Modeling Response to Stockout of Fashion Products in Omnichannel Retailing

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Abstract

Customers actively respond to stockout of products in one of the following ways in retailing: they switch to a substitutable products, or switch to another store where the stockout brand is available, or delay purchase (backlogging). We introduce a model of customers' active response to stockout of fashion brands. We model response to stockout of two brands sold by two stores. We define delay (backordering) and brand and store switching as *active response to stockout*. Unlike in the majority of earlier papers on substitutability, we consider realistic responses to a stockout, such as backlogging, or switching brands and/or stores. In particular, one interesting aspect of the response to a stockout is central to our research: how the opportunity to backorder or switch between brands and stores affects the profitability and the optimal order size of retailers. Furthermore, given the proliferation of retail brands, retailers of fashion products must consider how the variety of products might affect inventory and pricing decisions in the presence of strategic consumers. We developed a supply chain model consisting of stores that sell substitutable products at regular prices over a finite season, ending with clearance sales at reduced prices. The presented model includes active response of customers to a stockout between two substitutable brands sold by two stores belonging to a single retailer. Extensive numerical study was implemented in order to better understand the effect of response to stockout on optimal order sizes and equilibrium prices.

The main analytical results and numerical experiments presented in this study are that active response to stockout improves the omnichannel retailer's expected profits in the following ways: (i) backlogging brings additional revenue while, brand and store switching allows additional profits; (ii) the optimal inventory can be reduced, which helps decrease holding costs. The implication of our findings for retail managers is that retailers should consider the response to stockout and strategic consumers in their ordering and pricing decisions. Omnichannel fulfillment offers additional opportunities for retailers to benefit from active responses to stockout.

The research is organized as follows. In Chapter 1, we present the background of the research, research questions and the significance of the research. In Chapter 2, we review related literature. There are five academic streams associated with this

research: fashion supply chains, response to stockout, partial backlogging, omnichannel retailing, and pricing with strategic consumers. Chapter 3 introduces a base model, structure of supply chain, and associated assumptions. In addition, the same chapter presents the active response to stockout model (the main model in this research). In order to facilitate the study of the effect of response to stockout on optimal inventory and expected profits in omnichannel retailing, we extended the newsvendor model. In Chapter 4, we investigate how response to stockout positively affects pricing decisions using the concept of rational expectations. In Chapter 5, we conduct numerical experiments to find out how the presence of active response of customers to a stockout and holding costs in the newsvendor model would change the optimal order size and profitability. We conducted separate numerical experiments to find out how active response of customers to a stockout would affect pricing policy. Chapter 6 discusses the positive implications of active response of customers to a stockout for managers and consumers. Chapter 7 presents a summary and proposes topics for future research. Partial results of the presented work have been published in Ovezmyradov and Kurata (2018).

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CHAPTER 1 INTRODUCTION

The fashion supply chain is important for the world economy. The textile and apparel sectors provide employment to 75 million workers worldwide; the apparel market was valued at US$3 trillion in 2017 and has continued to expand (Fashion United, 2018). Lost sales, delay (hereinafter referred to as backlogging), brand switching, and store switching constitute usual consequences of stockout at retailers' stores (Corsten and Gruen, 2005). The responses not leading to lost sales can be categorized into active response of customers to stockout, including backlogging, brand switching, and store switching. In this research, a framework is developed to model the active response to stockout of fashion products in omnichannel retailing. Partial results of the presented work have been published in Ovezmyradov and Kurata (2018).

Mathematical modeling of the fashion supply chain at the marketing and operations interface is used to address two main effects of customer's active response to stockout: (i) the effect on optimal inventory and profitability and (ii) the effect on equilibrium prices when strategic consumers are present. Furthermore, this work addresses important emerging issues faced by fashion retailers in their supply chains that are relevant for practitioners in the global industry.

Results suggest that customers' active responses to stockout can be beneficial to retailers, as: (i) backlogging brings additional profits while spillover demand by brand and store switchers brings additional revenue; (ii) optimal inventory is reduced, allowing carrying costs of inventory to decrease; and (iii) regular prices may increase in equilibrium with strategic consumers in presence of active response to stockout.

This research is motivated in large part by developments in omnichannel retailing. Omnichannel order fulfillment is increasingly adopted by fashion retailers that integrate online and physical stores in order to create a seamless shopping experience for consumers (Piotrowicz and Cuthbertson, 2014). Fashion has become the top product category of online trade with consumers' online expenditure for apparel and accessories totaling $51.5 billion in 2015 (Halzack, 2016). Such

significant trends in consumer spending has urged apparel firms to shift to omnichannel retailing to remain competitive. Customers' active response to stockout of fashion products is an important aspect for omnichannel retailers to consider.

1.1 Background of research

Uncertain demand and high risk of overstock (unsold surplus) or understock (shortage) present constant challenges for fashion retailers. Fashion trends change every season, resulting in short life cycles of apparel products, which, coupled with long lead times in fashion supply chains, helps explain the high risk of overstock or understock. Fierce competition between numerous producers of textile and apparel with narrow profit margins further exacerbate inventory problems (Fernie and Sparks, 2014).

Recent decades have been marked by the unprecedented growth of large retail chains dominating the retailing sector of major developed countries worldwide. Such retailers offer the same product lines and brands in a wide range of categories, including fashion, across the global network. Walmart is a prominent example of a top retailer selling a wide range of products, from grocery to apparel (Walmart, 2017). Identical merchandise offered worldwide at large retailers increases the chance that customers will switch between brands and stores. Inventory management is a serious business issue: stockout and overstock combined (including lost sales and discounts) cost retailers US$1.1 trillion annually (Buzek et al., 2015). Stockout- and overstock-related revenue losses in the fashion supply chain may constitute 4% and 14.6% of retail sales, respectively, as shown in Table 1; inventory-carrying costs represent another major source of losses at 6.4%.

Table 1 Revenue losses in the apparel supply chain (percentage of retail sales)

	Fiber and textile	*Apparel*	*Retail*	*Total*
Markdowns	0.6	4.0	10.0	14.6
Stockouts	0.1	0.4	3.5	4.0
Inventory at 15% holding cost	1.0	2.5	2.9	6.4
Total	*1.7*	*6.9*	*16.4*	*25.0*

Note: Table adapted from Lowson et al. (1999).

Classic research on supply chain modeling assumes lost sales as the only response of customers to stockout, in which customers quit shopping without their intended purchase. However, an empirical study by Corsten and Gruen (2005) demonstrated that an active response was more common in cases of product shortage: customers tended to delay the purchase, switch to a similar brand offered within the same store, or switch to another store where they can buy the preferred brand.

Frequent promotions on fashion products may be responsible, in large part, for the recent demise of several department stores and specialty chains (Wahba, 2017). Yet, most retailers do not have an effective strategy for managing prices and promotions across channels (McGregor, 2016a).

Thus, this research aims to address how the active response of customers to a stockout affects stocking and pricing decisions of fashion retailers, focusing on the implications for omnichannel retailing.

1.2 Research questions

After experiencing stockout, some consumers choose to switch to a similar brand or go to another store to make their purchase rather than simply not making a purchase. Similarly, some consumers delay their purchase (backlog) in the case of a stockout, and some request backlogging in addition to brand or store switching. This study examines the combined effects of active response of customers to a stockout (backlogging, brand switching, and store switching) in a fashion supply chain to determine the manner in which these responses affect optimal ordering policy and expected profits by asking two main questions: (i) By what amount would the optimal order size and the expected profit of fashion retailer change in the presence of active response of customers to a stockout? (ii) How does active response of customers to a stockout affect fashion retailers' pricing decisions in the presence of the forward-looking behavior of strategic consumers? These two questions are addressed in Chapter 3 and Chapter 4, respectively.

1.3 Significance of the research

As industry experts have noted, the potential of quantitative models has yet to be realized by fashion retailers; however, there is a trend towards the wider acceptance of such models in the practice of decision-making (Şen, 2008). Quantitative and qualitative research has considered the effects of product availability on consumer behavior; however, despite the many empirical studies, few analytical models have been suggested that explicitly consider the active responses of consumers. One novel aspect of this research is in analyzing the effects of consumer behavior related to brand unavailability on fashion supply chain performance.

This study contributes to existing research by developing a modeling framework for fashion supply chains to investigate the effects of active response to retailer's stockout of fashion products. A theoretical analysis is provided so that fashion retailers can achieve a better understanding of the effects of customers' responses to stockout and thus be able to make more accurate decisions with respect to order sizes in the presence of active response to stockout and holding costs. A single-period model is extended to incorporate both the holding costs and active response of customers to stockout. This research differs from extant models of response to stockout by taking into account inventory holding costs in the newsvendor model. Findings show that the active response of customers to a stockout is likely to result in lower stock levels while leading to higher prices for retailers in equilibrium. The implications of active responses for omnichannel retailers are extensively discussed. Results were also compared with those obtained previously on the response to stockout, in which researchers have suggested that demand substitution between products likely has a positive impact on expected profits and could lead to changes in inventory levels. Furthermore, the dependency of the impact of order reduction on the presence of a competitive setting in a supply chain model is also discussed.

1.4 Methodology

The classic newsvendor inventory model of fashion supply chain for a single-period problem acts as the basis for this research. In this model, the fractile formula presents a critical ratio as a practical tool for finding optimal order size. In this work, the newsvendor model is able to account for product substitution. Nahmias and Cheng (2009) described the derivation of solutions for the newsvendor model, and Khouja (1999) reviewed newsvendor model extensions. An extension of the classic newsvendor model is introduced in Chapter 3 to serve as the main model, taking into account backlogging, brand switching, and store switching as active customer responses. Although relatively simple, this extension is suitable for the practical purposes of omnichannel retailers. An overview of the structure of the fashion supply chain analyzed here is presented in Figure 1.
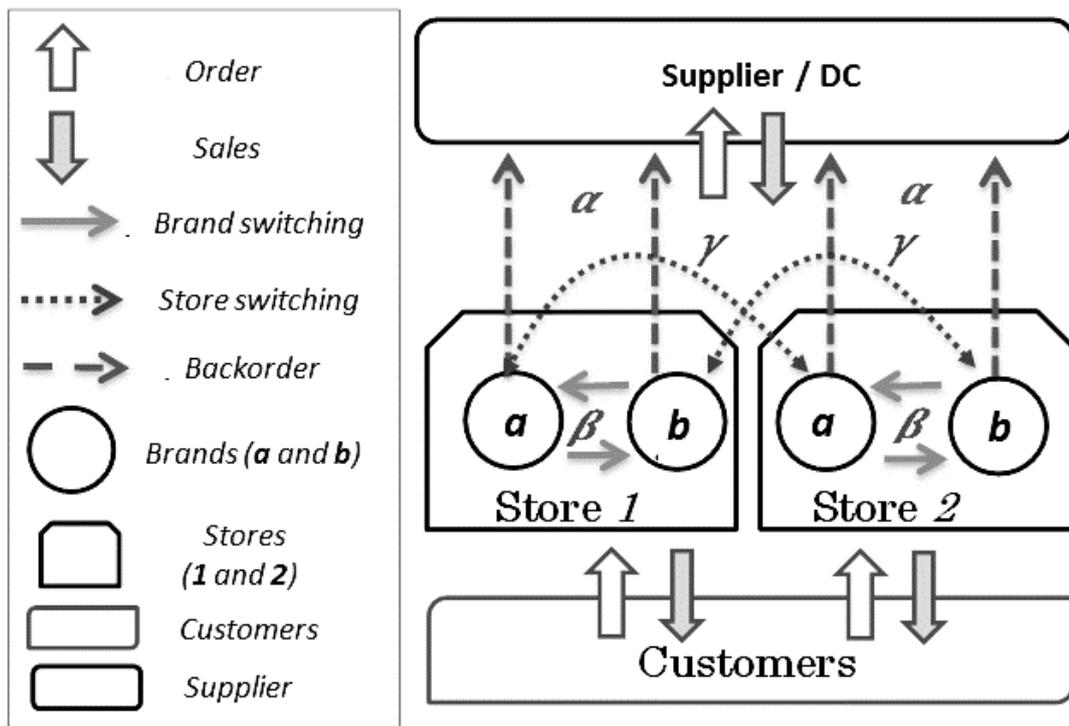
Figure 1. Supply chain structure (α, β, and γ denote backlogging, brand switching, and store switching customers, respectively)

Note: this figure is reproduction of Figure 1 in Ovezmyradov and Kurata (2018).

The main model is extended in Chapter 4 to analyze the effect of response to stockout on the pricing decisions of retailers using the concept of equilibrium with rational expectations from economic theory (Sargent, 2008). The model extension presents optimal decisions for each store and a continuum of identical consumers. This method has been used by previous researchers using similar models to model fashion supply chains (Su and Zhang, 2008; Cachon and Swinney, 2009; Cachon and Swinney, 2011; Gao and Su, 2016).

The extension of the main model considers equilibrium inventory and prices only at a particular store with all other parameters fixed during analysis, thus assuming that the direct effect of other store's decisions or overall market competition had negligible impact. This simplifying assumption, which ignores variability and interrelationships within the market and supply chain disturbances, was made for tractability even though it rendered the model less realistic.

The proposed models could be used to improve the accuracy of forecasting in the fashion supply chain by helping to better understand the effects of consumer behavior specific to the stockout of fashion products. Although this study was focused on fashion supply chains, results could be extended to other areas concerning the supply of products with uncertain demand and long lead times.

CHAPTER 2 LITERATURE REVIEW

Fashion supply chains, responses to stockout, partial backlogging, omnichannel retailing, and pricing with strategic consumers indicate the five main categories of literature related to this research; these are thus reviewed in this chapter.

2.1 Characteristics of fashion supply chains

Fashion and textile supply chains are of enormous significance for the global economy and have unique characteristics that set them apart from other types of supply chains (briefly described in Table 2 below). Textile production dates back to prehistoric times and was the central element of the Industrial Revolution that started in 18th century England and transformed global supply chains (Chapman, 1972).

A substantial proportion of the market belongs to fashion products, characterized by high demand uncertainty, long lead times, and a growing number of strategic consumers purchasing items during sale or clearance at a discounted price (Fernie and Sparks, 2014). The nature of fashion is such that even the slightest variation in size, shade of color, or style of clothing will result in the consumer refusing to buy a product or, if already purchased, avoid wearing it and returning for a refund. As trends changing each season, fashion products are often subject to high-impulse purchasing and have a short life cycle, typically three months. Numerous external factors may also have a significant impact on sales. For example, the unusually warm winter of 2015–2016 caused a slump in demand, inventory problems, and even the closing of many department stores and specialized fashion retailers (The New York Times, 2015).

Table 2 Main characteristics of fashion supply chains

Multiple stages of manufacturing and several sectors involved	• Production stages, including (but not limited to) fiber production; yarn manufacturing (spinning); fabric manufacturing (weaving or knitting); dyeing and finishing of fabric; and sewing (Fernie and Sparks, 2014; Şen, 2008).
Long lead times	• Lead times as long as one year or more are quite common, due to the complexity of the supply chain and economies of scale (Fernie and Sparks, 2014; Şen, 2008).
High uncertainty of demand	• The long lead time, volatile nature of fashion, and seasonal changes contribute to high uncertainties in predicting future demand (Fernie and Sparks, 2014).
Great risk of fashion product running out of stock (outstock) or surplus left after the end of sales season (overstock)	• Stockout and overstock are direct consequences of high demand uncertainty, which makes it difficult to forecast future sales (Fernie and Sparks, 2014). The increasing number of strategic consumers has exacerbated this problem (Cachon and Swinney, 2011).
Large scale of textile and fashion industry	• Textile manufacturing and trade accounts for a large share of the world economy, with an estimated value of US$3 trillion in 2017 (Fashion United, 2018).
Great economic and social role in employment and exports among population of developing countries	• Millions (the majority of them women) in Bangladesh, China, India, Vietnam and other developing countries have been drawn out of poverty due to the growth of textile and particularly clothing industries (Fashion United, 2014).
Substantial environmental impact	• Cotton, the most important natural fiber, requires vast quantities of water and intensive use of land, fertilizers, transportation, and storage. The production of wool and other natural fibers is also very resource-intensive. Synthetic fiber production has less of an overall environmental footprint but is associated with the chemical industry and corresponding ecological risks.
Some of the leading supply chain management concepts originated in textile and fashion industry	• The widely disseminated quick response (QR) was originally based on a textile industry research program in the United States in 1984 that revealed alarming levels of inventories (more on the history of QR can be found in Gunston and Harding, 1986) • The fast-fashion production system, as the name implies, has its origins in innovative fashion retailers such as Zara, whose spectacular growth owes much to their advanced supply chain design. It is the mode of operation employing quick response and highly fashionable product design capabilities. This definition of fast fashion was used by Cachon and Swinney (2011).

Nevertheless, future demand for non-fashion textile products with mainly deterministic demand patterns, to various extents, also proves challenging to predict as a result of the long lead times and fluctuating prices from the changing costs of natural and synthetic fibers. Traditionally, raw materials, namely fiber, constituted the largest cost in textile production. The price of natural fibers is heavily dependent on cotton harvests, which undergoes disruptions during periods of drought in producer countries. Synthetic fiber costs are influenced by oil and gas prices that are subject to sharp changes due to decisions made by oil-producing countries and other geopolitical factors. Demand uncertainty is reflected in this research by considering different probability distributions. For simplicity and tractability, the effects of unexpected or external uncertainties, such as disruptions of supply and cost changes on the operational performance of supply chain, are ignored.

Due to their importance and peculiarities, fashion supply chains receive much academic attention and have been the subject of numerous studies, reflected in entire special issues, books, and chapters of publications on supply chain management. Recent publications wholly dedicated to textile and fashion include Hines and Bruce (2007), Fletcher (2008), Şen (2008), Choi and Chiu, (2010), Choi (2012), Choi et al. (2013), and Fernie and Sparks (2014).

2.2 Response to stockout

Empirical studies on the substitution of products by consumers provide evidence that consumers commonly respond to stockout at retailer's stores by backlogging, brand switching, and store switching. For consistency, common responses to stockout are defined corresponding to existing empirical studies. Zinn and Liu (2001) found that four empirical papers reported varying levels of customer response to stockout: delay of purchase varied from 2.5% to 29.8%, whereas substitution varied from 22.2% to 83.4%. This discrepancy was reported to be caused by the use of different methodologies and research questions. ECR Europe (2003) found a ratio in Europe of product substitution to no-purchase or store switching of 69:31 during the first customer visit; the ratio nearly flipped after the second and third visits if the product remained out of stock. In a global study by Corsten and Gruen (2005), 9% of

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outstock situations were found to lead to no-purchase (lost sales); 31% of consumers switched to other store to buy the same product; 19% substituted to another product of the same brand; 26% chose a different substitutable brand; and 15% delayed the purchase of the preferred product. Although existing empirical studies predominantly report on the response to stockout of grocery and hygiene products, active response to stockout seems to be common for fashion products as well (Zinn and Liu, 2008). Researchers have increasingly studied the response of Internet shoppers to stockout; consumers have tended to switch to the physical store or to a shopping website of retailer after observing a stockout during online shopping (Peinkofer et al., 2015; Sides, 2016). Sampaio and Sampaio (2016) evaluated how consumers' responses could differ due to incentives offered by retailers to motivate them not to leave a store after a stockout, such as apologizing, giving a rain check, delivering home, trading up, or providing a discount. The existing empirical studies differ in scope and findings; however, spillover demand of brand switching and store switching consumers seem to be significant aspects of the active response of customers to stockout. Together, they account for approximately 76–87% of all the studied responses to product stockout.

Product surplus can be used to substitute a fraction of unsatisfied demand for an out-of-stock product. This aspect, also known as spillover demand, has been considered in several extensions of the newsvendor model, which can be categorized into research considering independent companies (Anupindi and Bassok, 1999; Mishra and Raghunathan, 2004; Netessine and Zhang, 2005; Hopp and Xu, 2008; and Wan et al., 2017) and those that study product assortments at a store of a single retailer (Khouja et al., 1996; Rajaram and Tang, 2001; Smith and Agrawal, 2000; Kök and Fisher, 2007; Fadıloğlu et al., 2010; Transchel, 2017; and Kurata et al. 2017).

Mathematical modeling aimed at optimization of the order sizes by two or more independent companies is first considered. For a supply chain comprising of one manufacturer and two dealers, Anupindi and Bassok (1999) demonstrated that Nash equilibrium leads to increase in the inventory and profits of a dealer by the fraction of customers who experienced a stockout but then searched for that product at another dealer. The expected profit of a dealer was also shown to increase in a centralized system. Manufacturers were shown to benefit from decentralized systems if the number of customers searching at another dealer after stockout was high enough.

Furthermore, this negative correlation coupled with a higher demand uncertainty could expand the benefit of product substitution. When vendor-managed inventory was introduced for retailers in a model with two manufacturers and one retailer, Mishra and Raghunathan (2004) found that active response to stockout offered an extra benefit due to an aversion to losing sales to the competitor, which led to more inventory and an increase in the competition due to brand substitution between manufacturers' brands. Netessine and Zhang (2005) demonstrated that the issue of supply chain coordination could be more relevant for complementary products: competing retailers were likely to understock complementary products but tended to overstock substitutable products. Hopp and Xu (2008) investigated optimal ordering decisions in non-competitive and competitive settings; they found that the competitive setting led to a decrease in price and increase in order size. Finally, Wan et al. (2017) found that customers' response to stockout of products at independently owned small retailers increased their initial optimal order sizes but boosted their profitability.

Customers' responses to stockout should be considered in the inventory policies regarding assortments of products. After extending the newsvendor model to include two substitutable product and finding upper and lower bounds on the optimal order size, Khouja et al. (1996) confirmed that, when product substitution was involved, quantities increased expected profits. Smith and Agrawal (2000) considered product substitution by customers within a store's assortment; active response to stockout led to a reduction in the optimal number of stocked items when fixed costs were present. Rajaram and Tang (2001) considered a single-retailer model and presented a heuristic for finding the optimal inventory of substitutable items. Active response to stockout was demonstrated to reduce the optimal order size and increase profitability. Designing or planning products as substitutable assortments was also offered as a more realistic approach to benefiting from active response of customers to stockout. Kök and Fisher (2007) applied a heuristic method for an assortment of substitutable brands and showed active response to increase profits of a supermarket chain. For an overview of the literature on substitutable products, readers could refer to Pentico (2008). Fadıloğlu et al. (2010) showed how optimizing substitutable shampoo brand inventories could boost profits at two supermarket chains. Transchel (2017) argued that neglecting stockout-based substitution could lead to mismatch of supply–demand

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within the entire product assortment, resulting in decreased profitability for high-quality products. In order to address the complexity of substitution models, a common assumption of symmetry was made, in which levels of customers' active response to stockout were identical, and stores or retailers were identical in pricing and costs. The same assumption has been made in this research. Overall, the extant literature on product substitution confirms that the active response to stockout can increase expected profits of retailers. Optimal order size is largely defined by the implications of active response to stockout and whether the modeling settings is competitive (two or more firms compete) or non-competitive (individual retailers decide on the optimal inventory within their stores).

2.3 Partial backlogging

A common type of response to stockout reported in operations research is backlogging. Partial backlogging has been studied comprehensively in the context of the economic order quantity model and to a lesser extent in newsvendor model settings. Whereas the majority of studies deal with partial backlogging from the perspective of business-to-business (B2B) delivery, partial backlogging is considered here from the customers' perspective.

