worldwide consumer goods industry. Jing and Lewis (2011) study the grocery industry and state that 8% of products in a supermarket are out of stock at any moment in time and the percentage rises to 15% for promotional items. The 2000 Philips fire indirectly caused a cell phone product stock-out for Ericsson, resulting in a huge loss of customers and US$2.34 billion loss in Eriksson's mobile phone division at the end of 2000 (Sheffi & Rice, 2005).

Stock-out not only causes the sales lost but also affects the suppliers and the retailers at both the operational and strategic levels (Gruen & Corsten, 2007). For example, stock-out distorts inventory information that is required for ordering and replenishment of the store and shelf. Gruen and Corsten (2007) provide a comprehensive examination of measurement approaches and strategies used to reduce retailer OOS. Operations and supply chain managers should particularly emphasize on better managing product inventory and preventing stock-out to improve customer satisfaction and retention (Aberdeen Group, 2004). In order to prevent stock-out, a deterministic model is developed to identify the base stock levels and lead times associated with the lowest cost solution for an integrated supply chain on a finite horizon (Ishii, Takahashi, & Muramatsu, 1988). Kang and Gershwin (2005) apply analytical and simulation modeling to demonstrate that even a small rate of stock loss undetected by the information system can lead to inventory inaccuracy that disrupts the replenishment process and creates severe OOS situations. Based on multi-agent simulation system Swarm, Lin, Huang, and Lin (2002) simulate and analyze the buyer-seller correlation in sharing information, and conclude that the more detailed information shared between firms, the lower the total cost and stock-out rate.

While it is necessary to be precautious to avoid stock-out, exploring strategies for alleviating the negative impact when stock-out does happen is also important. Existing literature has tested the impact of collaborative planning and design between supply chain members under the stock-out. Vendor-Managed Inventory (VMI) is studied for generating purchasing order under stock-out (Ovalle & Marquez, 2003). VMI is an effective structure for the supply chains when customers are unlikely to substitute to another brand in case of a stock-out (Kraiselburd, Narayanan, & Raman, 2004). VMI intensifies completion among manufacturers of competing brand, thus providing benefits to retailers (Mishra & Raghunathan, 2004). Dong et al. (2008) shed light on potential applications of backorders to retain customers from both the supply chain and marketing perspectives. In conclusion, IS has been a major approach for mitigating the negative impact of stock-out in supply chain practices. Chen, Amrik, and Daniel (2016) provide evidence that supply risk can be mitigated by high level of information and knowledge sharing as well as building trust, commitment and goal congruence in a buyer–supplier relationship. However, IS so far has been focusing on the information from the upstream supply chain members without considering customer response in case of stock-out. The values of IS are quite different under different conditions, such as apply different forecasting models (Zhao, Xie, & Leung, 2002). We hypothesize that sharing information under different customer response to stock-out may help identify responsive strategies to alleviate the negative impacts to the supply chain overall.

2.2. Customer response to retailer OOS

Research from marketing literature has identified five primary customer responses to stock-out (Gruen et al., 2002) including: (1) Buy item at another store (store switch); (2) Delay purchase (buy later at the same store); (3) Substitute-same brand (for a different size or type); (4) Substitute-different brand (brand switch); (5) Do not purchase the item (lost sale). Other than identifying the consumer behaviors following a stock-out, research also focuses on the estimation of stock-out costs. Anupindi, Dada, and Gupta (1998) are the first to estimate the effect of stock-out on customer demand using actual measures of product availability in accounting for lost sales and product substitution effects. When only sales and product availability data are observable, not all products are displayed in all periods (e.g. due to stock-out or availability controls), and the seller knows its aggregate market share (Vulcano, van Ryzin, & Ratliff, 2012). Based on a random utility model and partial data on product availability, Conlon and Mortimer (2008) estimate the substitution effects induced by stock-out. They use the expectation–maximization (EM) algorithm to account for the missing data on product availability faced by each customer. Customer response to stock-out has other implications for retail assortment, shelf space allotment, pricing, and logistics. For example, Kök and Fisher (2007) study an assortment planning model in which consumers might accept substitutes when their favorite product is unavailable. They develop an algorithmic process to help retailers compute the best assortment for each store. Price promotions have significant effect on consumer expectations of product availability and their reactions to stock-outs in an online retail environment. Consumers are actually less dissatisfied with a stock-out of a price promoted item than a non-price promoted product and are less likely to switch to another retailer's website. Price promotions actually create a type of switching cost in the online retail environment (Peinkofer, Esper, Smith, & Williams, 2015).