Several studies have assumed partial backlogging. Drake and Pentico (2011) modified the economic order quantity model considering price discounts for increased profitability under partial backordering. Sarkar and Sarkar (2013) extended an inventory model for deteriorating items with stock-dependent demand with a varying backlogging rate to determine the optimal cycle length while minimizing total expected costs (holding, shortage, ordering, deterioration, and opportunity costs). Taleizadeh (2017) developed a solution algorithm for a lot-sizing model under disruption with partial backordering of shortages. Recent papers on partial backlogging often focus on optimal ordering policy for deteriorating items (Tiwari, et al., 2018; Soni and Chauhan, 2018; Yang, 2018; Mashud et al., 2018).

In traditional retailing, backlogging can also refer to customers who postpone their purchase and return to the store later when the product is in-stock again; this type of backlogging is difficult for retailers to identify. It is easier to record common

transactions related to backlogging, such as *click and collect, order in-store,* and *deliver home*. In this regards, backlogging is directly related to omnichannel fulfillment. In the case of a stockout, the developed model allows for partial backlogging of a certain fraction of demand: a portion of customers who find that a preferred brand is unavailable delay purchase, and the retailer places an additional order to deliver the brand to these customers later. Only partial backlogging is assumed optimal for fashion businesses, corresponding to limited capacity.

2.4 Omnichannel retailing

This research was strongly motivated by the mounting interest in omnichannel retailing. This approach, according to DHL, requires separate sales channels to converge into a single seamless channel of orchestrated product flow designed to deliver products and a personalized shopping experience; omnichannel is thus the next logical evolutionary step after a multichannel (DHL Trend Research, 2015). Meanwhile, Lightspeed POS Inc. has interpreted omnichannel as the practice of providing a seamless experience as retailers sell to, communicate with, and interact with customers through the integration of online, mobile, and in-store channels, devices, and systems; although multichannel has provided multiple channels, there is little integration among them (Lightspeed, 2017). Business Insider has defined omnichannel as a cross-channel business model that connects a retailer's in-store, online, and mobile presence at different stages of the customer's purchase journey (Camhi, 2017).

For the purposes of this study, the categorization by Beck and Rygl (2015) has been used to distinguish omnichannel from multichannel or and cross-channel retailing: omnichannel retailing indicates that all channels are widespread such that the customer triggers full interaction and the retailer controls full integration. The retailer controls the integration of customer, pricing, and inventory data across all channels, and merchandise offered to consumers is consistent across all channels.

Research into omnichannel retailing has increased in recent years. Gao and Su (2016a) used mathematical modeling to consider how retailers could increase profits by introducing a buy-online-and-pick-up-in-store omnichannel initiative in the

presence of strategic consumers; they later analyzed the effect of information availability on the omnichannel consumers and retailers (Gao and Su, 2016b). Taleizadeh et al. (2017) has investigated the pricing policy for substitutable products in a two-echelon supply chain model with one retailer and two manufacturers offering their respective brands using traditional and online channels. Additionally, Ailawadi and Farris (2017) studied the number of visitors who visited a retailer but later bought a product elsewhere. These stockout and cross-channel conversions were identified as key metrics of omnichannel retailing. For further information on recent research into omnichannel retailing, readers can reference the review by Verhoef et al. (2015).

Omnichannel fulfillment implies that retailers have introduced an inventory system allowing certain products not in stock in a physical store to be delivered by other channels, i.e., backlogging and in-store pickup. Backlogging means that the delayed order can be filled from a retail distribution center (DC) or by transshipment from another retail store. Omnichannel fulfillment also promotes brand switching or store switching of customers by ensuring instant access to the inventory status of substitutable, in-stock brands or the availability of the same product at other stores, respectively. Omnichannel fulfillment for retailers means sales via all available channels, allowing both the customer and the business to benefit from full channel interaction. In contrast, only partial channel integration and interaction is possible in multichannel and cross-channel retailing.

2.5 Strategic consumers and pricing

Frequently discounted prices have trained many consumers to make purchases only during clearance sales. The poor performance of apparel stores belonging to Gap and its subsidiaries, namely Banana Republic and Old Navy, has been linked to the heavy discounts and promotions offered on a wide range of merchandise, including in-season clothing (Schlossberg 2016). This is a worrying trend for the entire retail sector.

When discussing pricing decisions in fashion retailing, strategic consumers should not be ignored. Strategic consumers attempt to maximize long-run utility from lower cost by strategically timing their purchases. In contrast, myopic consumers are

non-strategic consumers and usually purchase products at the full price because of an unwillingness to return to the retailer later (Cachon and Swinney, 2009). Su and Zhang (2008) investigated the possibility of using contracts for supply-chain coordination considering strategic consumers. Quick response was shown to reduce the impact of strategic consumers by reducing the probability of unsold inventory remaining for clearance sales, due to better matching of supply and demand (Cachon and Swinney, 2009, 2011). Gao and Su (2016a) investigated how store pick-up in omnichannel retailing affects the behavior of strategic consumers.

Similarly, the proposed model takes into account consumer valuations and the probability of future consumption in equilibrium with rational expectations. The model originally developed by Cachon and Swinney (2011) is used to compare optimal order sizes, equilibrium full prices, and expected profit in traditional, quick-response, enhanced-design, and fast-fashion systems in the presence of strategic consumer behavior. Cachon and Swinney (2011) concluded that the operational and behavioral components of quick-response and enhanced-design systems, when combined into a fast-fashion system, complement each other and lead to improved profitability, even with strategic consumers.

2.6 Novelty of the research

To the best of the authors' knowledge, the present study is among the first to discuss how consumer response to stockout serves as an important operational aspect of omnichannel retailing. This work is based on a model originally proposed by Kurata et al. (2017), which considers all operational aspects in one unified model, rather than focusing on a single aspect of the response, such as backlogging or switching to another product or store, as is commonly done. Unlike previous research, this research assumes partial backlogging; backlogging is considered an integral aspect of the response to stockout.

In contrast to traditional extensions of newsvendor models, this model considers holding costs, as they have been deemed important in defining the optimal order size. Inventory levels are of particular importance for omnichannel retailers.

Unlike the research on strategic consumers by Cachon and Swinney (2011), which mainly helps fashion retailers decide which of the four production systems should be adopted to achieve greater profits, this model focuses on how strategic consumers' response to stockout affects their forward-looking behavior. Consequently, production systems are not considered. Instead, the impacts of consumers' active responses to stockouts on strategic consumers are studied.

Finally, there is an obvious shortage of mathematical modeling research on omnichannel fulfillment, given that extant studies on omnichannel are almost exclusively devoted to either qualitative aspects or empirical investigations. Like Gao and Su (2016), this research also discusses the implications of strategic consumers for omnichannel retailing; however, the focus of the research is pricing in presence of the active response to stockout. A comprehensive model of omnichannel retailing that encompasses all characteristics, such as ease of mobile interface use and other subtle qualitative aspects, is not attempted. Rather, the focus is on customers' responses to stockout, a key operational aspect of omnichannel fulfillment that can be quantified and applied in inventory control. From an operational perspective, omnichannel fulfillment means that customers can check the availability of their desired products at local stores and reserve them for a store pick-up or home delivery. This, in turn, gives retailers a certain degree of control over customers' responses to stockout through loyalty programs, personalized offers, tailored promotions, as well as various data on shopping preferences obtained from shopping apps and personal accounts. This novel aspect concerning the response to stockout in omnichannel retailing has not been adequately examined by extant studies. A comparison between relevant previous papers and the novelty of this research is presented in Table 3, where a plus sign indicates the consideration of a topic.

Table 3 Most important studies related to this research and novelty

Topic	Taleizadeh (2017)	Anupindi and Bassok (1999)	Rajaram and Tang (2001)	Cachon and Swinney (2011)	Beck and Rygl (2015)	Kurata et al. (2017)	This paper
Partial backlogging	+	-	-	-	-	+	+
Brand switching	-	-	+	-	-	+	+
Store switching	-	+	-	-	-	+	+
Pricing with strategic consumers	-	-	-	+	-	-	+
Omnichannel retailing	-	-	-	-	+	-	+
Inventory holding cost in newsvendor model	-	-	-	-	-	-	+

CHAPTER 3 EFFECTS OF CUSTOMER RESPONSE TO FASHION PRODUCT STOCKOUT ON ORDER SIZES AND PROFITABILITY IN OMNICHANNEL RETAILING

This chapter presents the modeling framework of customers' active response to a stockout and discusses how customer behavior regarding unavailability of fashion products affects the optimal ordering policy and expected profits of omnichannel fashion retailers.

3.1 Base model: newsvendor model and holding costs

A supply chain of two stores belonging to the same fashion retailer selling substitutable brands is considered. Each store, represented by the numbers 1 and 2, is an independent profit maximizer selling two brands supplied by the same retailer (products are supplied by the retailer's own distribution center, DC) or an external supplier. The stores implement a make-to-stock inventory system. The decision variable corresponds to the order quantity q that maximizes the expected profit. Two brands, indexed as a and b, have the following exogenously set parameters: retail price p, wholesale price w, discounted (or clearance) sales price $v < p$ at the end of the sales season (net of any salvage cost associated with overstock), and unit production costs for supplier c. To avoid unrealistic outcomes, it is assumed that $p > w$ and $v < w$.

The following assumptions have been made for tractability and comparability:

1. Stores are symmetric in the sense that they stock the same brands, follow the same pricing strategy, and have similar internal costs, bargaining power, and customer search costs.

2. Stores are independent decision makers: the manager of each store decides the order size to maximize the profitability of the store.

3. Stores are located relatively distant from each other; thus, demand is independent and follows the same probability distribution.

4. This random demand follows a normal distribution. Each customer buys one unit of a fashion brand such that the total demand is equal to the number of customers in the local market.

5. The supplier is capable of delivering orders of any size, including unlimited backlog.

6. There is no extra goodwill cost in the case of shortage. A few fashion companies, such as ZARA, deliberately understock, thereby allowing stockout to occur and (reportedly) boosting the perceived value of the brand while discouraging strategic waiting for discounts (Fernie and Sparks, 2014; Cachon and Swinney, 2011).

7. Any unsold inventory remaining at the beginning of a clearance sale is made available to strategic consumers, after which any remaining stock is made available to an unlimited number of bargain hunters until all the overstock is sold. Cachon and Swinney (2009) made the same assumption and presented it as an analogy between a salvage market and discounted sales during the clearance period.

Many of the above assumptions are common to similar studies (e.g. Anupindi and Bassok, 1999; Mishra and Raghunathan, 2004). Overall, the model settings and assumptions used in this study correspond to the supply chain of a fashion product with uncertain demand and considerable inventory mismanagement costs.

The second assumption, which regards independent profit maximization by each store, is relevant for fashion retailers with a decentralized structure. The centralization of buying and replenishment (Şen, 2008) has taken place at some fashion retailers recently and many companies, including ZARA (Caro et al., 2010), started introducing analytical optimization methods for deciding how much to order at the company level. Many large retailers, predominantly those owning mono-brand stores, make decisions on merchandise centrally at a company's department level; however, certain categories of fashion retailers, such as franchising and specialty stores, often independently make these decisions (Brun and Castelli, 2008). Despite statistical methods being increasingly encouraged among fashion retailers, many procurement decisions are still made by individuals (Tyler, 2006). Even ZARA has traditionally relied on store managers to make ordering decisions (Ferdows 2004; Caro et al 2010).

Nordstrom is an example of a major department store that has heavily practiced decentralized buying decisions (Şen, 2008).

Major retailers worldwide have increasingly adopted omnichannel retailing. The proposed model does not incorporate direct (online shopping) channels; however, the findings of this research apply to omnichannel retailing. Subsequent sections of this chapter, including Table 5, discuss in detail how omnichannel fulfillment facilitates backlogging and switching between brands and stores. For instance, after experiencing a stockout in a physical store, a customer can immediately use a smartphone to check the website of a retailer (online channel) for availability and purchase, resulting in a "virtual" store switching across channels. Therefore, even though alternative channels are not explicitly reflected in the model itself, the model has direct business implications for omnichannel retailing. This is further discussed in Section 6.1. Table 4 presents the notations used in this chapter.

Table 4 Notations

p	Regular retail price per unit
w	Unit wholesale price
c	Unit production cost of manufacturer
v	Unit clearance price or discounted price
k	Additional cost of backlogging per unit
h	Holding cost as percentage of the unit purchasing cost
φ	Inventory depletion factor
α	Portion of customers who delay purchase (backlogging)
β	Portion of brand-switching customers
γ	Portion of store-switching customers
TAR	Total of the active response to stockout, $TAR = \alpha + \beta + \gamma$
f(x)	Probability density function of demand
F(x)	Cumulative distribution function of demand
μ, σ	Mean and standard deviation of demand
$n \in [a,b]$	Product brands
$s \in [1,2]$	Stores of retailer
$\Delta\pi$	Increase in profitability with active response of customers to a stockout as compared to classic newsvendor, $\Delta\pi = (\pi_A^* - \pi_C^*)/\pi_C^*$
Δq	Decrease in optimal order size with active response of customers to a stockout as compared to classic newsvendor, $\Delta q = (q_A^* - q_C^*)/q_C^*$
ΔCH	Incremental percentage cost of carrying inventory with the base model, $\Delta CH = (\pi_{CH} - \pi_C)/\pi_C$
ΔAH	Incremental percentage cost of carrying inventory with the model of active response of customers to a stockout, $\Delta AH = (\pi_{AH} - \pi_A)/\pi_A$
Subscripts and superscripts	
C	Notations of optimal order size and expected profit in the base model without holding costs (classic newsvendor), $\varphi h = 0$, $\alpha = \beta = \gamma = 0$
A	Notations of optimal order size and expected profit in the model of active response of customers to a stockout without holding costs, $\varphi h = 0$, $\alpha + \beta + \gamma > 0$
CH	Notations of optimal order size and expected profit in the base model including holding costs, $\varphi h > 0$, $\alpha = \beta = \gamma = 0$
AH	Notations of optimal order size and expected profit in the model of active response of customers to a stockout including holding costs, $\varphi h > 0$, $\alpha + \beta + \gamma > 0$

3.2 Consideration of holding cost in models with uncertain demand

The majority of newsvendor models in extant research tend to consider only understock and overstock costs while largely neglecting holding (inventory carrying) cost due to unsold overstock at the end of each period. The economic order quantity (EOQ) model for single-period deterministic demand includes inventory holding

costs. Holding costs arise due to the cost of capital, storage, insurance, and other costs of carrying inventory not explicitly linked to production. This research investigates the inclusion of inventory holding costs for models with uncertain demand as deterministic EOQ models do.

The reduction in inventory during a sales season in the newsvendor model can be represented in the form of the function $1 - t^n$, where t is a time point. The entire sales period is normalized to unity; therefore, $0 \leq t \leq 1$. A sensitivity coefficient, n, denotes the slowness of inventory reduction throughout a sales period. Integration of $1 - t^n$ with respect to t over the entire period yields $\varphi = \frac{n}{n+1}$, defined as the *inventory depletion factor*. An average inventory level over one period would then be equal to order size (starting inventory) multiplied by the inventory depletion factor φ. Figure 2 demonstrates how the three different patterns of inventory depletion in this research were distinguished.

Figure 2-(a) presents an *EOQ* pattern with *n = 1* and *φ = 0.5,* indicating a constant rate of reduction in inventory; this pattern is common in deterministic demand models. Another possible pattern, deemed a *fad*, is shown in Figure 2-(b), with *n = 0.5* and *φ = 0.33.* Here, sales peak at the beginning before a subsequent flattening. Figure 2-(c) shows a third pattern indicating a *holiday* with *n = 2 and φ = 0.7.* In this pattern, greatest sales take place closer to the end of a sales season due to a big event such as New Year's Eve. These inventory depletion patterns may also arise under various alternative conditions. For example, if a product is sold out prior to the end of sales season, the fad pattern takes place. The same pattern often happens due to demand that is dependent on inventory level (Urban, 2005). The holiday pattern better describes the majority of products that sell poorly during the sales season before having the remaining inventory being dumped to liquidators. This pattern also applies to the amelioration of inventory (Mondal et al., 2003). However, the focus of this research is not on the reasons for various patterns of inventory depletion, but rather on the effect of inventory holding costs on the active response of customers to stockout. These three patterns have been described to demonstrate the possible range of inventory reduction cases. The depletion factor and holding costs as a percentage of unit cost were assumed to be exogenously given to define total holding cost, φhw.
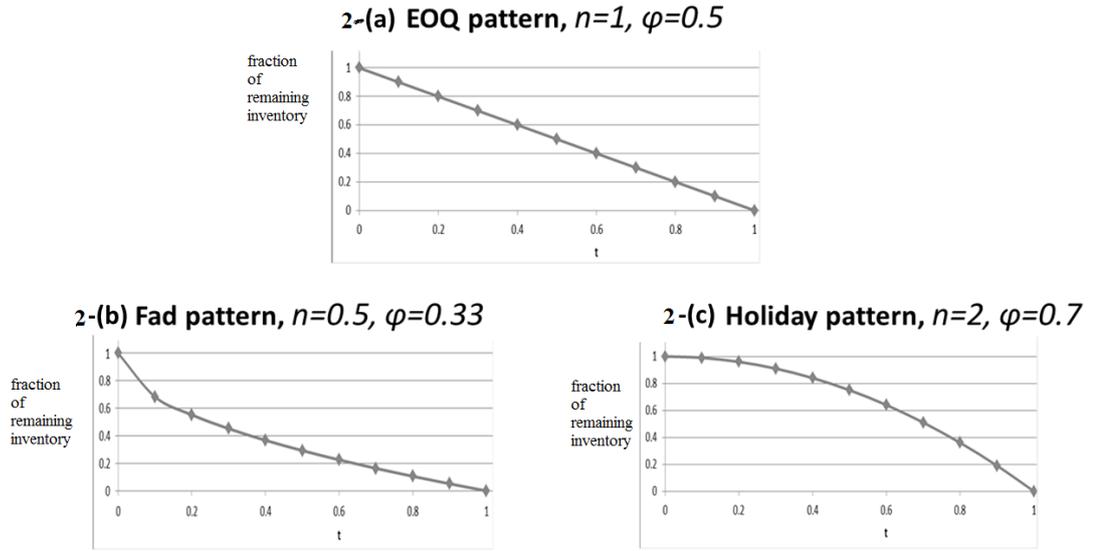
Figure 2. Patterns of inventory depletion over a sales season of fashion products

Note: this figure is reproduction of Figure 2 in Ovezmyradov and Kurata (2018).

3.3 Optimal order size in the base model

Holding costs were first added to the newsvendor model. The expected profit of retailer then becomes:

$$\pi_{1,a}^{CH} = p_{1,a}S_{1,a} - w_{1,a}q_{1,a} + v_{1,a}I_{1,a} - \varphi h w_{1,a}q_{1,a}. \tag{1}$$

The notation of π has indices for the corresponding store and brand given in subscripts that denote the specific brand within the store. The first term in Eq. (1) corresponds to the expected *sales* as follows:

$$p_{1,a}S_{1,a} = p_{1,a}\int_0^{q_{1,a}} x_{1,a} f(x_{1,a})dx_{1,a} + p_{1,a}q_{1,a}\int_{q_{1,a}}^{\infty} f(x_{1,a})dx_{1,a}$$

The second term of Eq. (1) denotes the *purchasing cost* as $w_{1,a}q_{1,a}$

The third term denotes the expected *salvage value* from sales at a clearance price as:

$$v_{1,a}I_{1,a} = v_{1,a} \int_0^{q_{1,a}} (q_{1,a} - x_{1,a})f(x_{1,a})dx_{1,a}$$

The last term denotes the *holding cost* as $\varphi hw_{1,i}q_{1,a}$.

The expected profits for the second product brand of the first store and for both products of the second store are determined by following an identical method. The first-order condition for maximizing expected profit gives an optimal order size that is an inverse of the cumulative distribution function evaluated at the critical ratio as follows:

$$q_{CH}^* = F\left(\frac{c_U}{c_O+c_U}\right)^{-1} = F\left(\frac{p-w-\varphi hw}{p-v}\right)^{-1}. \tag{2}$$

Both stores were assumed to have the same cost parameters and pricing policy. Therefore, brand and store indices are absent in Eq. (2) since the critical ratio is applicable to all brands at each store in the base model. Here, $c_U = p - w - \varphi hw$ denotes the underage (also known as stockout or shortage) cost per unit of lost sales and $c_O = w - v + \varphi hw$ denotes the overage (also known as overstock or surplus) cost per unit that could not be sold at regular price. Stockout and overstock situations often lead to huge losses of profit for retailers. Without the addition of the inventory holding costs, the base model would be the same as the classic newsvendor problem

This base model will serve as a benchmark to compare against the model of active response to stockout that includes backlogging and brand and store switching.

3.4 Model of active response to stockout

An out-of-stock product causes a substantial loss of fashion retailers' revenue. However, certain portions of customers facing stockout of their desired item choose to respond actively, rather than quit purchasing, by: backlogging (α), brand switching (β), or store switching (γ). If enough unsold items remain to satisfy the spillover demand of brand and store switchers, the lost sales at both stores would result in only $1 - \alpha - \beta - \gamma$ portion of customers facing stockout. Taking into account that $0 \leq \alpha, \beta, \gamma \leq 1$ and accepting the range of active response levels retailing firms

commonly observe (Zinn and Liu, 2001; Corsten and Gruen, 2005), the levels $\alpha, \beta,$ and γ can each be ranked as low (less than 0.1), medium (between 0.1 and 0.2), and high (exceeding 0.2). The range of outcomes of customer response is illustrated in Figure 3.
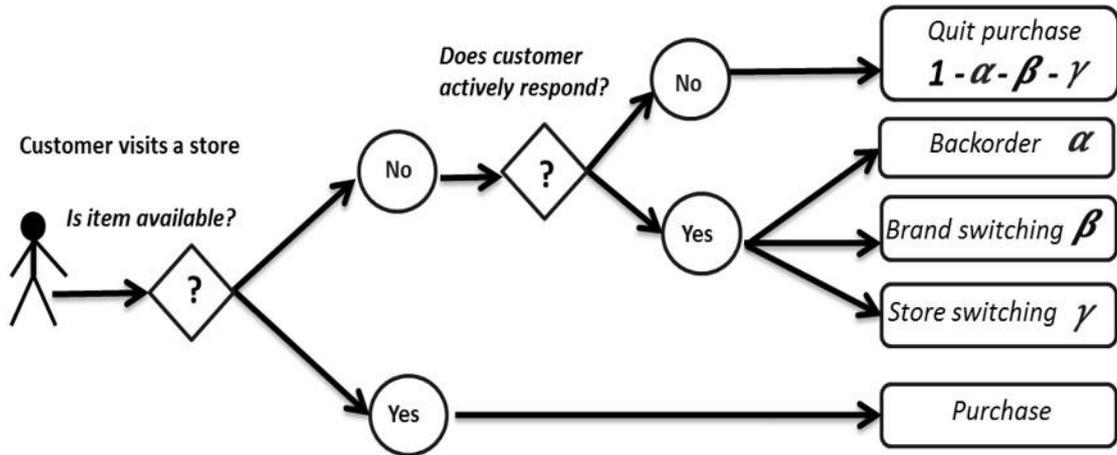
Figure 3. Scheme of active response of customers to stockout

Note: this figure is reproduction of Figure 3 in Ovezmyradov and Kurata (2018).

3.5 Interpretation of customers' active response to a stockout in omnichannel retailing

Delay of purchase or backlogging could be interpreted differently depending on the category of retail or product line: (i) customers come back to the store later after the product becomes available; otherwise (ii) customers ask the store staff to deliver the desired stockout brand later from either the DC or store upon replenishment. The first interpretation is likely to be relevant for products with a deterministic demand (such as many grocery products) that are periodically ordered by retailers. This interpretation of backlogging is less suitable for traditional fashion retailers however. Nevertheless, businesses have become increasingly capable of replenishing fashion products even before the completion of the sales season (Fisher et al., 2001). Modern omnichannel retailers provide the possibilities for their customers to effortlessly place additional orders of many fashion products in the case of a stockout. In omnichannel

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fulfillment, customer shopping does not necessarily mean visiting a physical store; it could also mean access to an online shop via a retailer's webpage using a computer, mobile phone, or tablet. With virtual access, a customer can easily check the inventory status at stores nearby using a mobile browser interface or shopping application. Alternatively, desktop browsers can be used to check availability. Customers can then order online and choose in-store pickup if a preferred product brand is out of stock at the shopping locations that are convenient for them. Meanwhile, customers visiting a physical shop can be encouraged to ask store staff to deliver a preferred product brand that is currently out of stock for either in-store pickup or direct delivery to home (store pickup is usually free for customers but home delivery might come at an additional cost).

Until a decade ago, measuring brand or store switching was costly and required long marketing studies that were difficult to conduct continuously (Corsten and Gruen, 2005). Omnichannel fulfillment now offers retailers easier ways to evaluate active response to stockout. Many retailers' websites offer suggestions to buy a substitutable product when the currently-searched brand is not available. Amazon.com is well known to show *Sponsored Products* and *What Other Items Do Customers Buy After Viewing This Item?* to customers during online shopping. This is a great example of how easy and efficient it could be for both shoppers and retailers to allow switching between brands online using automatically generated suggestions of substitutable brands that are personalized based on customers' historical data. A brief comparison of customers' active response to stockout in traditional retailing with omnichannel retailing is presented in Table 5.

Table 5 Meaning of each component of active response of customers to a stockout

Outcome of active response to stockout	Notation used in this research	Meaning of stockout outcome for customers in traditional retailing	Meaning for of stockout outcome customers specific to omnichannel fullfilment
Backlogging	α	· Item is delivered later specifically as per request of a customer. ·Customer visits the store once again when a periodically replenished brand that is currently out of stock becomes available again.	·Customer uses an option of *Click and Collect* by ordering online and picking it up in-store afterwards. ·Customer uses an option of *Order in-Store, Deliver Home* by requesting delivery to their home when the item becomes available. ·Customer adds an item that is currently out of stock to his or her online *Wish List* so that the item can be purchased later upon delivery of automatic notification when the item becomes available.
Brand switching	β	·Customer switches to another substitutable brand at the current store.	·Customer clicks on a link to suggested substitutable product brand while shopping online and then purchases the brand. ·Customer checks availability of substitutable brand at a preferred store online and then reserves the item to buy.
Store switching	γ	·Customer visits another store in which the desired product brand is still available.	·Customer clicks on a link to suggested alternative stores online and visits one of them afterwards to immediately purchase the item or reserve it to buy later. ·While visiting one store, customer checks online if the preferred brand that is currently out of stock is available at another store, resulting in a reservation to buy afterwards or immediate visit to purchase the same item. ·Stores of the retailer perform transshipment of outstock items.

Traditional brick-and-mortar retailers that have launched shopping websites often provide suggestions of physical stores located near customers' current location or home address; these suggestions can also be automatically displayed in case the desired product is out of stock. Customers clicking on links to suggested brands and purchasing a substitutable product afterwards is interpreted here as brand switching. A customer clicking on a link to an alternative shopping location suggested by the retailers' website and visiting that location to purchase is interpreted as store switching.

In some cases, retailers can record brand or store switching events by means of a membership card, coupon, or retailer's credit card. Certain transactions could be interpreted as suiting two types of active response. For example, clicking on a link to a suggested alternative store during online shopping could result in reservation for *click and collect* and that could be categorized as both backlogging and store switching. Individual retailers would have to decide how to classify each transaction related to brand or store switching. Importantly, all shopping transactions across integrated channels can be recorded with less effort in omnichannel retailing, sometimes even with customers that have no personal account at a retailer. Overall, this research investigates how convenient it could be to measure portions of backlogging, brand switching, and store switching customers in omnichannel fulfillment as compared with traditional retailing.

3.6 Assumptions for customer response to a stockout

Several assumptions were made to simplify the model analysis. The levels of brand switching, store switching, and backlogging were assumed to be exogenously given and not correlated between each other. Although restrictive, this assumption has been commonly made in the field. The levels of active response of customers to stockout at stores were assumed the same ($\alpha_{1,a} = \alpha_{1,b} = \alpha_{2,a} = \alpha_{2,b}, \beta_{1,a} = \beta_{1,b} = \beta_{2,a} = \beta_{2,b}, \gamma_{1,a} = \gamma_{1,b} = \gamma_{2,a} = \gamma_{2,b}$).

For tractability, the stores were assumed symmetrical, i.e., the parameters of customer demand, pricing, and costs were the same across all the product brands and stores. Such assumptions of symmetry are also common in extant literature on the

response to stockout (Anupindi and Bassok, 1999; Rajaram and Tang, 2001; Mishra and Raghunathan, 2004; Netessine and Zhang, 2005), and are necessary to isolate an effect of response to stockout from other, unconsidered effects.

As customers were assumed to not incur shopping travel costs during store switching, they were indifferent between visiting stores. The model includes two stores, located in one town or district, and owned by the same retailer. Though many theoretical studies consider the cost of shopping travel (or transportation cost) in modeling customers' behavior, such a cost is largely subjective and including it in a practical model for optimization would be problematic. It is less difficult to estimate the level of customers' active response to stockout than shopping costs for an omnichannel retailer.

Simultaneous brand switching and store switching was ignored as an outcome; e.g., customers facing a stockout of desired brand *a* at Store *1* could not choose to purchase a substitutable brand *b* after store switching to Store *2*.

Customers were also assumed to switch to the second store only; they could not switch to any other stores owned by the same or another retailer. No competing retailers offering the same substitutable product brands were assumed to exist. Switching to a competing retailer effectively means an outcome of lost sales for the considered retailer in the model. Empirical studies have indicated that customers of brick-and-mortar stores usually stay with the same retailer instead of switching to another store or shopping website; however, the opposite is more common when stockout happens during online shopping (Sides, 2016). For the purposes of this study, customers were assumed to only switch stores within the same retail chain.

3.7 Expected profit and optimal ordering with active response to stockout

The extension of the base model to include customers' active response to stockout is shown in Eq. (3). The expected profit of *Store 1* from sales of brand *a,* including backlogging, store switching, and brand switching, can be defined as follows:

$$\pi_{1,a}^{AH} = p_{1,a}S_{1,a} - w_{1,a}q_{1,a} - \varphi h w_{1,a} + (p_{1,a} - w_{1,a} - k)\, \alpha_{1,a}L_{1,a} +$$
$$p_{1,a}min\{(\beta_{1,b}L_{1,b} + \gamma_{2,a}L_{2,a}), I_{1,a}\} + v_{1,a}max\{(I_{1,a} - \beta_{1,b}L_{1,b} - \gamma_{2,a}L_{2,a}),\, 0\}, \quad (3)$$

where the expected *stockout of Brand a at Store 1* is

$L_{1,a} = \int_{q_{1,a}}^{\infty}(x_{1,a} - q_{1,a})f(x_{1,a})dx_{1,a}$, the expected *stockout of Brand b at Store 1* is

$L_{1,b} = \int_{q_{1,b}}^{\infty}(x_{1,b} - q_{1,b})f(x_{1,b})dx_{1,b}$, and the expected *stockout of Brand a at Store 2*

is $L_{2,a} = \int_{q_{2,a}}^{\infty}(x_{2,a} - q_{2,a})f(x_{2,a})dx_{2,a}$.

The fourth term in Eq. (3), $(p_{1,a} - w_{1,a} - k)\, \alpha_{1,a}L_{1,a}$, expresses additional profit from backlogging customers. The fifth term, $p_{1,a}min\{(\beta_{1,b}L_{1,b} + \gamma_{2,a}L_{2,a}), I_{1,a}\}$, indicates the additional sales revenue from brand switching and store switching customers' spillover demand with respect to the second brand and store: a portion β of the spillover demand from another substitutable brand at one store is satisfied by overstock remaining after selling the first brand at the same store. Similarly, a portion γ of the spillover demand for the first brand at the second store is satisfied if customers find the brand at the first store. The *min* operator ensures that extra sales due to spillover demand cannot be more than the expected surplus of unsold items. The last term of Eq. (3), $v_{1,a}max\{(I_{1,a} - \beta_{1,b}L_{1,b} - \gamma_{2,a}L_{2,a}),\, 0\}$, expresses the salvage revenue from clearance sales at a reduced price v contingent on the remaining surplus of unsold inventory remaining after all spillover demand is satisfied. This model, initially developed by Kurata et al. (2017) to focus on supply chain coordination, is believed to accurately reflect reality. The model extension proposed here specifically concentrates on active response to stockout in an omnichannel fashion retailing and supply chain setting of strategic consumers.

If active response levels are minimum ($\alpha = \beta = \gamma = 0$) and holding costs of inventory are ignored ($\varphi h = 0$), Eq. (3) becomes the expression of the expected profit

defined by the classic newsvendor model, denoted by π^C. Considering Eq. (3), a retailer's optimal inventory can be defined by the following proposition.

Proposition 1. *Assuming symmetrical stores and brands under the model of active response to stockout, optimal order size is defined as follows:*

$$(a)\ if\ (\beta + \gamma) \int_q^\infty (x - q)f(x)dx < \int_0^q (q - x)f(x)dx\ (the\ overstock\ case),$$

$$q_{AH}^* = F\left(\frac{p(1 - \alpha - \beta - \gamma) + \alpha(k + w) - w + v(\beta + \gamma) - \varphi hw}{p(1 - \alpha - \beta - \gamma) + \alpha(k + w) + v(\beta + \gamma) - v}\right)^{-1},$$

$$\frac{\partial\ q_{AH}^*}{\partial \beta} < 0, \frac{\partial\ q_{AH}^*}{\partial \gamma} < 0, \frac{\partial\ q_{AH}^*}{\partial \alpha} < 0.$$

(b) If $(\beta + \gamma) \int_q^\infty (x - q)f(x)dx \geq \int_0^q (q - x)f(x)dx$ *(the stockout case),*

$$q_{AH}^* = \int_0^{q_{AH}^*} x f(x)dx + (\beta + \gamma) \int_{q_{AH}^*}^\infty (x - q_{AH}^*)f(x)dx,$$

$$\frac{\partial\ q_{AH}^*}{\partial \beta} > 0, \frac{\partial\ q_{AH}^*}{\partial \gamma} > 0, \frac{\partial\ q_{AH}^*}{\partial \alpha} < 0.$$

Proof. In case the expected overstock exceeds the spillover demand *(a)*, the optimal order size can be derived from the first-order conditions maximizing Eq. (3). If the expected overstock is not sufficient to satisfy the spillover demand *(b)* from brand switching and store switching, it is optimal for the retailer to match the inventory with the corresponding levels of brand switching and store switching ensuring the expected overstock. Here, $q - \int_0^q x f(x)dx$ represents the expected spillover demand, $(\beta + \gamma) \int_q^\infty (x - q_{AH}^*)f(x)dx$. This leads to higher inventory in the presence of higher levels of brand and store switching as compared with medium and low levels.□

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Stores and brand indices were omitted in Proposition 1 for notational simplicity because the assumption of symmetry allows it. The active response model resulting Proposition 1 is similar to the original model developed by Kurata et al. (2017), but it has been extended to incorporate holding costs with two stores belonging to the same retailer. Proposition 1 implies that customers' active response to stockout leads to the following alternate cases for retailers' orders:

(i)   the overstock case: optimal order quantity for each store is expected to decrease when spillover demand of brand switching and store switching does not exceed the expected surplus of unsold items at the store

(ii)   the stockout case: optimal inventory is not likely to change substantially compared with the classic newsvendor model, since it becomes necessary for the retailer to match the overstock to the expected spillover demand from brand switching and store switching customers.

The simulations described in Chapter 5 support the prevailing effect of decreasing optimal inventory across a wide range of numerical experiments. The optimal inventory decrease is more marked if the backlogging level is sufficiently higher than the levels of brand switching and store switching.

The decrease in optimal inventory with moderate levels of brand switching and store switching among customers may seem counterintuitive: spillover demand could seem to result in an increase in the order quantities at both stores. However, analyzing the inventory from the retailer's viewpoint reveals that backlogging, brand switching, and store switching can decrease the negative consequence of lost sales for each store, leading to a reduction in optimal inventory to avoid a surplus exceeding spillover demand. The newsvendor critical ratio relevant to the overstock case in Proposition 1 states that the cost of stockout per unit is $C_U = p(1 - \alpha - \beta - \gamma) + \alpha(k + w) - w + v(\beta + \gamma) - \varphi hw$, and the unit cost of surplus inventory is $C_O = w - v + \varphi hw$. Overall, customers' active response to stockout in the case of overstock lowers the unit cost of a shortage. From the viewpoint of supply chain management, spillover demand from brand switching and store switching can be interpreted as a kind of risk

pooling of inventory across stores that decreases the need for safety stock. This decrease in corresponding inventory costs from risk pooling is beneficial, as has been confirmed by several studies (Eppen (1979) is among the earliest examples). Generally, both the stockout and overstock cases lead to better profitability for the retailer. Proposition 2 explains how consumers' active response to stockout could be beneficial for the performance of a supply chain.

Proposition 2. *Assuming symmetrical stores and ignoring backlogging costs (k = 0) for each store and brand, the expected profits and optimal order sizes in the presence or absence of active response to stockout compare as follows:*

(a) $\pi_A^* \geq \pi_C^*$.

(b) $\frac{\partial \pi_A^*}{\partial \beta} > 0$, $\frac{\partial \pi_A^*}{\partial \gamma} > 0$, $\frac{\partial \pi_A^*}{\partial \alpha} > 0$.

(c) $q_{CH}^* \leq q_C^*$; $q_{AH}^* \leq q_A^*$.

(d) $\pi_C^* \geq \pi_{CH}^*$; $\pi_A^* \geq \pi_{AH}^*$.

(e) $\Delta CH \geq \Delta AH$.

Proof. Statements (*a*) and (*b*) follow from comparing the expressions of expected profits in Eq. (1) and Eq. (3) considering the non-decreasing impact of α, β, and γ on the expected profits of the retailer. Statement (*c*) is inferred from the analysis of critical ratios and their corresponding solutions for optimal order size. Statements *(d)* and *(e)* are concluded from comparing Eq. (1) and Eq. (3) and considering holding costs φh with the non-decreasing effect of customers' active response to stockout on the optimal order size, resulting in an increase of profitability.□

These outcomes due to customers' active response to stockout and inventory holding cost implications are further discussed in Chapter 5. Briefly, customers' active response increase the expected profits of retailer due to three sources: (i) extra profit from backlogging $(p_{1,a} - w_{1,a} - k) \alpha_{1,a} L_{1,a}$, (ii) extra revenue from spillover

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demand $p_{1,\mathrm{a}} min\left\{(\beta_{1,\mathrm{b}}L_{1,\mathrm{b}} + \gamma_{2,\mathrm{a}}L_{2,\mathrm{a}}), I_{1,\mathrm{a}}\right\}$, and (iii) a likely decrease in optimal inventory, reducing inventory costs $\varphi hw_{1,a}(q_{\mathrm{C}}^* - q_{\mathrm{A}}^*)$. This quantifies the increase in profitability and reduction of inventory from customers' active response to stockout. Practitioners can use the modeling framework presented for more realistic cases of multiple stores that have asymmetric parameters.

3.8 Effect of backlogging cost

Backlogging orders were assumed to not cause additional costs per unit of delayed purchase for the retailer in Proposition 2. This assumption seems natural for periodically replenished products (e.g., basic textiles). In certain product categories, backlogging costs are small enough for mature companies with distribution centers for replenishment at negligible additional cost per unit of backlogged item. Furthermore, retailers have better flexibility to deliver online orders at lower cost by optimally adjusting time and location of delivery or by directly shipping to stores.

In fact, omnichannel fulfillment can reduce shipping costs for online orders. For example, it costs Walmart \$5 to deliver a package to a customer's home, but only 75 cents to ship the same package to one of its stores (Camhi, 2017). Extra shipping options, such as next-day delivery, was the most important capability in meeting customer expectations for omnichannel fulfillment (JDA Software, 2015). By share of contribution to profit margins of fashion retailers, 32% of apparel was bought in-store, 30% was bought online and delivered home, 23% was bought online and collected in-store, 12% was bought online and shipped from store (Camhi, 2017). Thus, the combination of last two fulfillment options specific to omnichannel retailing exceeds each of the traditional fulfillment options and their share is likely to grow further in fashion supply chains.

Of course, backlogging orders would result in substantial extra costs in some cases. Express delivery and other processes linked to extra orders are known to be costly for many products offered by online retailers. Proposition 2 suggests expected profits increase in active response of customers to stockout, but the outcome could be different if backlogging costs exist per unit of delayed purchase (e.g., free delivery for

customers). In such a general case, the difference in profitability (between π_A and π_C) becomes ambiguous since it would depend on the backlogging cost k. The decrease in profits due to backlogging costs ($\frac{\partial \pi_A}{\partial k} < 0$) would be higher if retailers' investments in backlogging are costly enough and if the proportion of customers backlogging is significantly higher than those who opt to switch brands or stores. If the backlogging effort is costly enough $k > (p - w)$, this would lead to $\pi_A < \pi_C$, and retailers would refrain from offering backlogging to their customers. Any comparisons between π_C^* and π_{AH}^* would be ambiguous because gain in profit is strongly dependent on the level of active response of customers to stockout with respect to the rate of inventory holding costs.

CHAPTER 4 CONSIDERATION OF RESPONSE TO STOCKOUT IN PRICING POLICY

In this chapter, we consider optimal pricing policy with consideration of product substitution. This chapter discusses how active response of customers to a stockout affects fashion retailers' pricing decisions in the presence of the forward-looking behavior of strategic consumers. We contribute to the existing literature on strategic customers' response to stockout with our finding that active response of customers to a stockout leads to a reduction of inventory, which could mitigate the negative consequences of the forward-looking behavior of strategic consumers for retailers by enabling them to hold lower inventory and charge higher prices.

4.1 Response to stockout and pricing in the presence of strategic consumers

Striking the right balance in pricing is tough for fashion retailers, but it could become a matter of survival for them when they are faced with millennial shoppers who are quite focused on value. The pricing confusion is reflected in the results from a recent Morgan Stanley survey of apparel stores (Garcia, 2017), which found that the prices of comparable items at traditional retailers such as Gap and American Eagle are approximately three times those at low-cost retailers such as Wal-Mart and Primark; the market performance of leading retailers varies within a wide range as well.

Strategic consumers (also known as forward-looking consumers) exacerbate the pricing problem, particularly in the fashion industry. Strategic consumers recognize that the price of a desired product is likely to reduce some time in the future and they time their purchase decisions after weighing their gains from future discounts against the risk of stockout in case of delayed consumption (Cachon and Swinney, 2011). Understanding how strategic consumers react to stockout is crucial in developing the right pricing strategy. By incorporating strategic consumer behavior into our analysis, we used an extension of the newsvendor model and the notion of rational expectations

commonly used by previous researchers to model the forward-looking behavior of strategic consumers to find the optimal prices in equilibrium.

Table 6 presents additional notations used in this Chapter.

Table 6 Additional notations related to strategic consumers

u	Reservation price of strategic consumers
δ	Discount of future consumption by strategic consumers
r	Consumers' perceived probability of getting a product in the future at clearance price

4.2 Rational expectations

To investigate retailers' optimum pricing decisions, we utilized the concept of rational expectations, which states that the players' beliefs are consistent with the actual outcomes in equilibrium. Rational expectations have been widely used by previous papers in operations research that studied pricing with strategic consumers in a newsvendor setting (Su and Zhang, 2008; Cachon and Swinney, 2009; Cachon and Swinney, 2011; Gao and Su, 2016). This model setting has strategic consumers who anticipate future discounts. Figure 4 shows that the model of behavior of strategic consumers in our research generally follows Cachon and Swinney (2011).
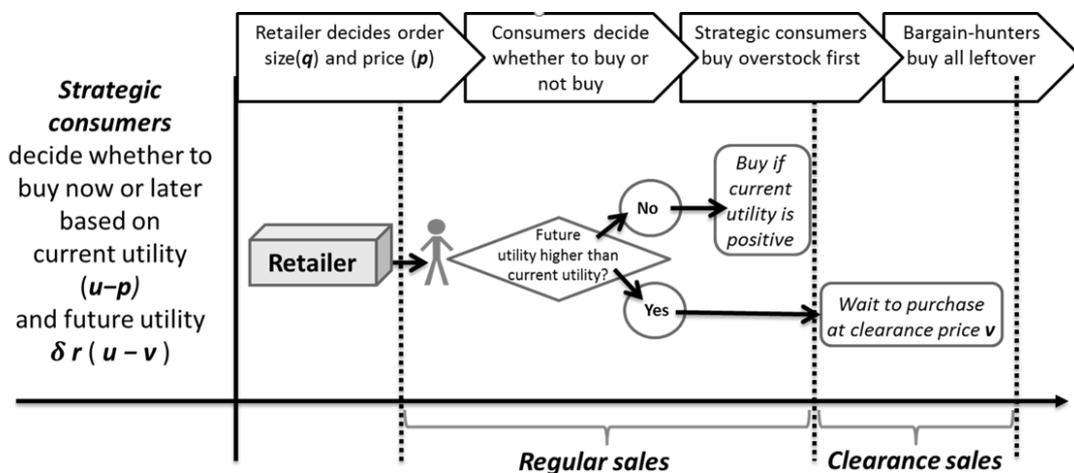
Figure 4. **Actions of retailers and consumers.**

4.3 Model of strategic consumers

In this model of strategic consumers and retailers, the former maximize their surplus utility from consumption, $(u-v)$, by deciding whether to buy a product now at full price, or later at the clearance price, while retailers maximize their profits by only stocking the product at an optimal inventory level. The maximum price, u, that consumers are willing to pay, is assumed to be homogeneous and equal to the personal utility of product consumption. We modeled the intensity of forward-looking behavior using the parameter δ ($0 \leq \delta \leq 1$) to denote the discount of future consumption by consumers, as assumed by Cachon and Swinney (2011). This parameter indirectly reflects the willingness of consumers to wait for future discounts. In the extreme case where $\delta = 0$, all consumers are *myopic*, i.e., they will not wait for future discounts, but buy the product immediately, if the regular price is equal to or less than their reservation price u. Myopic consumers are the most desirable type of customer for retailers, because the retailers can set the regular price to be equal to the reservation price u, thus ensuring maximum profit. Unfortunately for retailers, the situation changes for the worse where *strategic consumers* are involved, since these consumers nurture a belief about the likelihood of unsold products being available during clearance sales, r (in other words, probability of overstock, $0 \leq r \leq 1$). They compare the current surplus utility of consumption, $(u-v)$ to the future surplus, $\delta r(u-v)$. This probability turns out to be equal to the average probability of there being a clearance sale in the future, because a rational expectation of overstock probability by consumers would be correct in equilibrium. Obviously, the more intense the effect of strategic consumers, the worse is the detrimental impact on profitability.