In summary, literature on customer response to stock-out has mainly stemmed from marketing research. How the responses may potentially impact the overall supply chain performance remains less studied. It is very likely that the consumers switching brands, sizes and stores and/or delaying the purchases provides an inaccurate estimate to managers, which may lead to supply chain inefficiencies (Gruen et al., 2002). Therefore, we design this study around the customer response to stock-out and how such responses can impact the supply chain performance, and how combined customer responses with IS can make the supply chain effectively response to the disruptions.

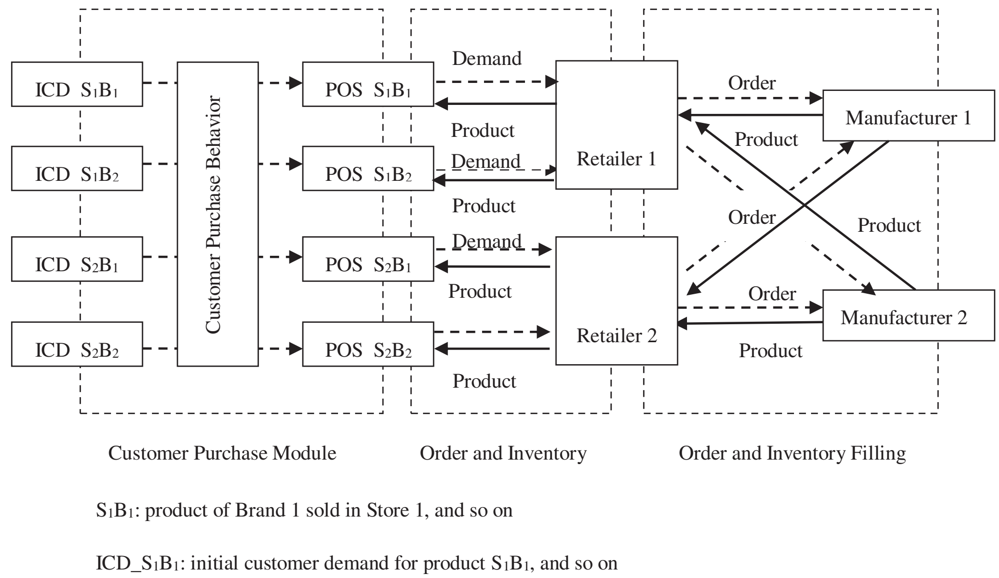
3. Research method

In this section, we present a Petri-net based simulation to investigate the impact of customer response on supply chain performance.

3.1. Petri-net based simulation

As a well-defined graphical technique Petri-net offers a solid mathematical foundation for the analysis of the dynamic behavior of complex systems, and have later been extended and applied to supply chain management (Zhang, Lu, & Wu, 2011). Mahdavi, Mohebbi, Zandakbari, Cho, and Mahdavi-Amiri (2009) study the BWE in a multi-stage supply chain and clarify the evaluation of inventory policies in various supply and demand uncertainties. Using the well-known Beer Game as an example, a systematic method supporting the bottom-up construction of reusable models of supply chains in the Petri-nets domain together with their associated experimental frames is presented in Landeghem and Bobeanu (2002) and Makajić-Nikolić, Panić, and Vujošević (2004). Wu and Blackhurst (2004) propose to synthesize supply chain entities into an integrated system and then analyze disruptions in the integrated supply chain. Further, Wu, Blackhurst, and O'grady, (2007) study the use of Petri-nets to determine how changes or disruptions propagate in supply chains and how those changes or disruptions affect the supply chain system. Tuncel and Alpan (2010) apply a Petri-net based model to analyze several disruptions (disruptions in demand, transportation, quality, etc.) at the same time in the same model.

Figure 1. Framework of supply chain network.



In general, Petri-nets provide a thorough understanding of the control logic of the network structure thus can be used to evaluate various operational strategies. In this research, Petri-nets enable us to quantify variance amplification at both the stock-out brand and the competing brand in response to a normally distributed demand from the end consumer (Figure 1).

Figure 1 presents the Petri-net based framework to study a three-echelon supply chain, including four kinds of customers (customers of product S_1B_1, customers of product S_1B_2, customers of product S_2B_1 and customers of product S_2B_2), two retailers (Store 1 vs. Store 2) and two manufacturers (Brand 1 vs. Brand 2). The two brands are competitive, and sold at two same stores. In the stores, available inventory is used to meet the customer demand immediately. Any demand that is not satisfied is added as stock-out of the retailer and any unsatisfied order at the manufacturers' is added as backlog.