In addition to strategic consumers, there are *bargain hunters* who only buy during clearance sales. Strategic consumers are assumed to buy overstock first, followed by bargain hunters. Therefore, the presence of such consumers does not directly affect the actions of strategic consumers; it only ensures that all overstock is sold during clearance sales. Additionally, consumers are all assumed to have an equal reservation price. Therefore, all consumers either purchase at the regular price, p, or at the clearance price, v. Although restrictive in realistic situations, these assumptions

about strategic consumers are made for tractability, both in our and related research (Cachon and Swinney, 2011).

4.4 Pricing Strategy

Strategic consumers will rationally choose the utility-maximizing actions. The current utility satisfying $u-p$ must be non-negative for strategic consumers to purchase a product at full price. The future utility satisfying $\delta r(u-v) > u-p$ must be non-negative for strategic consumers to purchase a product at clearance price. We ignore backlogging costs in this section. In such a scenario, Store 1's expected profit from product a with active response of customers to a stockout can be formulated as follows (results for Store 2 and brand b can be determined in an analogous manner):

$$\pi_{1,a}^A = p_{1,a}S_{1,a} - w_{1,a}q_{1,a} + (p_{1,a} - w_{1,a})\,\alpha_{1,a}\,L_{1,a} + p_{1,a}\min\{(\beta_{1,b}L_{1,b} + \gamma_{2,a}L_{2,a}), I_{1,a}\} + v_{1,a}\max\{(I_{1,a} - \beta_{1,b}L_{1,b} - \gamma_{2,a}L_{2,a}), 0\} \quad (4)$$

where the expected *sales of brand a at store1* is

$S_{1,a} = \int_0^{q_{1,a}} x_{1,a} f(x_{1,a})dx_{1,a} + q_{1,a}\int_{1,a}^\infty f(x_{1,a})dx_{1,a}$; the expected *overstock of brand a at store 1* is $I_{1,a} = \int_0^{q_{1,a}}(q_{1,a} - x_{1,a})f(x_{1,a})dx_{1,a}$; the expected *stockout of brand a at store 1* is $L_{1,a} = \int_{q_{1,a}}^\infty(x_{1,a} - q_{1,a})f(x_{1,a})dx_{1,a}$; the expected *stockout of brand b at store 1* is $L_{1,b} = \int_{q_{1,b}}^\infty(x_{1,b} - q_{1,b})f(x_{1,b})dx_{1,b}$; the expected *stockout of brand a at store 2* is $L_{2,a} = \int_{q_{2,a}}^\infty(x_{2,a} - q_{2,a})f(x_{2,a})dx_{2,a}$.

We now present our findings on pricing with active response of customers to a stockout and strategic consumers.

Proposition 3. *Under the model of active response of customers to a stockout, and assuming symmetric stores, there exists a unique equilibrium with rational expectations where all consumers purchase a product at its regular price. In this*

equilibrium, the prices are non-decreasing in levels of active response of customers to a stockout:

$$\frac{\partial p^A}{\partial \alpha} \geq 0, \frac{\partial p^A}{\partial \beta} \geq 0, \frac{\partial p^A}{\partial \gamma} \geq 0.$$

Proof. In the equilibrium with rational expectations, the store decides on a pricing strategy and order size that will maximize the expected profit, given that consumers all purchase the product at the regular price, *(q*, p*) =argmax $_{q,p}$ π (q, p).* There exists equilibrium with rational expectations between the retailer and homogeneous consumers. We do not consider the equilibrium where consumers purchase a product at the clearance price, because the retailer would not be interested in selling all the available stock of that product at the clearance price. We focus instead only on the equilibrium where the retailer induces all consumers to buy the product at the regular price. Consumers would purchase early given the regular price and a belief about the probability of a clearance sale. When consumers' expectations are rational, the likelihood of a future bargain, *r,* becomes equal to the actual probability of a consumer deviating from the equilibrium (one who decides to wait to buy during the clearance sale) getting the overstock product at the clearance price. This is possible only if the retailer has sufficient inventory, q^*, to satisfy the demand. Therefore, $r = F(q^*)$. The retailer maximizes the expected profit by setting the regular price to the maximum price that satisfies *u − p = **δ** r (u − v),* so that all consumers purchase the product at the regular price, because their current net utility from consumption at the regular price is equal to or higher than the expected utility in the future from consumption at the clearance price. Therefore, the retailer will set the optimal regular price at *p= u − **δ** r (u − v).* The optimal inventory service level can be derived from the first-order conditions presented earlier in Proposition 1. In the overstock case, the critical ratio for the profit maximizing solution can be defined as the lower bound on the reduction of inventory due to active response of customers to a stockout with low-to-average levels of *α, β,* and *γ.* Analysis of $F(q_A^*)$, together with the optimal regular price and Eq. (1), reveals that the optimal order size is likely to be lower and the regular price is likely to be higher relative to the classic newsvendor model when levels of active response of customers to a stockout are positive. □.

In the Proposition 3, the effect of active response of customers to a stockout on pricing is presented as the sensitivity analysis reflecting the general direction of changes in equilibrium prices. Due to complexity of the model, we could not provide precise optimal solutions in the Proposition. Overall, the effect of strategic consumers who have options of active response to a stockout is likely to result in retailers holding less stock and charging a higher regular price, which implies higher profits for retailers. We numerically analyze the outcomes of active response of customers to a stockout in terms of optimal inventory and pricing in the next chapter.

CHAPTER 5 NUMERICAL EXAMPLES

This chapter illustrates the effects of active response of customers to a stockout using simulation since Eq. (3) does not yield an analytical solution to find the optimal order size. In the next four sections, we numerically analyze the direction and magnitude of the change in the optimal order size and expected profit and the equilibrium price in the presence of active response of customers to a stockout. Table 7 provides a brief summary of the main findings derived from the numerical analyses. To summarize, the findings of simulations reveal that our main results hold under a wider range of parameters.

Table 7 Summary of numerical examples

Section	Figure	Summary of findings
5.1	5	Expected profit increases and inventory decreases in higher levels of active response of customers to a stockout.
	6	Backorders seem to have higher impact than brand and store switching on profits (especially with lower order sizes).
	7	Profitability increases substantially in high levels of active response of customers to a stockout.
	8	Higher depletion factor for average inventory decreases profits.
	9	With active response of customers to a stockout, the negative impact of inventory holding costs on profits becomes lower.
5.2	-	There is statistically significant decrease in optimal order size and increase in expected profits with higher levels of active response of customers to a stockout in case of normal distribution.
5.3	10	There is statistically significant decrease in optimal order size and increase in expected profits with higher levels of active response of customers to a stockout in case of uniform, exponential, and gamma distributions.
5.4	11	There is substantial loss of profit with strategic consumers but active response of customers to a stockout can partially compensate this loss since it mitigates forward-looking behavior.
	12	Equilibrium regular prices are higher in presence of active response of customers to a stockout.

As is common in operations research, we conduct sensitivity analyses to better understand and illustrate the outcomes of modeling. Notable researchers in the fields of management science relevant to this dissertation also widely used the sensitivity analysis (Rajaram and Tang, 2001; Su and Zhang, 2008; Cachon and Swinney, 2011).

5.1 Numerical experiments

In order to illustrate the impact of active response of customers to a stockout, the numerical experiments illustrating effects of active response of customers to stockout in this section have the following parameters (unless set otherwise when relevant so that parameters for certain simulations are different, in which case we directly state it): $p=250, w=100, c=50, v=25, \mu=350$ and $\sigma=150$. The cost of backlogging per unit is not included across all experiments ($k = 0$). The parameters of inventory holding cost (φ and h) are only present in Figures 8 and 9. We chose values for the parameters arbitrarily but considered empirical evidence of setting regular selling prices about twice as much as purchasing costs (Şen, 2008). In addition, parameters of random customer demand correspond to CV values observed in demand of fashion products as illustrated in the well-known case of Sport Obermeyer (Simchi–Levi et al., 2008).
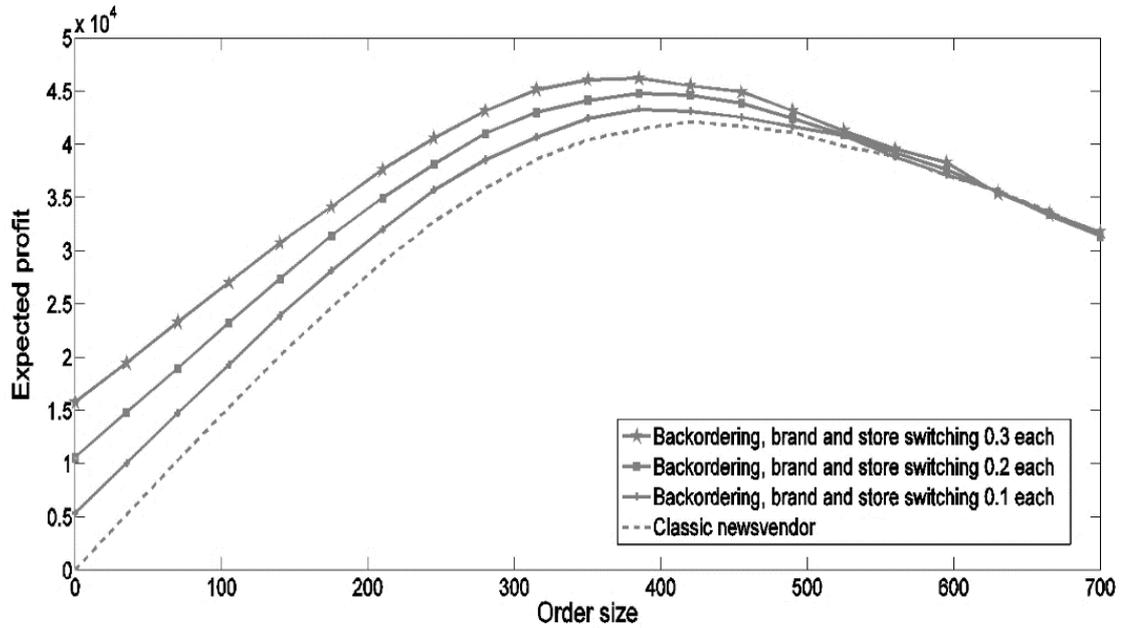
Figure 5. Increase in expected profit and reduction in optimal order size with higher levels of active response of customers to a stockout levels.

Note: this figure is reproduction of Figure 4 in Ovezmyradov and Kurata (2018).

The effect of active response of customers to a stockout on expected profits and optimal inventory of retailers should be considered for both overstock and stockout cases simultaneously. Figure 5 illustrates how retailers' expected profits improves with higher levels of active response of customers to a stockout. In addition, Figure 5 shows how optimal order size is reduced equally with respect to higher levels of active response to stockout α, β, and γ. The marginal value of this reduction decreases as compared to the total order quantity with higher levels of β and γ: general effect of the overstock case (optimal inventory reduction with active response of customers to a stockout) dominates the stockout case (no significant change in optimal inventory with active response of customers to a stockout). This overall effect of decrease in optimal order quantity with higher levels of active response of customers to a stockout would be negatively perceived by a supplier.

Figure 6 demonstrates the effect of α, β, and γ where levels of active response of customers to a stockout each is either set 0.2 or 0. The levels of α, β, and γ each separately seem to influence optimal order quantity in the same manner. The active

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response of customers to a stockout is likely to compensate for risks associated with understocking but risks of overstocking are not substantially affected. Figures 5 and 6 demonstrate how active response of customers to a stockout could have stronger effect on profitability if understock happens but when orders quantities exceed the optimal order size, active response of customers to a stockout has less impact. Overall, backlogging appears to have a stronger impact on profits and order quantities when compared to impact of brand switching and store switching. The implication of response to stockout for retailers is in providing unexpected competitive advantage when active response of customers to a stockout is facilitated.
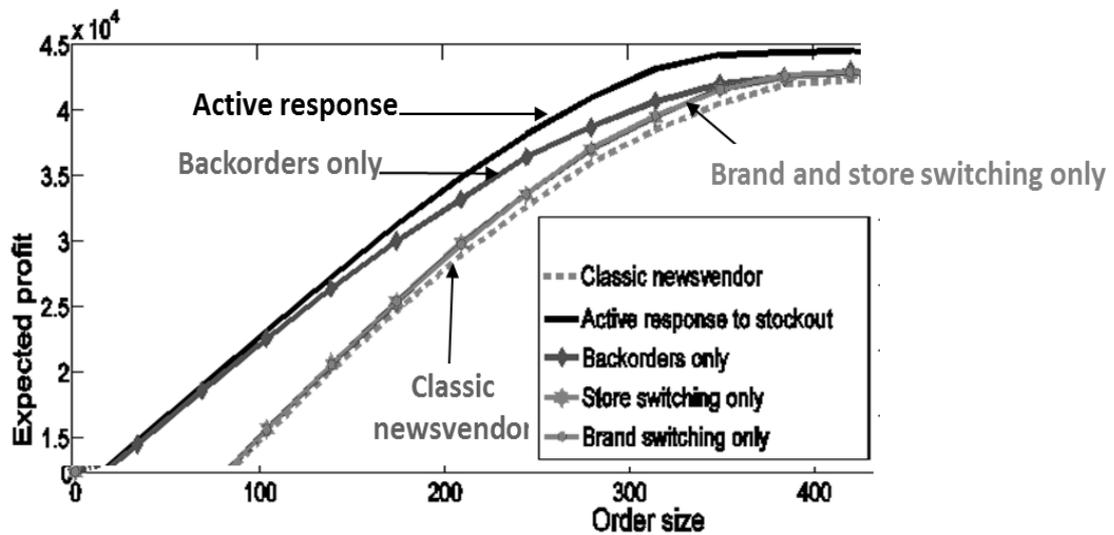
Figure 6. Expected profit with each component of active response of customers to a stockout.

Additional benefits of active response of customers to a stockout are shown in Figure 7 as follows: retailers could gain up to 10% more expected profits with the higher levels of active response of customers to a stockout (maximum $\alpha=\beta=\gamma=0.33$) as compared to the classic newsvendor model .
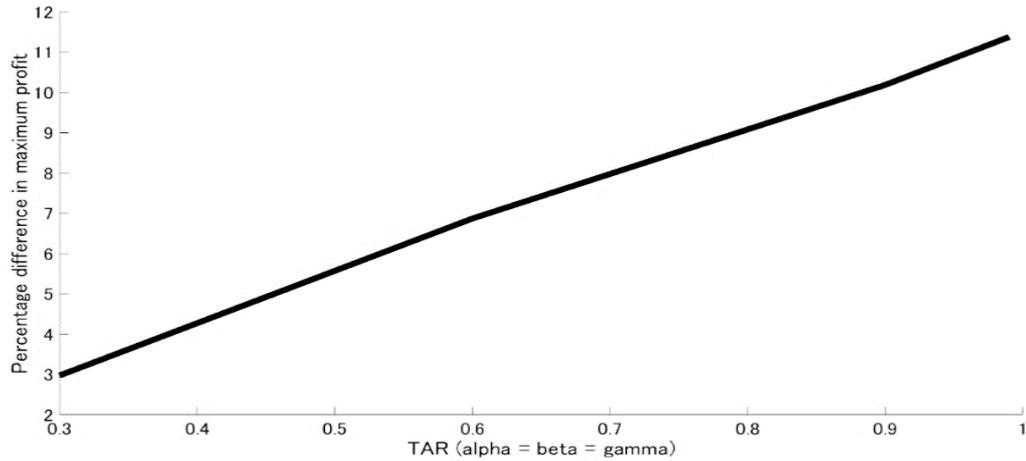
Figure 7. Percentage gain from TAR in expected profits.

Note: this figure is reproduction of Figure 6 in Ovezmyradov and Kurata (2018).

The relative impact of various levels of inventory holding costs on a supply chain performance is shown in the following example. Higher holding costs would predictably result in a significant reduction in retailer's profit and optimal order size as illustrated by the subsequent Figure 8 indicating the change in the retailer's optimal inventory and expected profits depending on the inventory depletion factor φ.
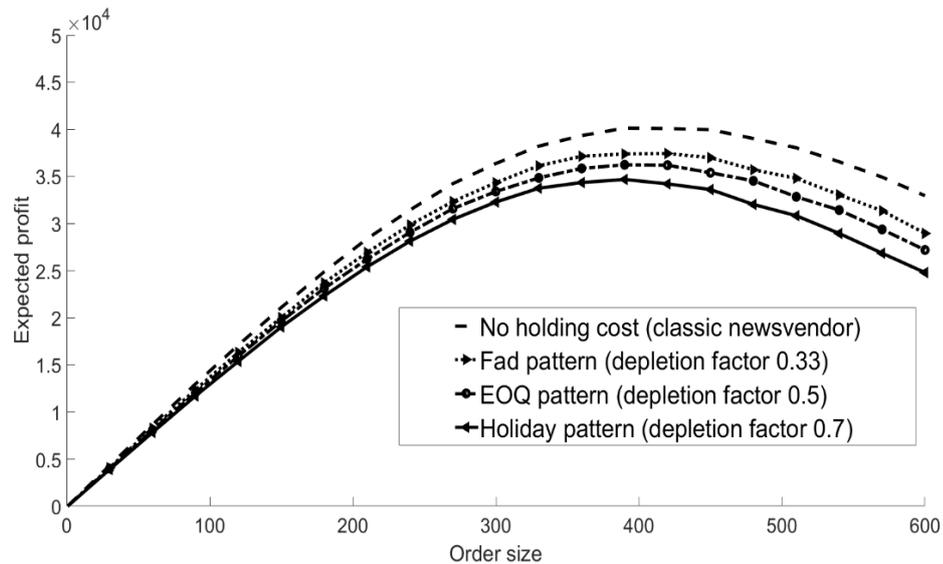
Figure 8. Effect of inventory depletion factor on expected profits.

Note: this figure is reproduction of Figure 7 in Ovezmyradov and Kurata (2018).

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Figure 9 implies the complementarity effect of the active response of customers to a stockout and reduction of inventory due to consideration of holding cost (defined as percentage difference in profits), revealing another positive outcome for the profitability of retailer. In this research, a conservative range of industry holding (carrying) costs of inventory was expressed as a percentage of the purchasing cost per unit. Inventory depletion factor is set at the level common for EOQ: $\varphi=0.5$. The modification of newsvendor model in this research takes into account the positive effect of lower holding costs of inventory for the retailer due to the reduction in average inventory, which, in turn, is result of active response. This is unlike many existing extensions of newsvendor model that do not explicitly consider inventory depletion factor.
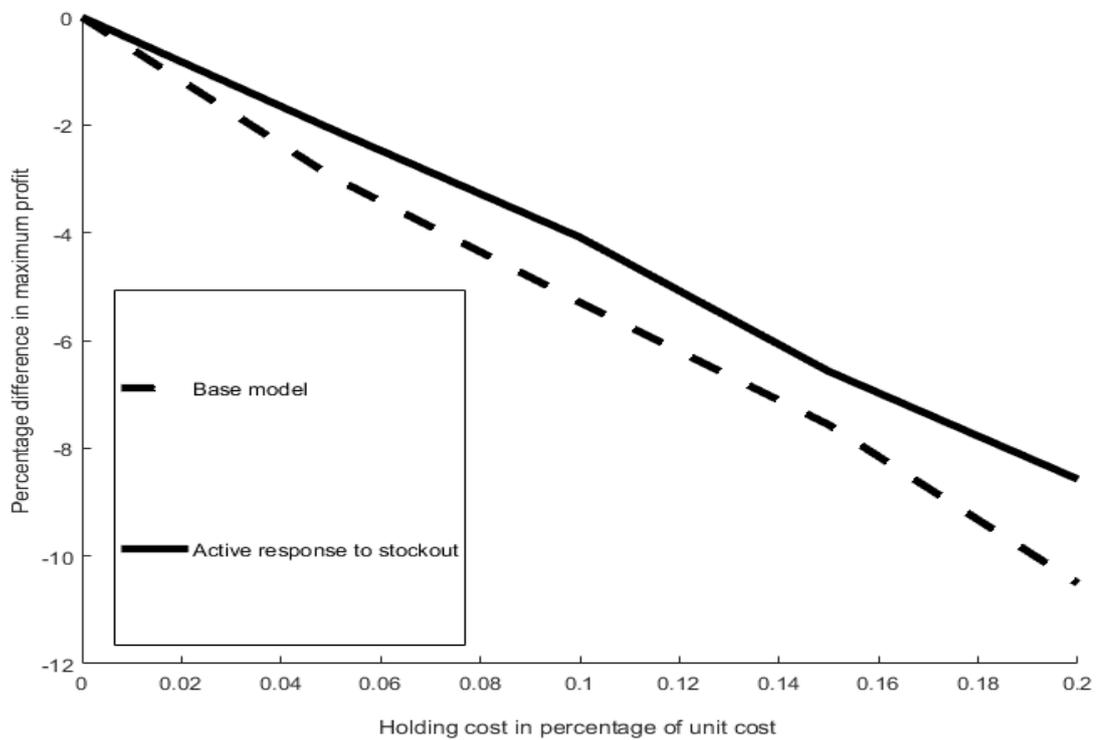
Figure 9. Percentage loss in profits (AH and CH) due to holding costs in the base model, assuming $\alpha = \beta = \gamma = 0$; and in the model of active response of customers to a stockout, assuming $\alpha = \beta = \gamma = 0.2$.

Note: this figure is reproduction of Figure 8 in Ovezmyradov and Kurata (2018).

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5.2 Comparison of profits and orders with normal distribution

From Figure 5 to Figure 9, we illustrated the outcome of only single set of numerical examples that graphically showed effects of active response of customers to a stockout. For checking the robustness of our results, it was necessary to conduct an extensive numerical study.

The first comparison in our numerical study employed a full factorial design to determine the increase in profit, $\Delta\pi = (\pi_A^* - \pi_C^*)/\pi_C^*$, and the decrease in order size, $\Delta q = (q_A^* - q_C^*)/q_C^*$, with the levels of factors presented in Table 8 for normally distributed demand. The ranges of the parameter values were chosen arbitrarily, but the ratios of selling prices to purchasing costs and variability of demand correspond to fashion products as presented in the well-known case of Sport Obermeyer (Simchi-Levi et al., 2008). Levels of $\alpha, \beta,$ and γ were chosen based on the range of observed levels of active response of customers to a stockout in retailing (Corsten and Gruen, 2005).

Table 8 Parameters used in the design of the simulation study

Parameter	Levels of factors
Regular price p	250
Wholesale price w	{100, 200}
Clearance price v	{25, 50}
Mean of demand μ	350
Standard deviation of demand σ	{50, 150}
Backordering α	{0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30}
Brand switching β	{0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30}
Store switching γ	{0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30}

In all, there were 6,912 instances with the normal-distribution-only comparison, formed from all combinations of the parameters, including two levels (high and low) for cost, clearance price, and three standard deviations; six levels for α, β, and γ each. It should be noted that each simulation run included three random variables of demand representing brand a at one store, brand b, and brand a at another store

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(meaning three separate standard deviations for each). We conducted *t-tests* with significance level (*alpha*) of 5%. We also conducted multiple comparisons with the type of critical value *Tukey-Kramer* used with *ANOVA* to determine which groups of factors were significantly different and to find interaction effects. The first null hypothesis states that there is no difference between the base model of classic newsvendor and active response of customers to a stockout model in terms of expected profit $H_0 : \pi_A^* = \pi_C^*$. The second null hypothesis states there is no difference between the base model and active response of customers to a stockout model in terms of optimum order size $H_0 : q_C^* = q_A^*$. We reject the first null hypotheses if $\Delta\pi>0$, and we reject the second null hypothesis if $\Delta q<0$. Overall, 71% of differences in all instances were found to be significant.

The results presented in Table 9 suggest that active response of customers to a stockout is beneficial for retailers. In particular, the average profit increase in active response of customers to a stockout could be substantial, from 0% to 80%, while the magnitude of reduction of the optimal order size ranges from 0% to 19%. When the profit margin is small (i.e. the purchase cost is high relative to the regular price), the increase in profitability is especially pronounced, but there is little change in the optimal order size. Meanwhile, reduction of the optimal order size seems to be larger with larger profit margins. Optimal inventory is lower and profitability is higher when the variability of demand is higher. We found two significant interaction effects existed between: (i) the purchasing cost and the standard deviation of demand; (ii) the clearance price and the standard deviation of demand.

5.3 Comparison of profits and orders with four common distributions

The second comparison compared the profits and order sizes for various distributions that are commonly assumed in engineering (Montgomery and Runger, 2010): *normal, uniform, exponential, and gamma*. This second comparison of different distributions consisted of 216 instances with limited combinations of parameters: only six levels for α, β, and γ. We used nonparametric *Friedman* test with significance level of 5%. Multiple comparisons with the *Bonferroni* type of critical value for nonparametric *Post-hoc* tests were conducted to find out which

groups of the factors were significantly different in the experiment. The parameters for each probability distribution were chosen so that the shape of the distribution function and the ranges of the random variables for each distribution approximately matched those of the benchmark normal distribution. Still, because of theoretical difficulties in comparing results among different distributions, the percentage change (i.e.., relative changes in maximum expected profit and optimum order size) was used instead of the absolute values of differences in order to compare the scenarios with different probability distributions.

Table 10 displays how the main effects of active response of customers to a stockout could depend on the specific distribution of demand. Again, there was a significant difference in the percentage decrease of the optimal order size and the percentage increase in the expected profits between the model of active response of customers to a stockout and the base (classic newsvendor) model across all instances, although the magnitude of the percentage difference varied for each distribution. The average effect of the increase in profits varies between 0 and 66%, while the effect of the reduction in order sizes varies between 0% and 19%. Differences in all instances were found to be significant.

The comparisons in this and previous sections showed how the active response of customers to a stockout led to substantial improvements in expected profits of retailers with wider range of demand distributions, 2%–45% higher on average compared to the classic newsvendor. The active response of customers to a stockout also led to decrease in the optimal inventory, between 0% and 7% on an average compared to the classic newsvendor.

To summarize this numerical study, there was, as could be expected, a significant increase in the expected profit with higher levels of active response. Another, less-intuitive, finding of this study is very important in terms of adopting a pricing strategy: the optimal order size in this model of active response of customers to a stockout is significantly lower than that in the classic newsvendor model. Figure 10 shows the average reduction effect on in optimal inventory with active response of customers to a stockout across all simulations. These observations hold under a wide range of main parameters.
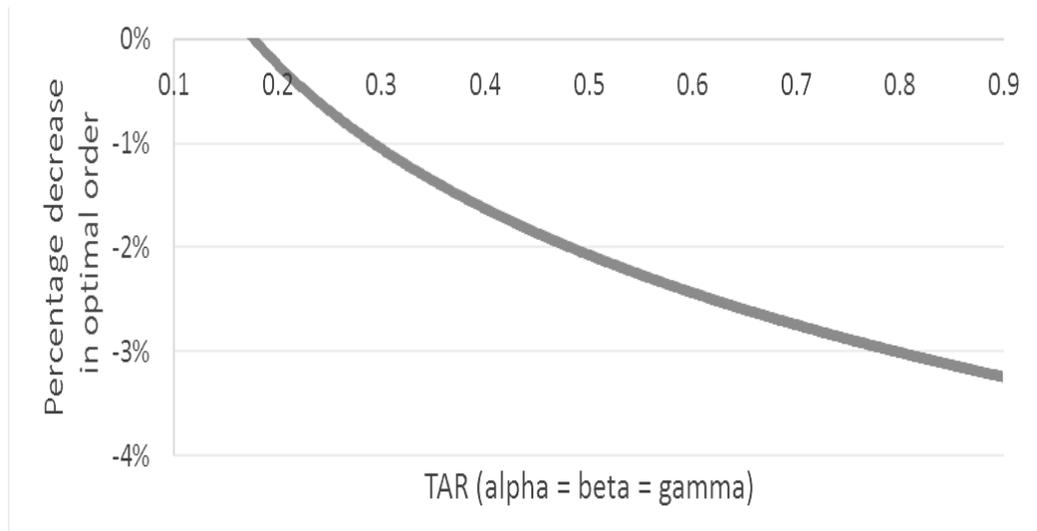
Figure 10. Percentage decrease in optimal order size with active response of customers to a stockout as compared to the classic newsvendor (*Δq*): average across all simulations.

Table 9 Comparison of the results of the simulation with the normal distribution of demand

TAR	w=100, v=25, σ=150		w=200, v=25, σ=150		w=100, v=50, σ=150		w=100, v=25, σ=50		For all simulations	
	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq
0.15	0.02	0.00	0.16	0.00	0.01	0.00	0.00	0.00	0.04	0.00
0.2	0.02	0.00	0.19	0.00	0.02	0.00	0.01	0.00	0.05	-0.01
0.25	0.03	-0.07	0.23	0.00	0.02	-0.01	0.01	-0.01	0.06	-0.01
0.3	0.04	-0.03	0.27	0.00	0.03	-0.02	0.01	-0.02	0.08	-0.01
0.35	0.05	-0.06	0.31	0.00	0.03	-0.04	0.01	-0.02	0.09	-0.01
0.4	0.05	-0.07	0.35	0.00	0.03	-0.06	0.01	-0.02	0.10	-0.01
0.45	0.06	-0.08	0.39	0.00	0.04	-0.06	0.02	-0.02	0.11	-0.02
0.5	0.06	-0.05	0.44	0.00	0.04	-0.06	0.02	-0.02	0.12	-0.02
0.55	0.07	-0.06	0.49	0.00	0.05	-0.06	0.02	-0.03	0.14	-0.02
0.6	0.08	-0.06	0.51	0.00	0.05	-0.06	0.02	-0.04	0.15	-0.02
0.65	0.09	-0.10	0.56	0.00	0.06	-0.07	0.02	-0.04	0.16	-0.02
0.7	0.09	-0.07	0.58	0.00	0.06	-0.07	0.03	-0.04	0.17	-0.03
0.75	0.10	-0.08	0.63	0.00	0.06	-0.13	0.03	-0.04	0.18	-0.03
0.8	0.10	-0.10	0.71	0.00	0.06	-0.13	0.03	-0.04	0.19	-0.03
0.85	0.12	-0.11	0.71	0.00	0.08	-0.11	0.03	-0.04	0.21	-0.04
0.9	0.12	-0.19	0.80	0.00	0.09	-0.05	0.04	-0.11	0.21	-0.04

Table 10 Comparison of the simulation results with different demand distributions

TAR	Normal: *350 (mean), 150 (standard deviation)*		Uniform: *0 (min), 800 (max)*		Exponential: *250 (mean)*		Gamma: *35 (alpha), 10 (beta)*	
	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq	Average $\Delta\pi$	Average Δq
0.15	0.03	0.00	0.04	0.00	0.08	0.00	0.00	0.00
0.20	0.02	-0.03	0.04	0.00	0.12	0.00	0.01	-0.02
0.25	0.03	-0.03	0.05	-0.01	0.14	0.00	0.01	-0.01
0.30	0.03	-0.03	0.06	-0.03	0.17	0.00	0.01	-0.02
0.35	0.04	-0.04	0.08	-0.06	0.20	0.00	0.01	-0.04
0.40	0.05	-0.05	0.09	-0.02	0.23	-0.02	0.02	-0.02
0.45	0.05	-0.08	0.10	-0.03	0.27	-0.03	0.02	-0.04
0.50	0.06	-0.08	0.11	-0.05	0.27	-0.05	0.02	-0.03
0.55	0.07	-0.09	0.12	-0.05	0.30	-0.03	0.02	-0.03
0.60	0.07	-0.09	0.14	-0.05	0.34	-0.04	0.03	-0.03
0.65	0.08	-0.10	0.15	-0.05	0.36	-0.02	0.03	-0.02
0.70	0.09	-0.11	0.15	-0.08	0.39	-0.03	0.03	-0.05
0.75	0.10	-0.14	0.18	-0.09	0.43	-0.03	0.03	-0.03
0.80	0.10	-0.17	0.18	-0.11	0.46	-0.04	0.03	-0.04
0.85	0.12	-0.18	0.19	-0.05	0.47	-0.03	0.04	-0.05
0.90	0.12	-0.19	0.20	0.00	0.48	-0.03	0.05	0.00

5.4 Numerical example of pricing with strategic consumers

To illustrate the impact of active response of customers to a stockout on pricing with strategic consumers, we conducted a numerical experiment in which we set $\alpha=\beta=\gamma$. Further, we arbitrarily set $u=360$, $\delta=0.6$, $w=100$, $v=25$, $\mu=350$, and $\sigma=100$. Figure 11 shows the comparison of profitability with different levels of forward-looking behavior and active response of customers to a stockout. The dashed line in Figure 11 shows the expected profit that can be achieved with non-strategic consumers ($\delta=0$) who purchase a product at the regular price if it is less than their reservation price. Conversely, a substantial loss of expected profit is observed with strategic consumers: profits are nearly halved with strategic consumers who have only 40% lower valuation of future consumption ($\delta=0.6$). Meanwhile, active response of customers to a stockout helps to compensate for part of this loss and reduces the risks of understocking for retailers.
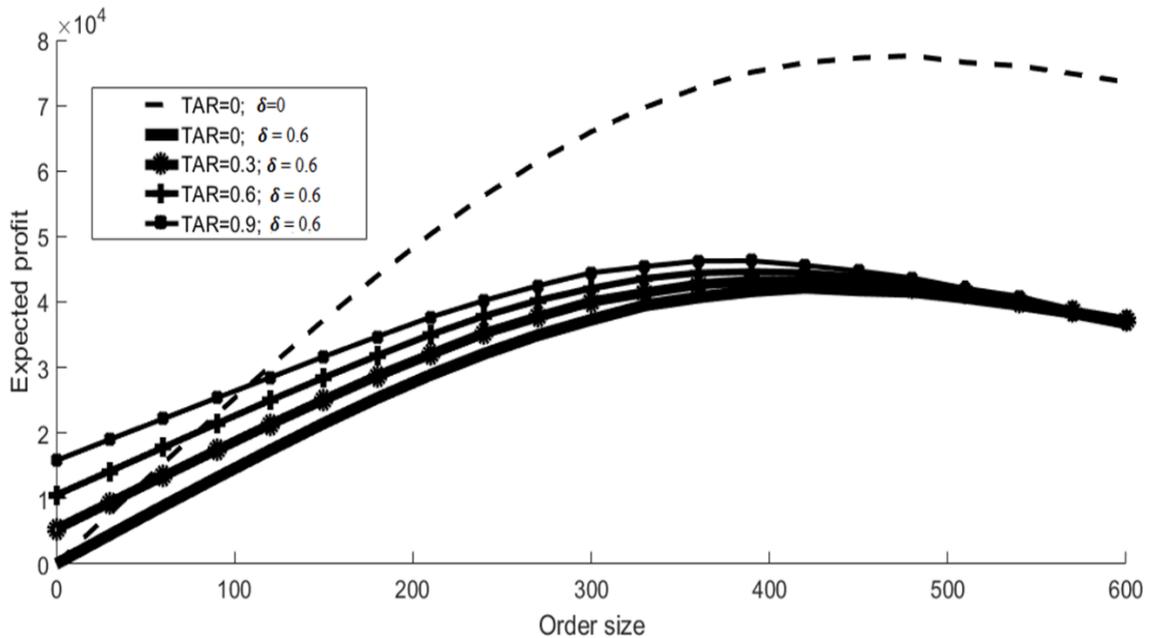
Figure 11. **Active response level and expected profit with various levels of forward-looking behavior of strategic consumers.**
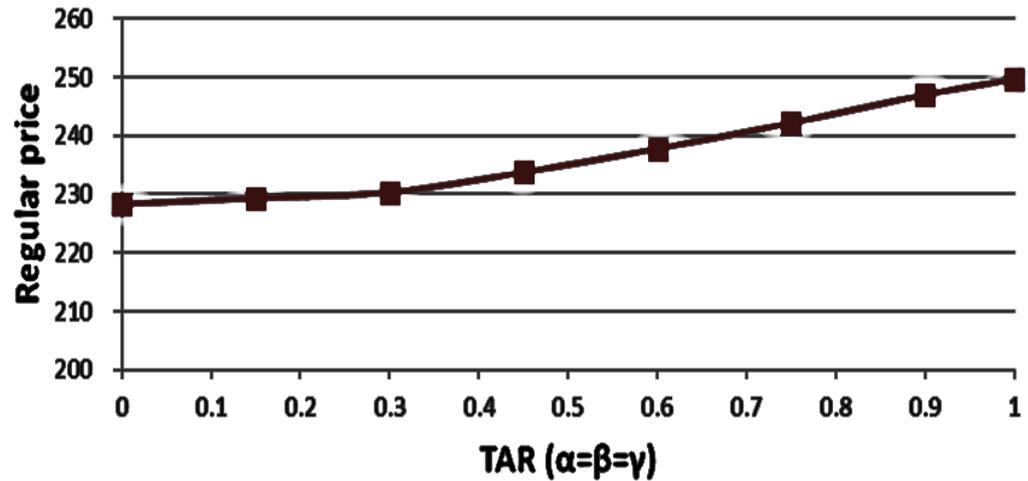
Figure 12. **Change of regular price with active response to stockout.**

The simulation results from Figure 12 seem to support the findings of Proposition 3: the regular prices in the equilibrium increase in α, β, and γ. As discussed in the proof of Proposition 3, $u-p* \geq \delta r(u-v)$ implies that the equilibrium prices (and consequently, the expected profits) are inversely proportional to inventory service levels. The numerical study in the previous section showed a robust effect of reduction in the optimal service level. Therefore, the results of the simulation conducted in this section are likely to hold under a wider range of parameters. Retailers are likely to hold less stock while charging higher prices as justification for the higher stockout risk for consumers. Fast-fashion retailer Zara achieved remarkable success partly because it deliberately understocked to reduce the overstock available for selling at clearance prices (Fernie, 2014). Naturally, such practices result in a greater probability of lost sales. However, lower stock also reduces the negative effects of strategic consumer behavior.

CHAPTER 6 MANAGERIAL IMPLICATIONS

A brief summary of the managerial implications of this work for retailers, suppliers, consumers, society, and omnichannel is provided in Table 11.

Table 11 Summary of managerial implications

Aspect	Summary of findings
Retailer	In case of an absence of competition, customers' active response to stockouts leads to lower inventory, higher profits, a reduction of inventory holding costs, and an ability to charge higher prices.
Supplier	Although suppliers and manufacturers might not be interested in encouraging customers' active responses because of lower order sizes, retailers could still achieve win-win situations by implementing special supply chain agreements with suppliers.
Consumers and society	Even though active response leads to lower availability and higher prices, consumers and society are likely to benefit in the long term due to improved economic and environmental sustainability of fashion businesses.
Omnichannel	Omnichannel fulfillment provides new opportunities for retailers to benefit from customers' active response due to advancements in information technology.

If everyone can win from customers responding actively to stockouts, how can businesses encourage it? This and other managerial implications are discussed in the subsequent sections. To summarize, retailers could provide incentives to suppliers by promoting product substitutability despite the order-reduction effect. This could be achieved, for example, by designing a special supply chain contract. Independent retailers could encourage customers' active responses. For stores belonging to the same retailing chain, omnichannel capabilities provide favorable conditions for managing responses through mobile interfaces, in-store pickup, online reservations, and loyalty programs, all of which facilitate easy access to data about product availability and alternative shopping options for consumers.

6.1 Implications for fashion retailers

When a product stockout occurs, customers may buy a substitutable product, purchase the product from another store, or delay the purchase, which is likely to result in lower stock levels. The implications of these responses to a fashion product stockout is described here in terms of inventory holding costs, optimal order quantities, and expected profits for retailers. Managers and personnel at apparel stores have long been aware of the benefits of active responses to a stockout. Fashion retailers such as GAP and JCrew have long practiced advising customers to try replacement products, such as a product of a different pattern, color, or brand, when the desired products were out of stock. If nothing suitable was found within the store, customers could be encouraged to visit the store later upon replenishment of desired item if allowed by store policy. Alternatively, store staff could suggest visiting another store. The extension of the newsvendor model introduced in this research could be particularly relevant, allowing retailers to analyze the responses to unavailability of fashion brands.

Research by Anupindi and Bassok (1999), Mishra and Raghunathan (2004), and Netessine and Zhang (2005) had suggested an optimal inventory increase with higher substitutability of products; this model indicates the opposite, that retailers' optimal inventory is likely to be lower when consumers actively respond to a stockout. This difference can be explained by the model settings: in this research, the same retailer owns two stores, whereas the aforementioned papers model competing firms. In this research, the large assumption of a lack of switching to products or stores of competing retailers was made for tractability and to isolate the effects of consumers' responses on the internal operations of retailer. It is well known from microeconomic theory that competition could have a huge impact on quantities and prices, as the models with substitution created by Cournot and Betrand demonstrate. Introducing competition to the existing model could change the main findings of the research. The possible effect of response to stockout from a microeconomic perspective of competition in the market is mentioned in the next chapter as an interesting direction of future work.

A reduction in optimal order sizes has been found in various models also analyzing retailers offering an assortment of substitutable products: Rajaram and Tang (2001) and Smith and Agrawal (2000). The findings presented here reinforce similar research by Kurata et al. (2017) that first suggested the possibility of optimal inventory reduction under certain conditions with one manufacturer and multiple retailers. Regardless of the presence of competition, independent competing retailers could still cooperate by aligning operations in a manner that facilitates an increase in profitability due to certain target levels of consumers responding actively to a stockout.

This research is not the first to show how information technology can boost the benefits of active responses to stockouts for retailers. Anupindi and Bassok (1999) described product substitution and store switching using a market search term as a demonstration of brand loyalty and communication level. Specifically, they introduced an idea of a web portal that is cooperatively managed by separate retailers to ensure convenient access to product availability data and alternative shopping places. Similarly, two factors promoting backlogging, brand switching, and store switching are suggested: (i) fashion brand loyalty or preference towards a certain retailer motivates brand switching or store switching, respectively, and encourages customers to request backlogging from store staff; (ii) communication technology allows for faster searching for alternative shopping places by effectively decreasing the efforts to find substitutable brands or stores.

For managers, underestimating holding costs and customers' active response could lead to a suboptimal ordering policy and excessive inventory levels. While few studies have discussed the implications of product substitution on pricing and the behavior of strategic consumers, findings suggest an important direction in which retailers can implement a stock reduction coupled with higher prices to balance the demand in the presence of strategic consumers and customers actively responding to stockouts.

6.2 Implications for external suppliers

The presented results would not be qualitatively affected whether the substitutable brands are store brands owned by the retailer or national brands from external suppliers. The origin of brands, however, would influence the profitability for external suppliers. Figure 13 illustrates the structure of the supply chain with external suppliers only: in contrast to Figure 1, stores do not sell store brands.
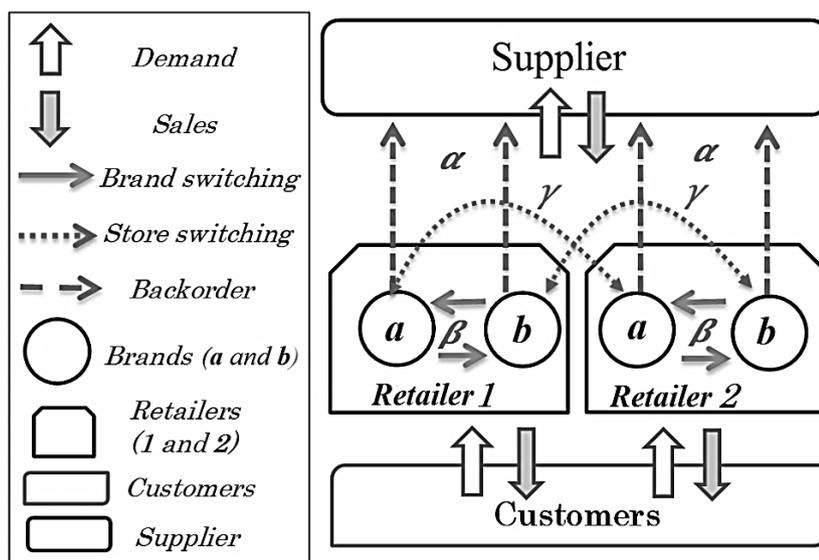
Figure 13. **Structure of the supply chain with external suppliers only**

Franchise or dealer agreements often impose territorial limits and limits on the number of authorized sales representatives or dealers or franchises in a certain area to ensure that sales areas do not overlap. VF Corporation is an American producer of apparel that presents an example of a fashion retailer selling substitutable apparel brands, such as Lee and Wrangler jeans. Those brands are sold in outlet stores owned by the firm and are supplied to exclusive dealer stores in the areas where stores owned by VF are not available (VF Corporation 2017). Many manufacturers seem to avoid enhancing substitutability of different products by making efforts to differentiate

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brands in a niche market. Caterpillar Inc. is a global manufacturer of a wide range of equipment that practices strict regulation of geographical areas designated for sales territories in the worldwide network of dealer (Court of Justice of the European Union, 2006).

In this section, retailers are assumed to only sell national brands; thus, external suppliers prefer large order sizes because the risk of surplus inventory only affects retailers. The profit function of suppliers considering customers' active response to a stockout for all of the brands ordered by retailers can be expressed as follows:

$$\pi_M = \sum_{s=1,2} \sum_{n=a,b} \left[q_{s,n}(w - c) + (w - c)\alpha \int_{q_{s,n}}^{\infty} (x_{s,n} - q_{s,n}) f(x_{s,n}) dx_{s,n} \right]. (5)$$

Additional orders from backlogging customers positively affect the expected profit of the suppliers. In contrast, spillover demand from customers switching brands or stores can decrease suppliers' profitability because retailers reduce their inventory size. This outcome is independent of whether all the products sold in retail stores are supplied by the same or different suppliers. Propositions 1 and 2 thus imply the likely outcome of a reduction in the profitability of suppliers. Therefore, suppliers might discourage brand switching and store switching across their brands.