3.1.1. Sub module of customers
The activities in the customer modules are:

(1) Each period of the simulation, the model will generate four kinds of initial customer demands (ICD) for all of the products (ICD_B_1S_1, ICD_B_2S_1, ICD_B_1S_2, and ICD_B_2S_2).
(2) In each store, if the store's stock is larger than the customer demand, take the ICD as the point-of-sales (POS).
(3) In each store, if the ICD is larger than the store's stock, then stock-out happens. For simplicity, let us assume each customer has one unit demand, and the number of customers who are not able to make the purchase is the unsatisfied demand. For each unsatisfied customer, he or she:

    (a) Has probability CR_1 to go to another store to buy the same brand;
    (b) Has probability CR_2 to delay the purchase and come back to the same store for the purchase;
    (c) Has probability CR_3 to substitute with same brand (for a different size or type) in the same store;
    (d) Has probability CR_4 to substitute with different brand in the same store;
    (e) Has probability CR_5 to leave without purchasing.

$$CR_1 + CR_2 + CR_3 + CR_4 + CR_5 = 1 \tag{1}$$

3.1.2. Sub module of retailer

Retailers perform the following activities:

(1) Receive the goods shipped from the manufacturers.
(2) Deliver the purchased product.
(3) Observe the POS data.
(4) Forecast the future demand based on historical POS data using moving average model (Chen, Drezner, Ryan, & Simchi-Levi, 2000).
(5) Form new orders to the manufacturers according to the expected demand and inventory position.

As we take all the customer demand that cannot be satisfied in the end as sales loss, the inventory position in the retailers is calculated as:

$$\text{Inventory position} = \text{on\_hand inventory} + \text{on\_order} \tag{2}$$

where on_hand inventory is the number of units held by the retailer, on_order is the number of units ordered but yet not received.

3.1.3. Sub module of manufacturer

Manufacturers' main activities are:

(1) Delivering the finished goods to the stock.
(2) Receiving the orders from different retailers, and combining the orders.
(3) Delivering the purchased goods, splitting the delivery according to the backlogs of each retailer (Wan & Evers, 2011). It is assumed that the manufacturer distinguishes these two retailers according to their order quantities. More specifically, if the manufacturer's on-hand inventory is not enough to satisfy orders from retailers, it is assumed that the manufacturer delivers the product to each retailer according to the ratio of its order quantity to the overall order quantity from both retailers. For example, if retailer 1 places 200 units to the manufacturer 1 and retailer 2 places 400 units while manufacturer 1 has only 300 units in stock, manufacturer 1 will deliver 100 units to retailer 1 and deliver 200 units to retailer 2. Manufacturer 2 adopts the same split rule.
(4) Forecasting the future demand based on historical order data of retailers using moving average model.
(5) Determining the amounts to produce in the following period according to the expected demand and inventory position.
(6) Recording on-hand inventory and the unsatisfied demand, and marking the unsatisfied demand as backlog.

All the unsatisfied orders at manufacturers are taken as backlog, the inventory position in the manufacturers is calculated as:

$$\text{Inventory position} = \text{on\_hand inventory} - \text{back log} + \text{on\_order} \tag{3}$$

where on_hand inventory is the number of units hold by manufacturer, back log is the number of units ordered by retailers but yet not delivered, on_order is the number of units placed to produce but yet not finished.

3.2. Assumptions
To more realistically model the supply chain, some important factors such as demand pattern, ordering policy, lead time, batch size and demand forecasting model are included in this study. Assumptions on these factors are discussed as follows.

3.2.1. Initial customer demand
In the model, assume product S_1B_1 will be stock-out, and we investigate the dynamics of the whole system after the stock-out happens. The initial demands are generated by the demand generator. Assume there is larger demand uncertainty for product S_1B_1 and consumers would face stock-out of their favorite brand. When experiencing stock-out, customer will choose among five alternatives: substitute stores, delay purchase, substitute sizes, substitute brands or give up purchase.

We set the initial demand of product S_1B_1 follow a normal distribution with the mean being 200 and the variance being 100^2. We assume that the initial demands for competing product are less fluctuate and follow a normal distribution with mean 200 and variance 20^2 as used in Chen et al. (2000) and Chatfield, Kim, Harrison, and Hayya (2004). In 2004, Chatfield et al. built up a supply chain model including one customer, one retailer, one wholesaler, one distributor and one factory to study the impact of IS on BWE, and compared the results with Chen et al. (2000) to verify their model. We study the similar supply network structure as the ones in Chatfield et al. (2004) and Chen et al. (2000) with added nodes representing customers. Chatfield et al. (2004) set the demand mean as 100 units, in our model, we set the demand mean as 200 units due to the added complexity of the supply network.

The retailers face uncertain customer demands, with the average demand per period for each product being 200 units. The retailers replenish their inventories by placing orders to the manufacturers, thus average demand per period for each manufacturer is 400 units.

3.2.2. Lead time and batch size
There is a fixed lead time between the time an order is placed by the trade partners and when it is received by the trade partners. The lead time for the retailers to place an order to the manufacturer is assumed to be zero. The lead time for the manufacturers to produce and deliver is assumed to be 4 days as suggested in Chatfield et al. (2004). Each simulation runs for 50 days. In order to mitigate the negative impacts of batching order, it is advocated that batch sizes should be reduced as much as possible (Potter & Disney, 2006). Therefore, in our model we set batch size 1 to control its impact.