It may be easier to persuade suppliers to accept backlogging. Despite the negative outcome for manufacturers or suppliers, retailers can still encourage them to promote brand and store switching as well; options to do so could include increasing purchasing price, sharing promotional expenses, or assisting in any backlogging costs. These options could allow each supply chain member to benefit from customers actively responding to a stockout.

Supply chain contracts are also widely used to coordinate fashion supply chains to avoid double marginalization. Double marginalization occurs when one firm in a supply chain makes a profit-maximization decision without considering other members' profits, leading to an overall decrease in profitability for the total chain.

Supply chain contracts can be used to avoid double marginalization and achieve a global optimum level of performance by adequately sharing risks and/or benefits among members.

6.3 Implications for consumers and society

Higher retail prices could seem detrimental for consumers from the short-term perspective; however, the effects of customers responding actively to stockouts is likely to be positive in the long-term for both retailers and consumers. Despite higher equilibrium pricing, lower inventories will be beneficial overall for environmental sustainability, as less natural resources will be consumed. Fashion industry professionals are concerned about $50 billion of annual deadstock in the US: fashion is the second-biggest polluting industry in the world after the oil industry (Ellison, 2017). Reducing order sizes would help reach the industry's sustainability goals and allow society to profit from the improved economic sustainability of the fashion industry. Finally, not all consumers exhibit strong forward-looking behavior and the negative consequences from strategic consumers might disadvantage them. Less overstock and more return on investment imply both economic and environmental benefits for the sustainability of fashion businesses that eventually will have positive impact on consumers in society (Choi and Chiu, 2010).

6.4 Implications for omnichannel fulfillment

Omnichannel retailing refers to retailing through multiple interacting channels (i.e., physical store, catalog, telephone, online shop, and mobile shop) while the retailer controls the full integration of pricing and inventory data on all channels (Beck and Rygl, 2015). Omnichannel implementation is a top priority for many modern fashion retailers; retailers see significant areas of growth but also face numerous challenges. A PwC survey of top retailers found that omnichannel fulfillment was a high or top priority on the business agenda for 71% of CEOs but only 19% could profitably fulfill omnichannel demand (JDA Software, 2015). Even

though 70% of fashion retailers surveyed offered smartphone apps enabling consumers to check online availability, only 17% allowed online check of in-store availability (Berg et al., 2015). As online retailers continue to expand their market share, traditional retailers are struggling, and more US retail stores are likely to close in 2018 than in the previous two years combined. Omnichannel fulfillment methods such as ship-from-store and click-and-collect can help brick-and-mortar retailers survive by increasing online sales, reducing shipping costs, and keeping their locations relevant. However, few retailers have been able to support these multiple channels at once, since successful implementation of omnichannel retailing requires an overhaul of existing systems and processes. One in eight American internet users indicated they were interested in the *shop online and in-store pickup* option and more than half have benefited from *the click and collect* option in the past year (Lightspeed, 2017). Overall, omnichannel fulfillment allows customers to move freely between online, mobile, and physical channels. Furthermore, it provides new possibilities for firms to measure and influence customers' delay of purchase, store switching, and brand switching. Retailers, suppliers, and manufacturers can all benefit from investing in omnichannel retailing because it allows for direct product feedback and customer relationships for marketing and merchandising purposes across all sales channels (DHL Trend Research, 2015). The developed model suggests important implications for businesses facing challenges with omnichannel fulfillment.

Findings of theoretical research on active response to stockout are often difficult to apply in practice because accurately measuring customer responses to marketing efforts is problematic and costly. Specifically, it is difficult to infer the level at which customers actively respond to a stockout from historical data on sales because patterns of brand switching and store switching are hidden inside common past demand data. Marketing research could yield estimates of the active response of customers to a stockout, but it is prohibitively expensive to conduct this research on a constant basis and is often limited in terms of product range and territory. Thus, earlier research has suggested concentrating on designing substitutable product assortments and implementing other activities (e.g., training store personnel on managing responses to stockout) rather than optimizing for substitution (Rajaram and Tang, 2001).

Fortunately for retailers, developments in omnichannel fulfillment beginning from the early 2000s could eliminate the inadequate utilization of consumers' active response to stockout. This quantitative research considers important developments that have occurred over the past two decades and are continuing to shape the global fashion markets. Omnichannel retailing, in particular, is increasingly attracting the interest of businesses and researchers (Verhoef et al. 2015). With fashion retailers increasingly adopting an omnichannel retailing strategy, consumers are becoming adept at comparing prices and checking the availability of their favorite brands online. Omnichannel retailers are uniquely positioned to exploit the active responses of customers to a stockout, as was explained in Section 3.5.

Omnichannel fulfillment provides unprecedented opportunities to benefit from customers willing to delay purchase or switch to another brand or store. As brand switching happens at the same store, it can be at least partially under the control of the respective retailer. On the other hand, control over store switching depends on retailing settings. Under a coordinated setting, when both stores belong to the same retailing chain or when independent retailers form a partnership, store switching could be influenced by providing customers with in-store or online access to data on availability at the other store. Table 12 shows how omnichannel retailers are able to gather, analyze, act on, and control the active responses of customers to a stockout.

Table 12. Conversion from source to sales in omnichannel setting

Data source	Conversion to sales in omnichannel
Online customer account	*Online check of inventory status by customers*
Mobile shopping app	*Reserve online, store pick-up*
Browser data	*Reserve in-store, home delivery*
Customer loyalty program	*Online suggestion of substitutable brand / store*

Wider use of Internet, POS, EDI, MIS, loyalty programs, shopping apps, and other technology has opened new opportunities for retailers to effectively measure and, to some extent, control the active response of customers to a stockout. Explosive growth in use of smartphones and social networking allows retailers to utilize a new wealth of consumer information technology in omnichannel initiatives. The rapid

growth of online sales promotes the active response of customers to a stockout. Cutting-edge technology offers additional opportunities to gain from the active response of customers to a stockout, e.g., geo-fencing and beacons can notify a customer via their smartphone about the availability of a desired product in proximity to their location. Many innovative fashion firms have started experimenting with conceptual apparel stores where products are scanned to give customers immediate access to data on alternative colors, sizes, and styles available in the current store or elsewhere, thus facilitating brand and store switching (McGregor, 2016b). However, omnichannel fulfillment requires large investments and the adaptation of a new inventory management system to achieve real-time visibility. Item-level RFID technology is spreading among omnichannel fashion retailers for in-store real-time item tracking. This research presents an additional insight into the benefits of investing in these new technologies.

CHAPTER 7 CONCLUSION AND FUTURE WORK

7.1 Conclusion

Brand and store switching (which are closely related concepts) together with backlogging can be collectively referred to as active response of customers to stockout which should be taken into account when making decisions on order size and profit. We extended the newsvendor model by incorporating active response of strategic consumers to stockout. Our model considers a single-period supply chain comprising two fashion stores, Store 1 and Store 2. Each store sells two substitutable brands a and b and implements a make-to-stock production system. The brands have a regular sales price, p; a wholesale price, w; and a clearance sales price, v. When a customer's fashion brand of choice is not available at a store, she or he may leave the store without buying anything, resulting in lost sales for the retailer. With backordering, a portion, α, of consumers who experience stockout, has the opportunity to place an order for the desired item. Alternatively, in omnichannel retailing, backordering could mean that a portion, α, of consumers who check the availability of the desired item online and face stockout, delay the purchase by opting to pick-up the item at the store or have it delivered to them. With the brand-switching section of consumers, the overstock of one product is used to substitute a certain β portion of the spillover demand from another substitutable product brand that is out of stock at the same store. Similarly, with store switching, γ portion of the spillover demand comes from another store that has stockout. Several assumptions were made for tractability. We assume absence of extra cost per unit of lost sales such as shortage penalty or goodwill cost. Outcome of lost sales is usually less severe for fashion firms and some of them even understock products to boost the sense of urgency and image. For tractability, the levels of active response to stockout at both stores are symmetric – they are assumed to be equal.

Since it was difficult to find a closed-form solution for optimal order size due to complexity of stockout case in the model of active response of customers to a

stockout, we conducted an extensive numerical study to test the whether the main effects of active response of customers to a stockout on expected profit and optimal order quantity would be robust. This study involved two separate comparisons between the classic newsvendor model and the model of active response of customers to a stockout: one comparison was only for normal distribution of demand, and another one was for additional distributions. Simulations included instances from every possible combination of the most important parameters including high and low levels of standard deviation of demand, unit cost of purchasing, and clearance price (salvage value per unit), as well as six levels of active response of customers to a stockout.

The following two main findings from the analysis of the supply chain model and numerical experiments suggest the positive effect of active response of customers to a stockout on supply chain performance for a fashion retailer:

1. Higher expected profits can be achieved owing to spillover demand from brand switching and store switching as well as additional profits from backlogging.
2. Decrease in the optimal inventory is likely to take place and that brings additional savings from reduced holding costs of inventory and lower propensity of strategic consumers to wait for future discount.

The decrease in optimal order quantity was highest with smaller profit margin per unit. The increase in profitability was not significant when the profit margin was low. Active response of customers to a stockout seems to be more beneficial in reducing optimal order quantities and improving profitability when demand variability is high.

Those findings show substantial effects of active response of customers to a stockout for fashion retailers resulting in higher profitability and smaller inventory. An additional finding is a comparison to previous studies revealing that the effect of decrease in order quantity would depend on model settings: inventory could be larger in case of competing retailers.

One theoretical contribution of this research is an attempt made towards incorporation of inventory's depletion rate in newsvendor model to investigate its effect on average relevant costs and optimal inventory since extant literature, to the best of our knowledge, did not properly address the issue that is related to real business issues. Three depletion patterns described in this research apply not only to the model of active response to stockout, but should also be taken into account in general within costing calculations related to average inventory in the framework of single-period inventory modeling in supply chain management.

The second research question was about how active response of customers to a stockout could affect pricing and the expected profits of the fashion retailer with strategic consumers. To investigate the effects of active response of customers to a stockout on ordering and pricing, we extended newsvendor model and used results of the extensive numerical study. To analyze the impact of active response of customers to a stockout on pricing, we used the notion of rational expectations to determine equilibrium prices. The results suggest that the presence of strategic consumers generally results in lower-than-expected profits for retailers. However, active response of customers to a stockout helps to mitigate this negative effect by enabling retailers to increase prices in equilibrium because at the same time, retailers are likely to reduce inventory, which would decrease the future expected utility for strategic consumers who wait for discounts. This finding appears counterintuitive: more opportunities for switching between brands and stores could seem to exacerbate the behavior of strategic consumers who will have alternatives in case of stockout. However, retailers can respond by reducing inventory with higher active response of customers to a stockout, which, in turn, increases the risks of waiting for discounts for strategic consumers.

Omnichannel retailing created an unprecedented new opportunity for gathering relevant data on parameters of brand and store switching required as inputs to our model by means of customer loyalty programs; mobile apps; browsing and purchasing history; and online surveys. In omnichannel retailing, customers can be directed to a store where the desired brand is in-stock, even before actual visit, by providing access

via shopping websites or apps of a retailer. In a traditional setting of competing stores of different retailers, such opportunity would understandably be limited. Omnichannel retailing demands higher stocking levels but active response of customers to a stockout ensures reduction of inventory leading to lower cost and less overstock. To summarize managerial implications of the main results, our research implies that omnichannel fulfillment creates extremely favorable conditions for retailers to gain from active responses to stockout of fashion products. We also discussed how to apply our modeling framework in retailing practice by means of simulation method.

We are unaware of any modeling research that has studied the effect of different levels of active response to stockout on changes in inventory in omnichannel retailing. We discussed the positive implications of effect of active response of customers to a stockout, both for retailers and customers. The main managerial implication for retailers is that they could carefully consider the levels of response to stockout and patterns of inventory holding cost in design and operation of fashion supply chains. The omnichannel fulfillment created very favorable conditions for retailers to accurately measure and encourage active response of customers to a stockout across stores and product assortments. Finally, this study contributes to extant literature by showing the managerial importance of inventory holding costs in the single-period model by revealing how they could decrease with active response of customers to a stockout.

7.2   Limitations of research

Chapters 3 and 4 of this dissertation presented analysis that was based upon assumptions of independent demands and symmetry of parameter in a simplified supply chain model that includes only two stores. In this single-period model, a retailer that owns the two stores aims at maximizing expected profit in selling two substitutable product brands. As the direction of future research, a model would become more realistic if it considered multiple stores of the retailer with asymmetric parameters and correlated demands.

Supply chain coordination is a mechanism to bring the local optimum that are the best for the individual stores to the global optimum that maximizes profitability of the entire supply chain including retailers and suppliers. In this research we considered each store as an independent decision maker. Considering widespread supply chain contracts as tools for coordinating a fashion supply chain in presence of active response of customers to a stockout could become a future direction of research.

We numerically analyzed the outcomes of active response of customers to a stockout in terms of optimal inventory and pricing. It should be noted that the analysis presented in Chapter 4 was based on the assumption that all consumers were homogeneous consumers sharing the same valuations. Therefore, analyzing a model where consumers have uncertain valuations with a certain probability distribution could become an interesting direction for future research. Another possible extension could relax the assumption that strategic consumers are given preference over bargain hunters during clearance sales, as assumed by Cachon and Swinney (2009).

7.3 Future work

The future work related to the fashion industry would focus on applications in apparel production and sales. Since the turn of the 21st century, the textile manufacturing has been undergoing huge developments, which affected the entire global economy and attracted the attention of governments and businesses worldwide, as well as considerable interest from the academic world. These can be summarized as follows:

- The increasing globalization of textile manufacturing and distribution, as trade barriers which have existed for decades are eliminated, leading to the decline of textile industries in developed countries and outsourcing to developing countries (Şen, 2008).

- The spectacular success of innovative fashion retailers, as exemplified by Zara with its radical new approach to supply chain management, and the dominance of major global retailers that offer an identical selection of fashion brands all over the world.

- The rapid growth in the use of advanced new RFID technologies in e-commerce and in-store tracking of products.

- The greening of fashion retailing as the environmental consciousness of consumers continues to grow, with issues of sustainable growth increasingly addressed by businesses and policy-makers.

Considering the aforementioned trends, reasonable directions for our future research could be as follows. First, active response of customers to a stockout could have an impact on sourcing decisions of managers at various stages of supply chain that could become a topic of additional study. Such multi-stage chains exhibit stronger bullwhip effects and vulnerability to supply disruptions. They necessitate closer coordination and exchange of information between suppliers and buyer. Another aspect of multi-stage supply chain worth considering is limited capacity of backlogging. Research to date in the field of textile and fashion supply chains has mainly focused on the downstream stages – sewing and retailing – although the upstream stages of fiber, yarn and fabric production are of no less importance for topics such as fast fashion and sustainability. Thus, an attempt could be made in the future research to consider active response of customers to a stockout in the fashion supply chain taken as a whole.

Second, it is worth looking into the role active response of customers to a stockout could play in the growing fast-fashion industry where fashion retailers face competition on price and ability to match customer's preferences. A game-theoretic model of competition between several retailers could be developed in which some retailers are fast-fashion companies and others are traditional companies. Unlike traditional retailers, fast-fashion retailers are characterized by the quick response production system and enhanced design capabilities which allows them to better match the needs of customers within a shorter time. The traditional retailer has the advantage of lower costs since there is no need for expensive investments in the quick response system. However, the traditional retailer also has the option to become a fast-fashion retailer after appropriate investment. Clearly, fast-fashion is capable of better matching the taste of each customer, while traditional apparel usually has lower

costs (meaning either a higher profit or lower price). Competition would take place in the following sequence. Initially, retailers simultaneously decide whether and how to enter the market, either with a traditional or fast-fashion system. In the second stage, the retailers choose a product line with a certain number of products and certain product features. In the final stage, retailers simultaneously set prices. The problem set by the model could be solved by backward solution in the three-stage sequential game. Customers could be assumed to be heterogeneous in fashion preferences.

Third, interesting extension of the presented model should involve exploring the effect of in-store tracking of the inventories of stores that use RFID and other advanced systems on active response of customers to a stockout. This direction of research would focus on developing a mathematical model that can capture the effect of item location tracking within a store floor on the inventory-related cost of a fashion item. The assumption of unlimited backlogging was quite restrictive but it was necessary in this research for tractability. We experimented with the extension of the main model on active response of customers to a stockout where the distribution center of the retailer had constrains on inventory. Unlike other models, this future model extension aims at determining how tracking the location of a fashion item within a store can reduce lost sales. Thus, a modeling approach could be utilized for the first time to define the value of active response of customers to a stockout in the in-store location information. We could not find analytical solutions and so far had to use simulations. The preliminary results suggest that the additional constrains do not qualitatively affect main findings of this research on response to stockout. This topic currently remains one of the active directions of our work

Finally, considering the effects of active response of customers to a stockout from a microeconomic perspective could become an interesting direction for future research. What could be implications of active response of customers to a stockout in terms of the surplus for consumers or social welfare (sustainability)? Furthermore, we analyzed the effect of response to stockout on equilibrium prices only at a particular store with all other parameters being fixed during the analysis, assuming that the direct effect of other store's decisions or overall market competition have negligible

impact. Future research could consider the entire market with all possible interrelationships and supply chain disturbances in order to render the model more realistic.

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APPENDICES

APPENDIX A: Matlab Code for Numerical Study to Compare Main Effects of Classic Newsvendor and Active Response to Stockout with Normal Distribution

```
%CODE TO COMPARE MAIN EFFECTS OF CLASSIC NEWSVENDOR AND ACTIVE
RESPONSE MODELS WITH NORMAL DISTRIBUTION (code mostly works in open-source
OCTAVE except for last lines)
xprice=[250]; xcost=[100,200]; xmcost=[0]; xsalvage=[25,50]; xmdemand=[350]; xsigma=[50,150];
xgoodwill=0;
xmdemand2=[350];xsigma2=[50,150];xmdemandj=[350];xsigmaj=[50,150];xalpha=[0.05,0.1,0.15,0.2,
0.25,0.3];xbeta=[0.05,0.1,0.15,0.2,0.25,0.3];xgamma=[0.05,0.1,0.15,0.2,0.25,0.3];
parameternames                                                                              =
{'price','purchase_cost','production_cost','salvage_value','mean_demand','st_deviation_sigma','goodwill
_cost_shortage','mdemand2','sigma2','mdemandj','sigmaj','alpha','beta','gamma','totalAR','optimal_quant
ity0','optimal_quantityAR','theor_CR','theor_AR','theor_qty0','theor_qtyAR','optimalCR','optimalCR_A
R','optimal_fillrate','optimal_fillrateAR','optimal_profit','optimal_profitAR','qty_decrease_ARtheor','qty
_decreaseAR','profit_increaseAR','ttest2_profit'}; %names for second table of output below
%enter main parameters above, give a short name describing each parameter in "parameternames";
minqty=300; maxqty=500; spacing=2;maxtrial=1;
%enter parameters for range of order quantities above, match "maxqty" to demand parameters (mean /
sigma or maximum possible demand);
format bank; %format numbers to avoid scientific notation by setting "currency" format with two digits
after the decimal point;
allqty=linspace(minqty, maxqty, spacing); %all quantities for each simulation instance;
nwprofit=zeros(maxtrial,length(allqty));
nwprofitar=zeros(maxtrial,length(allqty)); %preallocate for speed - set starting order quantity to zero
(refine to smaller increment and higher order size later for narrow interval to find accurate maximum
profit);
nwsales=zeros(maxtrial,length(allqty));
nwpurchasecost=zeros(maxtrial,length(allqty));
nwsalvage=zeros(maxtrial,length(allqty));
nwshortage=zeros(maxtrial,length(allqty));
nwbackorder=zeros(maxtrial,length(allqty));
nwbrandswch=zeros(maxtrial,length(allqty));
nwstoreswch=zeros(maxtrial,length(allqty));
nwsalvagear=zeros(maxtrial,length(allqty));
[vprice,vcost,vmcost,vsalvage,vmdemand,vsigma,vgoodwill,vmdemand2,vsigma2,vmdemandj,vsigmaj
,valpha,vbeta,vgamma]                                                                        =
ndgrid(xprice,xcost,xmcost,xsalvage,xmdemand,xsigma,xgoodwill,xmdemand2,xsigma2,xmdemandj,x
sigmaj,xalpha,xbeta,xgamma); %combinations grid
combinations                                                                                 =
[vprice(:),vcost(:),vmcost(:),vsalvage(:),vmdemand(:),vsigma(:),vgoodwill(:),vmdemand2(:),vsigma2(:)
,vmdemandj(:),vsigmaj(:),valpha(:),vbeta(:),vgamma(:)]; %all combinations of parameters
combinationssize = size(combinations); %show size of elements in vector (rows,columns);
```

```matlab
allcombinations = numel(combinations); %show number of elements;
pricec=combinations(:,1);costc=combinations(:,2);mcostc=combinations(:,3);salvagec=combinations(:,
4);mdemandc=combinations(:,5);sigmac=combinations(:,6);              goodwillc=combinations(:,7);
mdemand2c=combinations(:,8);sigma2c=combinations(:,9);mdemandjc=combinations(:,10);sigmajc=c
ombinations(:,11);alphac=combinations(:,12);betac=combinations(:,13);gammac=combinations(:,14);
%name each parameter for simulations;
instancerow=1; %initial instance
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);mdemand=mdemandc(instancerow);sigma=sigmac(instancerow);
goodwill=goodwillc(instancerow);mdemand2=mdemand2c(instancerow);sigma2=sigma2c(instancerow
);mdemandj=mdemandjc(instancerow);sigmaj=sigmajc(instancerow);alpha=alphac(instancerow);beta=
betac(instancerow);gamma=gammac(instancerow);
resultofinstance=zeros((combinationssize(1)), size(parameternames,2)); % final results including all
parameters (columns of instances) plus additional results derived from simulations;
%in "resultofinstance" above, columns MUST be equal to number of extra outputs inside
"resultofinstance" plus initial parameters!
for trialin=1:combinationssize(1) %repeat each simulation updating parameters till final instance is
reached;
for trialq = 1:spacing  %repeat each simulation updating order quantities;
for trials=1:maxtrial  %repeat each simulation specified number of trials;
nwsales(trials,trialq)=(min(allqty(trialq),(max(max(normrnd(mdemand,sigma),0),0))));
nwpurchasecost(trials,trialq)=allqty(trialq)*cost;
nwsalvage(trials,trialq)=max(allqty(trialq)-(max(normrnd(mdemand,sigma),0)),0);
nwshortage(trials,trialq)=max((max(normrnd(mdemand,sigma),0))-allqty(trialq),0);
nwbackorder(trials,trialq)=alpha*max(normrnd(mdemand,sigma)-allqty(trialq),0);
nwbrandswch(trials,trialq)=min(max(allqty(trialq)-
normrnd(mdemand,sigma),0),beta*(max(normrnd(mdemandj,sigmaj)-allqty(trialq),0)));
nwstoreswch(trials,trialq)=min(max(allqty(trialq)-
normrnd(mdemand,sigma),0),gamma*(max(normrnd(mdemand2,sigma2)-allqty(trialq),0)));
nwsalvagear(trials,trialq)=max((allqty(trialq)-(normrnd(mdemand,sigma)))-
beta*(max(normrnd(mdemandj,sigmaj)-allqty(trialq),0))-gamma*(max(normrnd(mdemand2,sigma2)-
allqty(trialq),0)),0);
end;
nwprofit=price*nwsales-nwpurchasecost+salvage*nwsalvage-goodwill*nwshortage;  %matrix of all
trial simulations for a certain order size in classic newsvendor;
nwprofitar=price*nwsales-nwpurchasecost+salvage*nwsalvagear-goodwill*nwshortage+(price-
cost)*nwbackorder+price*nwbrandswch+price*nwstoreswch;
Expectprofit = mean(nwprofit); %average across simulations for an instance related to the current order
size;
Expectprofitar = mean(nwprofitar);
Expectsales = mean(nwsales);
Expectshortage = mean(nwshortage);
Expectsalvage = mean(nwsalvage);
Expectsalvagear = mean(nwsalvagear);
Expectbackorder = mean(nwbackorder);
Expectbrandswch = mean(nwbrandswch);
Expectstoreswch = mean(nwstoreswch);
Expectfillr0=Expectsales./(Expectsales+Expectshortage); % filling rate found separately because it is
different from inventory service level;
Expectfillrar=(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch)./(Expectsales+Exp
ectbackorder+Expectbrandswch+Expectstoreswch+Expectshortage);
Stockouts=sum(nwshortage>0); % sumber of stockout events;
Stockoutsar=sum(nwshortage-nwbackorder>0);
CR0real=1-(Stockouts/maxtrial); % critical fractile or ratio of newsvendor model;
CRarreal=1-(Stockoutsar/maxtrial);
```

```
end;
[Maxeprofit,indexmax]=max(Expectprofit); % specifying index corresponding to position of maximum
profit in matrix of all average profits for all instances;
[Maxeprofitar,indexmaxar]=max(Expectprofitar);
Maxeqty=allqty(indexmax); % defining order quantity linked to the maximum profit across all
instances;
Maxeqtyar=allqty(indexmaxar);
TAR=alpha+beta+gamma; % total level of active response to stockout;
MaxCR0real=CR0real(indexmax);
MaxCRarreal=CRarreal(indexmaxar);
Maxeqtyfillr0=Expectfillr0(indexmax);
Maxeqtyfillrar=Expectfillrar(indexmaxar);
CR0=(price-cost)/(price-salvage); crqty0 = norminv(CR0,mdemand,sigma);
CRar=(price*(1-alpha-beta-gamma)+alpha*cost-cost+salvage*(beta+gamma))/(price*(1-alpha-beta-
gamma)+cost*alpha+salvage*(beta+gamma)-salvage);crqtyar = norminv(CRar,mdemand,sigma);
Maxqtytoartheor=(Maxeqtyar-crqtyar)/(Maxeqtyar);
Maxqtytoar=(Maxeqty-Maxeqtyar)/(Maxeqty);
Maxprofitoar=(Maxeprofitar-Maxeprofit)/(Maxeprofit); %AR to CR0 (classic newvsvendor) ratios of
optimal quantities and profit;
[h,p,ci,stats] = ttest2(nwprofit,nwprofitar); %two sample t-test between profits for classic newsvendor
and AR models;
Maxp=p(indexmax);
resultofinstance(instancerow,:)=[price,cost,mcost,salvage,mdemand,sigma,goodwill,mdemand2,sigma2
,mdemandj,sigmaj,alpha,beta,gamma,TAR,Maxeqty,Maxeqtyar,CR0,CRar,crqty0,crqtyar,MaxCR0real,
MaxCRarreal,Maxeqtyfillr0,Maxeqtyfillrar,Maxeprofit,Maxeprofitar,Maxqtytoartheor,Maxqtytoar,Ma
xprofitoar,Maxp];
instancerow=min(instancerow+1,combinationssize(1));
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);mdemand=mdemandc(instancerow);sigma=sigmac(instancerow);
goodwill=goodwillc(instancerow);mdemand2=mdemand2c(instancerow);sigma2=sigma2c(instancerow
);mdemandj=mdemandjc(instancerow);sigmaj=sigmajc(instancerow);alpha=alphac(instancerow);beta=
betac(instancerow);gamma=gammac(instancerow);
end;
maxprofitfactor=resultofinstance(:,30);                    maxqtyfactor=resultofinstance(:,16);
maxqtyarfactor=resultofinstance(:,17);                     quantityfactor=resultofinstance(:,29);
costfactor=resultofinstance(:,2);salvagefactor=resultofinstance(:,4);tarfactor=resultofinstance(:,15);sig
mafactor=resultofinstance(:,6);sigma2factor=resultofinstance(:,9);sigmajfactor=resultofinstance(:,11);a
lphafactor=resultofinstance(:,12);betafactor=resultofinstance(:,13);gammafactor=resultofinstance(:,14);
[p2,tbl,stats,terms] = anovan(maxprofitfactor,{costfactor salvagefactor tarfactor sigmafactor
sigma2factor         sigmajfactor          alphafactor          betafactor
gammafactor},'model','interaction','varnames',{'costfactor' 'salvagefactor' 'tarfactor' 'sigmafactor'
'sigma2factor' 'sigmajfactor' 'alphafactor' 'betafactor' 'gammafactor'});
multicomparison12   =   multcompare(stats,'Dimension',[1    2]);    %?multicomparison13   =
multcompare(stats,'Dimension',[1 3]); %multiple comparisons to find out which groups of the factors
inside [..] are significantly different; type of critical value by default 'tukey-kramer' ('hsd') is suitable
for ANOVA;
[p3,tbl,stats,terms]   =   anovan(quantityfactor,{costfactor salvagefactor tarfactor sigmafactor
sigma2factor              sigmajfactor              alphafactor              betafactor
gammafactor},'model','interaction','varnames',{'costfactor' 'salvagefactor' 'tarfactor' 'sigmafactor'
'sigma2factor' 'sigmajfactor' 'alphafactor' 'betafactor' 'gammafactor'});
[h4,p4,ci4,stats4] = ttest2(maxqtyfactor,maxqtyarfactor) %two sample t-test between optimal quantities
for classic newsvendor and AR models;
multicomparisonqty12 = multcompare(stats,'Dimension',[1 3]);
```

namemulticompare = {'factor1','factor2','lowerbound','difference_1_vs_2','upperbound','pvalue'};
%definitions of output for multicompare;names for second table of output below, upper and lower bounds at default 95% confidence;
outputtable1 = array2table(resultofinstance,'VariableNames',parameternames); %create a table with labels for all results of instances;
outputtable2 = array2table(multicomparison12,'VariableNames',namemulticompare);
outputtable3 = array2table(multicomparisonqty12,'VariableNames',namemulticompare);
sprintf('(i) rows = total number of instances = %d ;(ii) columns = number of parameters in each instance = %d ; (iii) total number of elements = %d.', combinationssize(1), combinationssize(2), allcombinations) %display needed values on screen
save('algorithmnwresults') %save all current workspace variables to MAT-file;
% if export to Excel needed, enter (does not work in Octave well):
writetable(outputtable1,'algorithmnwAR.xls');xlswrite('algorithmnwAR.xlsx',stats,'multicomparestats');
xlswrite('algorithmnwAR.xlsx',outputtable2,'multiplecomparison1n2');

APPENDIX B: Matlab Code for Numerical Study to Compare Main Effects of Classic Newsvendor and Active Response to Stockout with Different Distributions

```
%comparing active response (AR) effects between several distributions;
xprice=[250];   xcost=[100];   xmcost=[0];   xsalvage=[25];   xmdemand=[350];   xsigma=[150];
xgoodwill=0;
xmdemand2=[350];xsigma2=[150];xmdemandj=[350];xsigmaj=[150];xalpha=[0.05,0.1,0.15,0.2,0.25,0
.3];xbeta=[0.05,0.1,0.15,0.2,0.25,0.3];xgamma=[0.05,0.1,0.15,0.2,0.25,0.3];
parameternames                                                                  =
{'price','purchase_cost','production_cost','salvage_value','mean_demand','st_deviation_sigma','goodwill
_cost_shortage','mdemand2','sigma2','mdemandj','sigmaj','alpha','beta','gamma','totalAR','optimal_quant
ity','optimal_quantityAR','theor_CR','theor_AR','theor_qty0','theor_qtyAR','optimalCR','optimalCR_A
R','optimal_fillrate','optimal_fillrateAR','optimal_profit','optimal_profitAR','qty_decrease_ARtheor','qu
antity_decreaseAR','profit_increaseAR','pfriedman'};
%enter main parameters above, give a short name describing EACH parameter in "parameternames"
minqty=0; maxqty=800; spacing=1;maxtrial=40000;
allqty=linspace(minqty, maxqty, spacing); %all quantities for each simulation instance
%starting from normal PDF - result1;
nwprofit=zeros(maxtrial,length(allqty));  nwprofitar=zeros(maxtrial,length(allqty));  %preallocate  for
speed - set starting order quantity to zero (refine to smaller increment and higher order size later for
narrow interval to find accurate maximum profit);
nwsales=zeros(maxtrial,length(allqty));nwpurchasecost=zeros(maxtrial,length(allqty));nwsalvage=zero
s(maxtrial,length(allqty));nwshortage=zeros(maxtrial,length(allqty));nwbackorder=zeros(maxtrial,lengt
h(allqty));nwbrandswch=zeros(maxtrial,length(allqty));nwstoreswch=zeros(maxtrial,length(allqty));nw
salvagear=zeros(maxtrial,length(allqty));
[vprice,vcost,vmcost,vsalvage,vmdemand,vsigma,vgoodwill,vmdemand2,vsigma2,vmdemandj,vsigmaj
,valpha,vbeta,vgamma]                                                            =
ndgrid(xprice,xcost,xmcost,xsalvage,xmdemand,xsigma,xgoodwill,xmdemand2,xsigma2,xmdemandj,x
sigmaj,xalpha,xbeta,xgamma); %combinations grid
combinations                                                                     =
[vprice(:),vcost(:),vmcost(:),vsalvage(:),vmdemand(:),vsigma(:),vgoodwill(:),vmdemand2(:),vsigma2(:)
,vmdemandj(:),vsigmaj(:),valpha(:),vbeta(:),vgamma(:)]; %all combinations of parameters
combinationssize = size(combinations); %show size of elements in vector (rows,columns);
allcombinations = numel(combinations); %show number of elements;
pricec=combinations(:,1);costc=combinations(:,2);mcostc=combinations(:,3);salvagec=combinations(:,
4);mdemandc=combinations(:,5);sigmac=combinations(:,6);            goodwillc=combinations(:,7);
mdemand2c=combinations(:,8);sigma2c=combinations(:,9);mdemandjc=combinations(:,10);sigmajc=c
ombinations(:,11);alphac=combinations(:,12);betac=combinations(:,13);gammac=combinations(:,14);
%name each parameter for simulations;
instancerow=1;
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);mdemand=mdemandc(instancerow);sigma=sigmac(instancerow);
goodwill=goodwillc(instancerow);mdemand2=mdemand2c(instancerow);sigma2=sigma2c(instancerow
);mdemandj=mdemandjc(instancerow);sigmaj=sigmajc(instancerow);alpha=alphac(instancerow);beta=
betac(instancerow);gamma=gammac(instancerow);
```

resultofinstance1=zeros((combinationssize(1)), size(parameternames,2)); % final results which includes all parameters (columns of instances) plus additional results derived from simulations;
%do not forget that in "resultofinstance" above, columns MUST be equal to number of extra outputs inside "resultofinstance" plus initial parameters!
for trialin=1:combinationssize(1) %repeat each simulation updating parameters till final instance is reached;
for trialq = 1:spacing %repeat each simulation updating order quantities;
for trials=1:maxtrial %repeat each simulation specified number of trials;
nwsales(trials,trialq)=(min(allqty(trialq),(max(max(normrnd(mdemand,sigma),0),0))));
nwpurchasecost(trials,trialq)=allqty(trialq)*cost;
nwsalvage(trials,trialq)=max(allqty(trialq)-(max(normrnd(mdemand,sigma),0)),0);
nwshortage(trials,trialq)=max((max(normrnd(mdemand,sigma),0))-allqty(trialq),0);
nwbackorder(trials,trialq)=alpha*max(normrnd(mdemand,sigma)-allqty(trialq),0);
nwbrandswch(trials,trialq)=min(max(allqty(trialq)-
normrnd(mdemand,sigma),0),beta*(max(normrnd(mdemandj,sigmaj)-allqty(trialq),0)));
nwstoreswch(trials,trialq)=min(max(allqty(trialq)-
normrnd(mdemand,sigma),0),gamma*(max(normrnd(mdemand2,sigma2)-allqty(trialq),0)));
nwsalvagear(trials,trialq)=max((allqty(trialq)-(normrnd(mdemand,sigma)))-
beta*(max(normrnd(mdemandj,sigmaj)-allqty(trialq),0))-gamma*(max(normrnd(mdemand2,sigma2)-allqty(trialq),0)),0);
end;
nwprofit=price*nwsales-nwpurchasecost+salvage*nwsalvage-goodwill*nwshortage;
nwprofitar=price*nwsales-nwpurchasecost+salvage*nwsalvagear-goodwill*nwshortage+(price-cost)*nwbackorder+price*nwbrandswch+price*nwstoreswch;
Expectprofit = mean(nwprofit); Expectprofitar = mean(nwprofitar);
Expectsales = mean(nwsales); Expectshortage = mean(nwshortage);Expectsalvage = mean(nwsalvage);
Expectsalvagear = mean(nwsalvagear);Expectbackorder = mean(nwbackorder); Expectbrandswch = mean(nwbrandswch);Expectstoreswch = mean(nwstoreswch);
Expectfillr0=Expectsales./(Expectsales+Expectshortage);
Expectfillrar=(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch)./(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch+Expectshortage);
Stockouts=sum(nwshortage>0);Stockoutsar=sum(nwshortage-nwbackorder>0);CR0real=1-(Stockouts/maxtrial);CRarreal=1-(Stockoutsar/maxtrial);
end;
[Maxeprofit,indexmax]=max(Expectprofit); [Maxeprofitar,indexmaxar]=max(Expectprofitar);
Maxeqty=allqty(indexmax);Maxeqtyar=allqty(indexmaxar);TAR=alpha+beta+gamma;
MaxCR0real=CR0real(indexmax);MaxCRarreal=CRarreal(indexmaxar);
Maxeqtyfillr0=Expectfillr0(indexmax);Maxeqtyfillrar=Expectfillrar(indexmaxar);
CR0=(price-cost)/(price-salvage); crqty0 = norminv(CR0,mdemand,sigma); CRar=(price*(1-alpha-beta-gamma)+alpha*cost-cost+salvage*(beta+gamma))/(price*(1-alpha-beta-gamma)+cost*alpha+salvage*(beta+gamma)-salvage);crqtyar = norminv(CRar,mdemand,sigma);
Maxqtytoartheor=(Maxeqtyar-crqtyar)/(Maxeqtyar); Maxqtytoar=(Maxeqty-Maxeqtyar)/(Maxeqty);
Maxprofitoar=(Maxeprofitar-Maxeprofit)/(Maxeprofit); %AR to CR0 (classic newvsvendor) ratios of optimal quantities and profit;
nwprofitboth=[reshape(nwprofit,[],1),reshape(nwprofitar,[],1)]; %turn "nwprofit" and "nwprofitar" each to 1-column array and then join them to combined 2-column array;
p1 = friedman(nwprofitboth,maxtrial,'off'); % maxtrial is number of replicates per cell;
resultofinstance1(instancerow,:)=[price,cost,mcost,salvage,mdemand,sigma,goodwill,mdemand2,sigma2,mdemandj,sigmaj,alpha,beta,gamma,TAR,Maxeqty,Maxeqtyar,CR0,CRar,crqty0,crqtyar,MaxCR0real,MaxCRarreal,Maxeqtyfillr0,Maxeqtyfillrar,Maxeprofit,Maxeprofitar,Maxqtytoartheor,Maxqtytoar,Maxprofitoar,p1];
instancerow=min(instancerow+1,combinationssize(1));
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(instancerow);mdemand=mdemandc(instancerow);sigma=sigmac(instancerow);
goodwill=goodwillc(instancerow);mdemand2=mdemand2c(instancerow);sigma2=sigma2c(instancerow

);mdemandj=mdemandjc(instancerow);sigmaj=sigmajc(instancerow);alpha=alphac(instancerow);beta=betac(instancerow);gamma=gammac(instancerow);

end;

%uniform PDF- result2

xprice=[250]; xcost=[100]; xmcost=[0]; xsalvage=[25]; xminrndi=[0]; xmaxrndi=[800]; xgoodwill=0; xminrndi2=[0];xmaxrndi2=[800];xminrndij=[0];xmaxrndij=[800];xalpha=[0.05,0.1,0.15,0.2,0.25,0.3];xbeta=[0.05,0.1,0.15,0.2,0.25,0.3];xgamma=[0.05,0.1,0.15,0.2,0.25,0.3];

parameternames = {'price','purchase_cost','production_cost','salvage_value','mean_demand','st_deviation_sigma','goodwill_cost_shortage','minrndi2','maxrndi2','minrndij','maxrndij','alpha','beta','gamma','totalAR','optimal_quantity','optimal_quantityAR','theor_CR','theor_AR','theor_qty0','theor_qtyAR','optimalCR','optimalCR_AR','optimal_fillrate','optimal_fillrateAR','optimal_profit','optimal_profitAR','qty_decrease_ARtheor','quantity_decreaseAR','profit_increaseAR','pfriedman'};

nwprofit=zeros(maxtrial,length(allqty)); nwprofitar=zeros(maxtrial,length(allqty)); %preallocate for speed - set starting order quantity to zero (refine to smaller increment and higher order size later for narrow interval to find accurate maximum profit);

nwsales=zeros(maxtrial,length(allqty));nwpurchasecost=zeros(maxtrial,length(allqty));nwsalvage=zeros(maxtrial,length(allqty));nwshortage=zeros(maxtrial,length(allqty));nwbackorder=zeros(maxtrial,length(allqty));nwbrandswch=zeros(maxtrial,length(allqty));nwstoreswch=zeros(maxtrial,length(allqty));nwsalvagear=zeros(maxtrial,length(allqty));

[vprice,vcost,vmcost,vsalvage,vminrndi,vmaxrndi,vgoodwill,vminrndi2,vmaxrndi2,vminrndij,vmaxrndij,valpha,vbeta,vgamma] = ndgrid(xprice,xcost,xmcost,xsalvage,xminrndi,xmaxrndi,xgoodwill,xminrndi2,xmaxrndi2,xminrndij,xmaxrndij,xalpha,xbeta,xgamma); %combinations grid

combinations = [vprice(:),vcost(:),vmcost(:),vsalvage(:),vminrndi(:),vmaxrndi(:),vgoodwill(:),vminrndi2(:),vmaxrndi2(:),vminrndij(:),vmaxrndij(:),valpha(:),vbeta(:),vgamma(:)]; %all combinations of parameters

combinationssize = size(combinations); %show size of elements in vector (rows,columns);

pricec=combinations(:,1);costc=combinations(:,2);mcostc=combinations(:,3);salvagec=combinations(:,4);minrndic=combinations(:,5);maxrndic=combinations(:,6); goodwillc=combinations(:,7); minrndi2c=combinations(:,8);maxrndi2c=combinations(:,9);minrndijc=combinations(:,10);maxrndijc=combinations(:,11);alphac=combinations(:,12);betac=combinations(:,13);gammac=combinations(:,14); %name each parameter for simulations;

instancerow=1;

price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(instancerow);minrndi=minrndic(instancerow);maxrndi=maxrndic(instancerow);

goodwill=goodwillc(instancerow);minrndi2=minrndi2c(instancerow);maxrndi2=maxrndi2c(instancerow);minrndij=minrndijc(instancerow);maxrndij=maxrndijc(instancerow);alpha=alphac(instancerow);beta=betac(instancerow);gamma=gammac(instancerow);

resultofinstance2=zeros((combinationssize(1)), size(parameternames,2)); % final results which includes all parameters (columns of instances) plus additional results derived from simulations;

for trialin=1:combinationssize(1) %repeat each simulation updating parameters till final instance is reached;

for trialq = 1:spacing %repeat each simulation updating order quantities;

for trials=1:maxtrial %repeat each simulation specified number of trials;

nwsales(trials,trialq)=(min(allqty(trialq),(max(max(randi([minrndi,maxrndi]),0),0))));

nwpurchasecost(trials,trialq)=allqty(trialq)*cost;

nwsalvage(trials,trialq)=max(allqty(trialq)-(max(randi([minrndi,maxrndi]),0)),0);

nwshortage(trials,trialq)=max((max(randi([minrndi,maxrndi]),0))-allqty(trialq),0);

nwbackorder(trials,trialq)=alpha*max(randi([minrndi,maxrndi])-allqty(trialq),0);

nwbrandswch(trials,trialq)=min(max(allqty(trialq)-randi([minrndi,maxrndi]),0),beta*(max(randi([minrndij,maxrndij])-allqty(trialq),0)));

nwstoreswch(trials,trialq)=min(max(allqty(trialq)-randi([minrndi,maxrndi]),0),gamma*(max(randi([minrndi2,maxrndi2])-allqty(trialq),0)));

nwsalvagear(trials,trialq)=max((allqty(trialq)-(randi([minrndi,maxrndi])))-beta*(max(randi([minrndij,maxrndij])-allqty(trialq),0))-gamma*(max(randi([minrndi2,maxrndi2])-allqty(trialq),0)),0);

end;

nwprofit=price*nwsales-nwpurchasecost+salvage*nwsalvage-goodwill*nwshortage;

nwprofitar=price*nwsales-nwpurchasecost+salvage*nwsalvagear-goodwill*nwshortage+(price-cost)*nwbackorder+price*nwbrandswch+price*nwstoreswch;

Expectprofit = mean(nwprofit); Expectprofitar = mean(nwprofitar);

Expectsales = mean(nwsales); Expectshortage = mean(nwshortage);Expectsalvage = mean(nwsalvage); Expectsalvagear = mean(nwsalvagear);Expectbackorder = mean(nwbackorder); Expectbrandswch = mean(nwbrandswch);Expectstoreswch = mean(nwstoreswch);

Expectfillr0=Expectsales./(Expectsales+Expectshortage);

Expectfillrar=(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch)./(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch+Expectshortage);

Stockouts=sum(nwshortage>0);Stockoutsar=sum(nwshortage-nwbackorder>0);CR0real=1-(Stockouts/maxtrial);CRarreal=1-(Stockoutsar/maxtrial);

end;

[Maxeprofit,indexmax]=max(Expectprofit); [Maxeprofitar,indexmaxar]=max(Expectprofitar);

Maxeqty=allqty(indexmax);Maxeqtyar=allqty(indexmaxar);TAR=alpha+beta+gamma;

MaxCR0real=CR0real(indexmax);MaxCRarreal=CRarreal(indexmaxar);

Maxeqtyfillr0=Expectfillr0(indexmax);Maxeqtyfillrar=Expectfillrar(indexmaxar);

CR0=(price-cost)/(price-salvage); crqty0 = unifinv(CR0,minrndi,maxrndi); CRar=(price*(1-alpha-beta-gamma)+alpha*cost-cost+salvage*(beta+gamma))/(price*(1-alpha-beta-gamma)+cost*alpha+salvage*(beta+gamma)-salvage);crqtyar = unifinv(CRar,minrndi,maxrndi);

Maxqtytoartheor=(Maxeqtyar-crqtyar)/(Maxeqtyar);Maxqtytoar=(Maxeqty-Maxeqtyar)/(Maxeqty);