3.2.3. Order-up-to policy
Most authors apply "order-up-to" policy, including Chen et al. (2000) and Lee, Padmanabhan, and Whang (2004), which means that if the current inventory position is less than a certain level (the order-up-to point), the firm places an order to bring its inventory up to this level; otherwise, none order is placed. Since the periodic order-up-to policy works well for independent, identically distributed demands, we use the policy for all the firms in our simulation. Ordering decisions are as follow:

$$Q_t = Y_t - \text{Inventory position} \tag{4}$$

where O_t is the ordering decision made at the end of period t, Y_t is the order-up-to point used in period t and the inventory position is calculated as showed in Section 3.1.

The order-up-to point is updated every period according to:

$$Y_t = \widehat{D}_t^L + SS \tag{5}$$

where SS is the safety stock, and $\widehat{D}_t^L$ is the forecasted mean demand during lead time estimated as:

$$\widehat{D}_t^L = \widehat{D}_t \times \text{lead time} \tag{6}$$

where $\widehat{D}_t$ is the forecasted demand in the next period. To simplify the analysis, we set SS equals to zero, and increase the lead time by one. This is often used in practice: the value of lead time is inflated and the extra inventory represents the SS (Chen et al., 2000).

As lead-times are fixed in the simulation at previously mentioned levels, the order-up-to point mainly depends on the forecasting methods used to determine $\widehat{D}_t$.

3.2.4. Demand forecasting methods
As a simple and useful forecasting method, the moving average forecasting method is well accepted. We use the moving average to predict demand in the next period by averaging the actual demand in the last n time periods (Chen et al., 2000).

$$\widehat{D}_t = [D_{t-0} + \dots + D_{t-n+1}]/n \tag{7}$$

In the simulation, D_{t-0} is the actual demand received in day $t - 0$, and n is the number of days to be averaged. For simplicity, we set $n = 6$ (Wright & Yuan, 2008).

4. Experimental design and results analysis
In this section, we design a series of experiments to study the impact of customer response to retailer OOS on both the stock-out supply chain and the competing supply chain. Furthermore, we investigate the efficiency of IS on improving supply chain performance.

4.1. Simulation experiment I: customer responses
The first set of experiment is designed to understand how these five types of customer response (switch store, delay purchase, substitute within the same brand, switch brand and give up purchase) will impact the brands' (both the stock-out brand and the competing brand) BWE, on-hand inventory and backlog level. Therefore, in our first experiment, we set the manufacturers only receive order information from different retailers and make their own forecast based on the orders placed by retailers. The forecast is then used to update the order-up-to point, and consequently the production size for the current period.

Given the five patterns of customer response are components of a mixture, and consequently, their levels are not independent, see below:

$$0 \le \mathrm{CR}_i \le 1 \quad i = 1, 2, \dots \tag{8}$$

where $\mathrm{CR}_1 + \mathrm{CR}_2 + \mathrm{CR}_3 + \mathrm{CR}_4 + \mathrm{CR}_5 = 1$.

We design a mixture experiments (Montgomery, 2007) to study the effects of customer responses on supply chain performance. A {p,m} simplex lattice design for p components of points defined by the following coordinate settings: the proportions assumed by each component take the $m + 1$ equally values from 0 to 1,

$$\mathrm{CR}_i = 0, 1/m, 2/m, \dots, 1 \quad i = 1, 2, \dots, p \tag{9}$$

and all possible combinations of the proportions from Equation (9) are used. In our model, $p = 5$ and we set $m = 5$. Then

$$\mathrm{CR}_i = 0, 1/5, 2/5, \dots, 1 \quad i = 1, 2, \dots, 5 \tag{10}$$

so the simplex lattice consists of $(p + m - 1)!/[m!(p - 1)!] = 126$ runs.

For each of the simulation, we collect three main outputs: BWE, on-hand inventory, and backlog level within the supply chain.

The BWE in a supply chain is measured by the ratio of the variance of the production rate placed by the factory, var(MPR) and the variance of the customer demand, var(CD) (Bayraktar, Koh, Gunasekaran, Sari, & Tatoglu, 2008; Chen et al., 2000; Wan & Evers, 2011; Wright & Yuan, 2008). A smaller BWE presents less amplification of the order. The BWE = 1 represents the case that the variance of the customer demand does not change. The BWE > 1 means that the variance of manufacturer order is higher than the variance of customer demand, and therefore the demand is amplified along the supply chain.

$$\mathrm{BWE} = \mathrm{var}(\mathrm{MPR})/\mathrm{var}(\mathrm{CD}) \quad (11)$$

We sum the on-hand inventory at each echelon of each brand as the whole on-hand inventory level of the brand. As we are exploring the impact of customer response, the unsatisfied demand at retailer echelon is no long taken as backlog, and the backlog level at each manufacturer is summed as the whole backlog level of the brand.

Out of 50 days of simulation, data for 10 replications are used for simulation output analysis to determine the critical value for a pattern of customer response at which supply chain performance changes significantly. The ANOVA test results for the main effects are shown in Tables 1a and 1b.

We develop a number of insights based upon the results of this experiment. For the stock-out brand (see Table 1a), both customers who tend to purchase at another store, and who tend to delay purchase have positive, significant impact on supply chain's BWE, on-hand inventory and backlog level. That is, the more customers choose to switch store or delay their purchase, the worse the BWE, the larger the on-hand inventory, and the larger the backlog will be induced. More interesting, customers who tend to purchase a different brand also have positive, significant impact on supply chain's

Table 1a. Model fitting for the stock-out brand (without information sharing)

Response	Term	Intercept	CR_1	CR_2	CR_3	CR_4	CR_5
BWE	Estimate	10.6456	5.4399	1.9756	0.0170	0.2830	0.0046
	p-value	<.0001*	<.0001*	<.0001*	0.9621	0.4296	0.9819
On_hand inventory	Estimate	38,910.535	5,129.8318	2,056.1121	−75.9000	−108.0955	0.0003
	p-value	<.0001*	<.0001*	<.0001*	0.7553	0.6573	0.9873
Backlog	Estimate	2,374.5777	2,670.7242	616.1061	−17.9606	218.0227	0.0001
	p-value	<.0001*	<.0001*	<.0001*	0.8341	0.0122*	0.9916

*Indicates statistic significance.

Table 1b. Model fitting for the competing brand (without information sharing)

Response	Term	Intercept	CR_1	CR_2	CR_3	CR_4	CR_5
BWE	Estimate	15.5895	1.9828	0.7615	0.0282	43.8123	0.0005
	p-value	<.0001*	0.0992	0.5244	0.9812	<.0001*	0.9965
On_hand inventory	Estimate	39,301.361	76.2242	−31.6758	6.9333	958.2121	0.0045
	p-value	<.0001*	0.4308	0.7431	0.9428	<.0001*	0.9813
Backlog	Estimate	−31.5738	76.5045	28.9561	0.1045	2,220.9318	0.0067
	p-value	0.4365	0.1763	0.6076	0.9985	<.0001*	0.9942

*Indicates statistic significance.

backlog level (see Table 1a). Therefore, when the stock-outs happen, three specific customer groups (switch store, delay and switch brand) shall be focused to make supply chain more efficiency. Specifically, the impact magnitude from customer who tends to purchase at another store is larger than customer who tend to delay purchase or switch brand (see the estimated parameters in Table 1a). This is echoed in research looking to retail OOS reduction (Gruen & Corsten, 2007). Our research quantifies which type of customer is most influential. From the perspective of customer's store preference, it is more influential for retailer when most of the customers choose to switch store. It is supposed that customers choosing to switch store would decrease customer satisfaction and cause indirect loss of store loyalty (Gruen & Corsten, 2007). Since both the manufacturer and retailer suffer from customers switching store, it is recommended that both the manufacturer and the retailer work together to develop customer's store loyalty and mitigate supply chain inefficiency.

In addition, it is observed that comparing with "do not purchase" type of customer, customers tend to substitute within the same brand help keep the sales balance for both the manufacturer and the retailer. We recommend that the brand manufacturer and the retailer should work together to incent the customers especially those who prefer purchasing at another store to substitute the same brand in other sizes in the same store. This is a win-win strategy for both manufacturer and retailer. First of all, it would reduce the sales lost. Secondly, as more customers are incented to purchase the same brand in other sizes, less percentage customers would left to switch store or delay purchase, the BWE would be mitigated, and then on-hand inventory and backlog level would be reduced correspondingly. This is one of customer demand shift strategies, and has been successfully applied to deal with supply chain disruption. For example, after the Taiwan earthquake in 1999, Dell encountered a supply disruption. They successfully shifted customer demands from the unviable components by promoting special offers to manipulate customer product choice (Martha & Subbakrishna, 2002). This is an effective method to keep the demand stable.

For the competing brand (see Table 1b), we observe only customer who tends to purchase a different brand has positive, significant impact on the competing brand's supply chain efficiency. Customer purchasing a different brand may increase the market share of the competing brand. However, this purchasing behavior may provide an inaccurate image to managers leading to the "temporal" demand amplification (Lee et al., 1997). As Gruen and Corsten (2007) show that for the percentage of customers substituting another item for a stock-out item, this switching behavior inflates the sales of the items that are in stock (beyond their normal demand). Therefore, when stock-outs happen at one brand, the managers of its competing brand shall collaborate with the retailers to figure out which part of demand is switched from the stock-out brand, also known from the "temporal" customers. On the other side, competing brand shall grab this opportunity to increase its loyalty customer by impressing these "temporal customers" with high quality product. Once the customers are loyal to the brand, the demand fluctuation would be reduced, and so does the BWE.

In addition, according to the literature in marketing research, in case of different product types and regions, when experiencing stock-outs, customers have different responses. We use the data

Figure 2. Experiment result of five specific product categories.

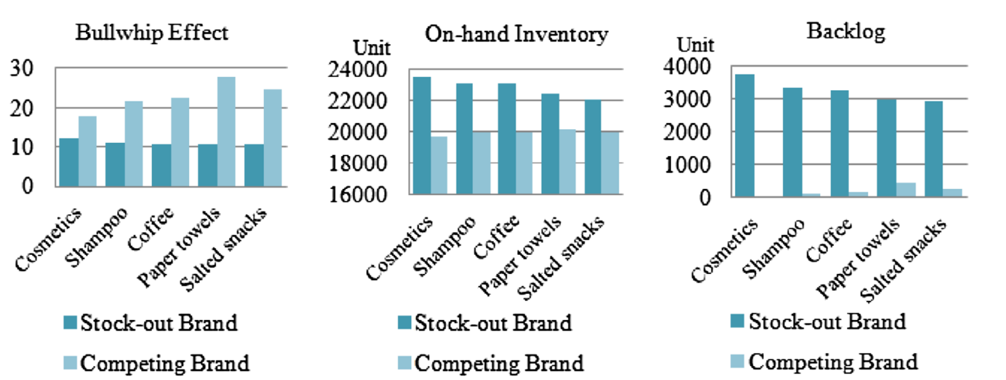


Table 2. Customer responses to stock-out

Response to stock-out		Commodity type				
		Cosmetics (%)	Shampoo (%)	Coffee (%)	Paper towels (%)	Salted snacks (%)
CR_1	Purchase at another store	43	32	29	21	21
CR_2	Delay purchase	22	21	21	17	9
CR_3	Substitute within the same brand	12	19	13	18	20
CR_4	Substitute with a different brand	8	18	20	32	25
CR_5	Do not purchase	15	10	17	12	25

Source: Adapted from Gruen et al. (2002).

adapted from Gruen et al. (2002) (see Table 2) to investigate how supply chain performance will be affected by customer responses for each specific product categories. For each specific simulation, we collect three main outputs: BWE, on-hand inventory, and backlog level within the supply chain.

For each specific setting of the customer responses, we perform 10 runs in order to get robust results. We average the 10 replications for each scenario. Figure 2 shows the experiment results.

From Figure 2, we observe that for all the five product categories, not only the stock-out brand but also its competing brand suffer from the BWE, and the BWE differs under different product. In addition, the on-hand inventories and backlog levels are quite different under different product categories. For the stock-out brand, it is observed that the BWE, inventory level and backlog of cosmetics are bigger than other product categories. This could be explained by the customer's purchasing behavior as Gruen et al. (2002) has found that cosmetics customers have strong probability to switch store to purchase their preferred brand when experiencing stock-out in a store. This phenomenon is consistent with what we have found, that is, the more customers choose to switch store, the bigger BWE, inventory and backlog the stock-out brand will suffer. Therefore, the cosmetics managers shall focus on developing customer's store loyalty with the retailer and make sure other sizes of the cosmetic product will be available when one of the size experiencing stock-out.

Figure 2 also suggests there may exist a distinction between Paper towels and the other four products for the competing brand, which is shown in the data collected from Gruen and Corsten (2007) and Gruen et al. (2002), the customers of paper towels have the biggest probability to switch brand among the five product categories we have studied. In fact, we suppose that the impact of customers who choose to switch brand is a significant factor for competing brand, therefore, we not only suggest that the manager should distinguish the customers temporally switching from the stock-out brand we also recommend that the manufacturer explores customer segmentation opportunities and develops customer loyalty to the new brand.

4.2. Simulation experiment II: IS

In this set of experiment, we seek to understand the value of IS on mitigating the BWE, on-hand inventory and backlog level under different customer responses. When retailers share the POS data being observed with manufacturers, the manufacturers would make forecasts with that information and fine-tune their inventory system parameters accordingly. Specifically, instead of historical order data from retailers, the manufactures would make demand forecast base on the POS data of each retailer when they choose IS mitigation strategy. Using the moving average, the predict demand in the next period of manufactures would be:

$$\widehat{D}_t = [\mathrm{POS}_{t-0} + \ldots + \mathrm{POS}_{t-n+1}]/n \tag{12}$$

POS_{t-0} is the actual POS data received in day $t - 0$, and n is the number of days to be averaged. For simplicity, we set $n = 6$ (Wright & Yuan, 2008).

Since the customers' demand stream will have a variance less than or equal to the variance of the retailers' orders, the assumption is that manufacturer using customer demand information will smooth the fluctuations in the order-up-to point and the resulting production stream will have a lower variance (Chatfield et al., 2004).

We follow the experiment design of experiment I, apply $\{p,m\}$ simplex lattice design, we have $(p + m - 1)!/[m!(p - 1)!] = 126$ runs. Instead of transforming order information to manufacturers, in this set of experiment, the retailers transform both order information and POS data to their manufacturers. For each specific setting of the customer responses, we perform 10 runs in order to get robust results. We average the 10 replications for each scenario. The improvement of BWE, on-hand inventory and backlog before and after IS are applied to compare the improvement effect of IS.

The Infor_Gain of BWE is defined as:

$$\text{Infor\_Gain}\,(\text{BWE}) = \frac{\text{BWE}\,(\text{without IS}) - \text{BWE}\,(\text{with IS})}{\text{BWE}\,(\text{without IS})} \times 100\% \tag{13}$$

The same calculation method is applied to Infor_Gain of on-hand inventory and backlog. Since we use 0.2 as the step size to design the experiment, and according to Gruen et al. (2002), the average percentages across 11 categories they have studied are between 11 and 32%, so we set three levels of strength for each type of customer response(see Table 3). We show the Infor_Gains in Figure 3. The horizontal axis presents the levels of customer's store switching strengths from low probability to high probability. When Infor_Gain > 0, the performances have been improved by sharing information, the bigger Infor_Gain, the bigger improvement has been made through IS.

As showed in Figure 3, all the Infor_Gains of BWE are bigger than 0 and smaller than 1, which means IS does not eliminate the BWE, but somehow it does mitigate the BWE of both the stock-out

Table 3. Levels of customer response probability

Levels	Low (L)	Medium (M)	High (H)
Probability of customer response	0–0.2	0.2–0.4	0.4–1.0

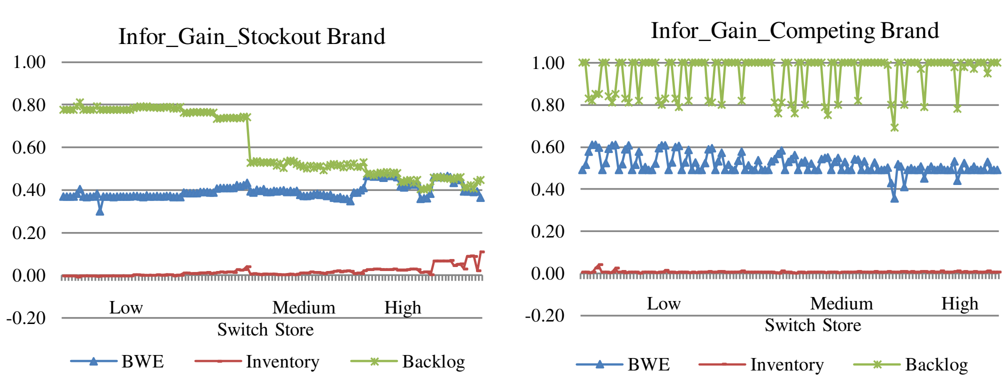


Figure 3. Improvement of supply chain performance with and without IS.

brand and the competing brand. Our results with regard to IS confirm much of what has been found when analyzing simpler systems without considering customer response, for example in Chen et al. (2000), Dejonckheere, Disney, Lambrecht, and Towill (2004), and Chatfield et al. (2004). Similar conclusion is reached in the term of inventory and backlog level, and it is valuable for both the stock-out brand and the competing brand to share information no matter the composition of customer response.

We find it is interesting that for the stock-out brand, in the term of on-hand inventory, it is not so valuable to use the POS data to estimate demand under some scenarios (see Figure 3 left), especially for compositions of low store switching probability. Under these compositions, the Infor_Gain of on-hand inventory is even a little bit smaller than 0. That is, if the supply chain manager cares more about on-hand inventory, when most of customers tend to substitute within the same brand in other sizes, or switch brand, or give up purchase, it is not so valuable to share information. For the stock-out brand, we also find that as the strength of store switch goes from low to high, the Infor_Gains of backlog will decrease, while the Infor-Gains of BWE will increase. That means it is better for the managers to make tradeoff under specific cost structure for the whole supply chain performance.

The values of all three indices for both the stock-out brand and the competing brand are quite different under different customer response compositions (see Figure 3). We conclude that the values of IS on mitigating the BWE are quite different under different customer response composition. This motivates us to conduct in-depth analysis to assess the significance of customer responses on the mitigation value of IS. The results are showed in Tables 4a and 4b.

As with experiment I, based upon the results of experiment II, we develop some different insights. For the stock-out brand, the value of IS is significantly impacted by two types of customers, customers who tend to switch store and customers who tend to delay their purchase. Therefore, in order to improve the value of IS, the managers should pay more attention to these types of customers, especially the customers who switching store for the magnitude of CR_1 is bigger than CR_2.

Table 4a. Model fitting for the stock-out brand (with information sharing)

Response	Term	Intercept	CR_1	CR_2	CR_3	CR_4	CR_5
BWE	Estimate	6.8030	2.8120	0.1316	−0.0047	−0.0894	0.2674
	p-value	<.0001*	<.0001*	0.2204	0.9649	0.4043	0.8946
On-hand inventory	Estimate	39,086.5750	−118.3939	414.5637	−13.9424	21.5303	1.9450
	p-value	<.0001*	0.0105*	<.0001*	0.7598	0.6369	0.9991
Backlog	Estimate	528.9913	1,997.0364	298.2561	−3.8803	−3.6924	0.1863
	p-value	<.0001*	<.0001*	<.0001*	0.9415	0.9444	0.9373

*Indicates statistic significance.

Table 4b. Model fitting for the competing brand (with information sharing)

Response	Term	Intercept	CR_1	CR_2	CR_3	CR_4	CR_5
BWE	Estimate	8.3426	0.0608	0.1545	−0.0459	14.7760	0.0573
	p-value	<.0001*	0.7789	0.4762	0.8324	<.0001*	0.8921
On-hand inventory	Estimate	39,122.218	−19.6484	−57.9939	4.4909	71.7788	0.9731
	p-value	<.0001*	0.5240	0.0618	0.8841	0.0213*	0.9411
Backlog	Estimate	−9.6193	0.4076	2.6591	0.6985	414.8106	0.7549
	p-value	0.6026	0.9873	0.9175	0.9783	<.0001*	0.9888

*Indicates statistic significance.

Another interesting finding is that for the stock-out brand, customers choose to purchase at another store have negative, significant impact on on-hand inventory (see Table 4a), which means that when none of the customer choose to switch store, it would be worse to share information. That explains the negative index value of on-hand inventory for compositions of low store switching (see Figure 3 left). However, Gruen et al. (2002), study 11 product categories (including cosmetics, diapers, fem hygiene, pet food, toothpaste, and so on), which present 11 different kinds of customer response compositions, the average percent of customer switching store reaches up to 32%. Otherwise, in nowadays online shopping environment, when encounters stock-out, more and more people would choose to purchase at another store. Therefore, we assume that in real commercial environment, the percent of customer switching store would bigger than 20%. Look into our experiment results, when $CR_1 \geq 20\%$, it turns to be valuable to share information.

For the competing brand, customers who choose to switch brand have significant impact on the value of IS (see Table 4b). Therefore, for a specific product category, the more customers tend to switch brand, the more valuable for the competing brand to build up IS contract with their retailers. For example, from Table 2, we find that customers of paper towel has the highest probability to switch brand in case of stock-out, that means it is most valuable for the manager of paper towels to share information.

5. Conclusions and future research

In this paper, a high-level Petri-net model is developed to study the impact of customer response to stock-out on the supply chain performance. Two brands are included in the simulated supply network with one of them encountering stock-out at one of the two retailers due to strong demand fluctuation. The supply chain performance is represented by BWE, on-hand inventory, and backlog level of both the stock-out brand and the competing brand. Simulation results show that for the stock-out brand, more significant impacts on BWE, on-hand inventory and backlog level are three types of customer behavior out of five, which are, purchasing at another store, delaying the purchase, and substituting with a different brand. Considering the magnitude of the impact, it is suggested that the stock-out brand work together with their retailers to develop customers' store loyalty and encourage customers to substitute within the same brand in a different size. For the competing brand, since substituting a different brand is the significant factor for supply chain performance, the manufacturer and its retailers should make great effort to distinguish the demand switched from the stock-out brand from the real demand and grab the opportunity to develop more loyalty customers. Furthermore, although enhancing the marketing strategy with IS can significantly alleviate these disturbances, the value of IS is significantly impact by customer responses. Managers can increase the value of IS through properly inducing customers' purchase behavior.

While successful, we note some limitations in this research. First, this study assumes that all the firms in the model use a simple time series forecasting method. It will be interesting to look at how other forecasting methods, such as two-parameter double exponential smoothing method or three-parameter Winters' method. Secondly, more advanced inventory decision method such as EOQ can be incorporated in the model. In addition, this research is based on the general situation of customer response instead of specific behaviors towards specific products. In the future, we plan to explore more product specific customer responses and validate the proposed method in this research.

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