Maxprofitoar=(Maxeprofitar-Maxeprofit)/(Maxeprofit); %AR to CR0 (classic newvsvendor) ratios of optimal quantities and profit;

nwprofitboth=[reshape(nwprofit,[],1),reshape(nwprofitar,[],1)]; %turn "nwprofit" and "nwprofitar" each to 1-column array and then join them to combined 2-column array;

p2 = friedman(nwprofitboth,maxtrial,'off'); % maxtrial is number of replicates per cell;

resultofinstance2(instancerow,:)=[price,cost,mcost,salvage,minrndi,maxrndi,goodwill,minrndi2,maxrndi2,minrndij,maxrndij,alpha,beta,gamma,TAR,Maxeqty,Maxeqtyar,CR0,CRar,crqty0,crqtyar,MaxCR0real,MaxCRarreal,Maxeqtyfillr0,Maxeqtyfillrar,Maxeprofit,Maxeprofitar,Maxqtytoartheor,Maxqtytoar,Maxprofitoar,p2];

instancerow=min(instancerow+1,combinationssize(1));

price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(instancerow);minrndi=minrndic(instancerow);maxrndi=maxrndic(instancerow);

goodwill=goodwillc(instancerow);minrndi2=minrndi2c(instancerow);maxrndi2=maxrndi2c(instancerow);minrndij=minrndijc(instancerow);maxrndij=maxrndijc(instancerow);alpha=alphac(instancerow);beta=betac(instancerow);gamma=gammac(instancerow);

end;

%exponential PDF- result3

xprice=[250]; xcost=[100]; xmcost=[0]; xsalvage=[25]; xexpmean=[250]; xgoodwill=0;

xexpmean2=[250];xexpmeanj=[250];xalpha=[0.05,0.1,0.15,0.2,0.25,0.3];xbeta=[0.05,0.1,0.15,0.2,0.25,0.3];xgamma=[0.05,0.1,0.15,0.2,0.25,0.3];

parameternames = {'price','purchase_cost','production_cost','salvage_value','mean_demand','goodwill_cost_shortage','expmean2','expmeanj','alpha','beta','gamma','totalAR','optimal_quantity','optimal_quantityAR','theor_CR','theor_AR','theor_qty0','theor_qtyAR','optimalCR','optimalCR_AR','optimal_fillrate','optimal_fillrateAR','optimal_profit','optimal_profitAR','qty_decrease_ARtheor','quantity_decreaseAR','profit_increaseAR','pfriedman'};

nwprofit=zeros(maxtrial,length(allqty)); nwprofitar=zeros(maxtrial,length(allqty)); %preallocate for speed - set starting order quantity to zero (refine to smaller increment and higher order size later for narrow interval to find accurate maximum profit);

```
nwsales=zeros(maxtrial,length(allqty));nwpurchasecost=zeros(maxtrial,length(allqty));nwsalvage=zero
s(maxtrial,length(allqty));nwshortage=zeros(maxtrial,length(allqty));nwbackorder=zeros(maxtrial,lengt
h(allqty));nwbrandswch=zeros(maxtrial,length(allqty));nwstoreswch=zeros(maxtrial,length(allqty));nw
salvagear=zeros(maxtrial,length(allqty));
[vprice,vcost,vmcost,vsalvage,vexpmean,vgoodwill,vexpmean2,vexpmeanj,valpha,vbeta,vgamma]    =
ndgrid(xprice,xcost,xmcost,xsalvage,xexpmean,xgoodwill,xexpmean2,xexpmeanj,xalpha,xbeta,xgamm
a); %combinations grid
combinations                                                                                =
[vprice(:),vcost(:),vmcost(:),vsalvage(:),vexpmean(:),vgoodwill(:),vexpmean2(:),vexpmeanj(:),valpha(:
),vbeta(:),vgamma(:)]; %all combinations of parameters
combinationssize = size(combinations); %show size of elements in vector (rows,columns);
pricec=combinations(:,1);costc=combinations(:,2);mcostc=combinations(:,3);salvagec=combinations(:,
4);expmeanc=combinations(:,5);goodwillc=combinations(:,6);
expmean2c=combinations(:,7);expmeanjc=combinations(:,8);alphac=combinations(:,9);betac=combina
tions(:,10);gammac=combinations(:,11);  %name each parameter for simulations;
instancerow=1;
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);expmean=expmeanc(instancerow);maxrndi=maxrndic(instancerow);
goodwill=goodwillc(instancerow);expmean2=expmean2c(instancerow);maxrndi2=maxrndi2c(instancer
ow);expmeanj=expmeanjc(instancerow);maxrndij=maxrndijc(instancerow);alpha=alphac(instancerow);
beta=betac(instancerow);gamma=gammac(instancerow);
resultofinstance3=zeros((combinationssize(1)),  size(parameternames,2));  % final  results  which
includes all parameters (columns of instances) plus additional results derived from simulations;
%do not forget that in "resultofinstance" above, columns MUST be equal to number of extra outputs
inside "resultofinstance" plus initial parameters!
for  trialin=1:combinationssize(1) %repeat each simulation updating parameters till final instance is
reached;
for trialq = 1:spacing  %repeat each simulation updating order quantities;
for trials=1:maxtrial  %repeat each simulation specified number of trials;
nwsales(trials,trialq)=(min(allqty(trialq),(max(max(exprnd(expmean),0),0))));
nwpurchasecost(trials,trialq)=allqty(trialq)*cost;
nwsalvage(trials,trialq)=max(allqty(trialq)-(max(exprnd(expmean),0)),0);
nwshortage(trials,trialq)=max((max(exprnd(expmean),0))-allqty(trialq),0);
nwbackorder(trials,trialq)=alpha*max(exprnd(expmean)-allqty(trialq),0);
nwbrandswch(trials,trialq)=min(max(allqty(trialq)-exprnd(expmean),0),beta*(max(exprnd(expmeanj)-
allqty(trialq),0)));
nwstoreswch(trials,trialq)=min(max(allqty(trialq)-
exprnd(expmean),0),gamma*(max(exprnd(expmean2)-allqty(trialq),0)));
nwsalvagear(trials,trialq)=max((allqty(trialq)-(exprnd(expmean)))-beta*(max(exprnd(expmeanj)-
allqty(trialq),0))-gamma*(max(exprnd(expmean2)-allqty(trialq),0)),0);
end;
nwprofit=price*nwsales-nwpurchasecost+salvage*nwsalvage-goodwill*nwshortage;
nwprofitar=price*nwsales-nwpurchasecost+salvage*nwsalvagear-goodwill*nwshortage+(price-
cost)*nwbackorder+price*nwbrandswch+price*nwstoreswch;
Expectprofit = mean(nwprofit); Expectprofitar = mean(nwprofitar);
Expectsales = mean(nwsales); Expectshortage = mean(nwshortage);Expectsalvage = mean(nwsalvage);
Expectsalvagear  =  mean(nwsalvagear);Expectbackorder  =  mean(nwbackorder); Expectbrandswch =
mean(nwbrandswch);Expectstoreswch = mean(nwstoreswch);
Expectfillr0=Expectsales./(Expectsales+Expectshortage);
Expectfillrar=(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch)./(Expectsales+Exp
ectbackorder+Expectbrandswch+Expectstoreswch+Expectshortage);
Stockouts=sum(nwshortage>0);Stockoutsar=sum(nwshortage-nwbackorder>0);CR0real=1-
(Stockouts/maxtrial);CRarreal=1-(Stockoutsar/maxtrial);
end;
[Maxeprofit,indexmax]=max(Expectprofit); [Maxeprofitar,indexmaxar]=max(Expectprofitar);
```

Maxeqty=allqty(indexmax);Maxeqtyar=allqty(indexmaxar);TAR=alpha+beta+gamma;
MaxCR0real=CR0real(indexmax);MaxCRarreal=CRarreal(indexmaxar);
Maxeqtyfillr0=Expectfillr0(indexmax);Maxeqtyfillrar=Expectfillrar(indexmaxar);
CR0=(price-cost)/(price-salvage); crqty0 = expinv(CR0,expmean,maxrndi); CRar=(price*(1-alpha-beta-gamma)+alpha*cost-cost+salvage*(beta+gamma))/(price*(1-alpha-beta-gamma)+cost*alpha+salvage*(beta+gamma)-salvage);crqtyar = expinv(CRar,expmean,maxrndi);
Maxqtytoartheor=(Maxeqtyar-crqtyar)/(Maxeqtyar);Maxqtytoar=(Maxeqty-Maxeqtyar)/(Maxeqty);
Maxprofitoar=(Maxeprofitar-Maxeprofit)/(Maxeprofit); %AR to CR0 (classic newvsvendor) ratios of optimal quantities and profit;
nwprofitboth=[reshape(nwprofit,[],1),reshape(nwprofitar,[],1)]; %turn "nwprofit" and "nwprofitar" each to 1-column array and then join them to combined 2-column array;
p3 = friedman(nwprofitboth,maxtrial,'off'); % maxtrial is number of replicates per cell;
resultofinstance3(instancerow,:)=[price,cost,mcost,salvage,expmean,goodwill,expmean2,expmeanj,alpha,beta,gamma,TAR,Maxeqty,Maxeqtyar,CR0,CRar,crqty0,crqtyar,MaxCR0real,MaxCRarreal,Maxeqtyfillr0,Maxeqtyfillrar,Maxeprofit,Maxeprofitar,Maxqtytoartheor,Maxqtytoar,Maxprofitoar,p3];
instancerow=min(instancerow+1,combinationssize(1));
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(instancerow);expmean=expmeanc(instancerow);goodwill=goodwillc(instancerow);expmean2=expmean2c(instancerow);expmeanj=expmeanjc(instancerow);alpha=alphac(instancerow);beta=betac(instancerow);gamma=gammac(instancerow);
end;
%gamma PDF- result4
xprice=[250]; xcost=[100]; xmcost=[0]; xsalvage=[25]; xalphag=[35]; xbetag=[10]; xgoodwill=0; xalphag2=[35];xbetag2=[10];xalphagj=[35];xbetagj=[10];xalpha=[0.05,0.1,0.15,0.2,0.25,0.3];xbeta=[0.05,0.1,0.15,0.2,0.25,0.3];xgamma=[0.05,0.1,0.15,0.2,0.25,0.3];
parameternames = {'price','purchase_cost','production_cost','salvage_value','mean_demand','st_deviation_sigma','goodwill_cost_shortage','alphag2','betag2','alphagj','betagj','alpha','beta','gamma','totalAR','optimal_quantity','optimal_quantityAR','theor_CR','theor_AR','theor_qty0','theor_qtyAR','optimalCR','optimalCR_AR','optimal_fillrate','optimal_fillrateAR','optimal_profit','optimal_profitAR','qty_decrease_ARtheor','quantity_decreaseAR','profit_increaseAR','pfriedman'};
nwprofit=zeros(maxtrial,length(allqty)); nwprofitar=zeros(maxtrial,length(allqty)); %preallocate for speed - set starting order quantity to zero (refine to smaller increment and higher order size later for narrow interval to find accurate maximum profit);
nwsales=zeros(maxtrial,length(allqty));nwpurchasecost=zeros(maxtrial,length(allqty));nwsalvage=zeros(maxtrial,length(allqty));nwshortage=zeros(maxtrial,length(allqty));nwbackorder=zeros(maxtrial,length(allqty));nwbrandswch=zeros(maxtrial,length(allqty));nwstoreswch=zeros(maxtrial,length(allqty));nwsalvagear=zeros(maxtrial,length(allqty));
[vprice,vcost,vmcost,vsalvage,valphag,vbetag,vgoodwill,valphag2,vbetag2,valphagj,vbetagj,valpha,vbeta,vgamma] = ndgrid(xprice,xcost,xmcost,xsalvage,xalphag,xbetag,xgoodwill,xalphag2,xbetag2,xalphagj,xbetagj,xalpha,xbeta,xgamma); %combinations grid
combinations = [vprice(:),vcost(:),vmcost(:),vsalvage(:),valphag(:),vbetag(:),vgoodwill(:),valphag2(:),vbetag2(:),valphagj(:),vbetagj(:),valpha(:),vbeta(:),vgamma(:)]; %all combinations of parameters
combinationssize = size(combinations); %show size of elements in vector (rows,columns);
pricec=combinations(:,1);costc=combinations(:,2);mcostc=combinations(:,3);salvagec=combinations(:,4);alphagc=combinations(:,5);betagc=combinations(:,6); goodwillc=combinations(:,7);alphag2c=combinations(:,8);betag2c=combinations(:,9);alphagjc=combinations(:,10);betagjc=combinations(:,11);alphac=combinations(:,12);betac=combinations(:,13);gammac=combinations(:,14); %name each parameter for simulations;
instancerow=1;
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(instancerow);alphag=alphagc(instancerow);betag=betagc(instancerow);
goodwill=goodwillc(instancerow);alphag2=alphag2c(instancerow);betag2=betag2c(instancerow);alpha

```
gj=alphagjc(instancerow);betagj=betagjc(instancerow);alpha=alphac(instancerow);beta=betac(instance row);gamma=gammac(instancerow);
resultofinstance4=zeros((combinationssize(1)), size(parameternames,2)); % final results which includes all parameters (columns of instances) plus additional results derived from simulations;
%do not forget that in "resultofinstance" above, columns MUST be equal to number of extra outputs inside "resultofinstance" plus initial parameters!
for trialin=1:combinationssize(1) %repeat each simulation updating parameters till final instance is reached;
for trialq = 1:spacing %repeat each simulation updating order quantities;
for trials=1:maxtrial %repeat each simulation specified number of trials;
nwsales(trials,trialq)=(min(allqty(trialq),(max(max(gamrnd(alphag,betag),0),0))));
nwpurchasecost(trials,trialq)=allqty(trialq)*cost;
nwsalvage(trials,trialq)=max(allqty(trialq)-(max(gamrnd(alphag,betag),0)),0);
nwshortage(trials,trialq)=max((max(gamrnd(alphag,betag),0))-allqty(trialq),0);
nwbackorder(trials,trialq)=alpha*max(gamrnd(alphag,betag)-allqty(trialq),0);
nwbrandswch(trials,trialq)=min(max(allqty(trialq)-
gamrnd(alphag,betag),0),beta*(max(gamrnd(alphagj,betagj)-allqty(trialq),0)));
nwstoreswch(trials,trialq)=min(max(allqty(trialq)-
gamrnd(alphag,betag),0),gamma*(max(gamrnd(alphag2,betag2)-allqty(trialq),0)));
nwsalvagear(trials,trialq)=max((allqty(trialq)-(gamrnd(alphag,betag)))-
beta*(max(gamrnd(alphagj,betagj)-allqty(trialq),0))-gamma*(max(gamrnd(alphag2,betag2)-
allqty(trialq),0)),0);
end;
nwprofit=price*nwsales-nwpurchasecost+salvage*nwsalvage-goodwill*nwshortage;
nwprofitar=price*nwsales-nwpurchasecost+salvage*nwsalvagear-goodwill*nwshortage+(price-
cost)*nwbackorder+price*nwbrandswch+price*nwstoreswch;
Expectprofit = mean(nwprofit); Expectprofitar = mean(nwprofitar);
Expectsales = mean(nwsales); Expectshortage = mean(nwshortage);Expectsalvage = mean(nwsalvage);
Expectsalvagear = mean(nwsalvagear);Expectbackorder = mean(nwbackorder); Expectbrandswch = mean(nwbrandswch);Expectstoreswch = mean(nwstoreswch);
Expectfillr0=Expectsales./(Expectsales+Expectshortage);
Expectfillrar=(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch)./(Expectsales+Exp
ectbackorder+Expectbrandswch+Expectstoreswch+Expectshortage);
Stockouts=sum(nwshortage>0);Stockoutsar=sum(nwshortage-nwbackorder>0);CR0real=1-
(Stockouts/maxtrial);CRarreal=1-(Stockoutsar/maxtrial);
end;
[Maxeprofit,indexmax]=max(Expectprofit); [Maxeprofitar,indexmaxar]=max(Expectprofitar);
Maxeqty=allqty(indexmax);Maxeqtyar=allqty(indexmaxar);TAR=alpha+beta+gamma;
MaxCR0real=CR0real(indexmax);MaxCRarreal=CRarreal(indexmaxar);
Maxeqtyfillr0=Expectfillr0(indexmax);Maxeqtyfillrar=Expectfillrar(indexmaxar);
CR0=(price-cost)/(price-salvage); crqty0 = gaminv(CR0,alphag,betag); CRar=(price*(1-alpha-beta-
gamma)+alpha*cost-cost+salvage*(beta+gamma))/(price*(1-alpha-beta-
gamma)+cost*alpha+salvage*(beta+gamma)-salvage);crqtyar = gaminv(CRar,alphag,betag);
Maxqtytoartheor=(Maxeqtyar-crqtyar)/(Maxeqtyar);Maxqtytoar=(Maxeqty-Maxeqtyar)/(Maxeqty);
Maxprofitoar=(Maxeprofitar-Maxeprofit)/(Maxeprofit); %AR to CR0 (classic newvsvendor) ratios of optimal quantities and profit;
nwprofitboth=[reshape(nwprofit,[],1),reshape(nwprofitar,[],1)]; %turn "nwprofit" and "nwprofitar" each to 1-column array and then join them to combined 2-column array;
p4 = friedman(nwprofitboth,maxtrial,'off'); % maxtrial is number of replicates per cell;
resultofinstance4(instancerow,:)=[price,cost,mcost,salvage,alphag,betag,goodwill,alphag2,betag2,alpha
gj,betagj,alpha,beta,gamma,TAR,Maxeqty,Maxeqtyar,CR0,CRar,crqty0,crqtyar,MaxCR0real,MaxCRa
rreal,Maxeqtyfillr0,Maxeqtyfillrar,Maxeprofit,Maxeprofitar,Maxqtytoartheor,Maxqtytoar,Maxprofitoar
,p4];
instancerow=min(instancerow+1,combinationssize(1));
```

```
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);alphag=alphagc(instancerow);betag=betagc(instancerow);
goodwill=goodwillc(instancerow);alphag2=alphag2c(instancerow);betag2=betag2c(instancerow);alpha
gj=alphagjc(instancerow);betagj=betagjc(instancerow);alpha=alphac(instancerow);beta=betac(instance
row);gamma=gammac(instancerow);
end;
%lognormal PDF- result5
xprice=[250]; xcost=[100]; xmcost=[0]; xsalvage=[25]; xmeanl=[6]; xsigmal=[1]; xgoodwill=0;
xmeanl2=[6];xsigmal2=[1];xmeanlj=[6];xsigmalj=[1];xalpha=[0.05,0.1,0.15,0.2,0.25,0.3];xbeta=[0.05,
0.1,0.15,0.2,0.25,0.3];xgamma=[0.05,0.1,0.15,0.2,0.25,0.3];
parameternames                                                                               =
{'price','purchase_cost','production_cost','salvage_value','mean_demand','st_deviation_sigma','goodwill
_cost_shortage','meanl2','sigmal2','meanlj','sigmalj','alpha','beta','gamma','totalAR','optimal_quantity','o
ptimal_quantityAR','theor_CR','theor_AR','theor_qty0','theor_qtyAR','optimalCR','optimalCR_AR','opt
imal_fillrate','optimal_fillrateAR','optimal_profit','optimal_profitAR','qty_decrease_ARtheor','quantity_
decreaseAR','profit_increaseAR','pfriedman'};
nwprofit=zeros(maxtrial,length(allqty)); nwprofitar=zeros(maxtrial,length(allqty)); %preallocate for
speed - set starting order quantity to zero (refine to smaller increment and higher order size later for
narrow interval to find accurate maximum profit);
nwsales=zeros(maxtrial,length(allqty));nwpurchasecost=zeros(maxtrial,length(allqty));nwsalvage=zero
s(maxtrial,length(allqty));nwshortage=zeros(maxtrial,length(allqty));nwbackorder=zeros(maxtrial,lengt
h(allqty));nwbrandswch=zeros(maxtrial,length(allqty));nwstoreswch=zeros(maxtrial,length(allqty));nw
salvagear=zeros(maxtrial,length(allqty));
[vprice,vcost,vmcost,vsalvage,vmeanl,vsigmal,vgoodwill,vmeanl2,vsigmal2,vmeanlj,vsigmalj,valpha,v
beta,vgamma]                                                                                   =
ndgrid(xprice,xcost,xmcost,xsalvage,xmeanl,xsigmal,xgoodwill,xmeanl2,xsigmal2,xmeanlj,xsigmalj,x
alpha,xbeta,xgamma); %combinations grid
combinations                                                                                   =
[vprice(:),vcost(:),vmcost(:),vsalvage(:),vmeanl(:),vsigmal(:),vgoodwill(:),vmeanl2(:),vsigmal2(:),vmea
nlj(:),vsigmalj(:),valpha(:),vbeta(:),vgamma(:)]; %all combinations of parameters
combinationssize = size(combinations); %show size of elements in vector (rows,columns);
pricec=combinations(:,1);costc=combinations(:,2);mcostc=combinations(:,3);salvagec=combinations(:,
4);meanlc=combinations(:,5);sigmalc=combinations(:,6);          goodwillc=combinations(:,7);
meanl2c=combinations(:,8);sigmal2c=combinations(:,9);meanljc=combinations(:,10);sigmaljc=combin
ations(:,11);alphac=combinations(:,12);betac=combinations(:,13);gammac=combinations(:,14);
%name each parameter for simulations;
instancerow=1;
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);meanl=meanlc(instancerow);sigmal=sigmalc(instancerow);
goodwill=goodwillc(instancerow);meanl2=meanl2c(instancerow);sigmal2=sigmal2c(instancerow);mea
nlj=meanljc(instancerow);sigmalj=sigmaljc(instancerow);alpha=alphac(instancerow);beta=betac(instan
cerow);gamma=gammac(instancerow);
resultofinstance5=zeros((combinationssize(1)), size(parameternames,2)); % final results which
includes all parameters (columns of instances) plus additional results derived from simulations;
for trialin=1:combinationssize(1) %repeat each simulation updating parameters till final instance is
reached;
for trialq = 1:spacing %repeat each simulation updating order quantities;
for trials=1:maxtrial %repeat each simulation specified number of trials;
nwsales(trials,trialq)=(min(allqty(trialq),(max(max(lognrnd(meanl,sigmal),0),0))));
nwpurchasecost(trials,trialq)=allqty(trialq)*cost;
nwsalvage(trials,trialq)=max(allqty(trialq)-(max(lognrnd(meanl,sigmal),0)),0);
nwshortage(trials,trialq)=max((max(lognrnd(meanl,sigmal),0))-allqty(trialq),0);
nwbackorder(trials,trialq)=alpha*max(lognrnd(meanl,sigmal)-allqty(trialq),0);
nwbrandswch(trials,trialq)=min(max(allqty(trialq)-
lognrnd(meanl,sigmal),0),beta*(max(lognrnd(meanlj,sigmalj)-allqty(trialq),0)));
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```
nwstoreswch(trials,trialq)=min(max(allqty(trialq)-
lognrnd(meanl,sigmal),0),gamma*(max(lognrnd(meanl2,sigmal2)-allqty(trialq),0)));
nwsalvagear(trials,trialq)=max((allqty(trialq)-(lognrnd(meanl,sigmal)))-
beta*(max(lognrnd(meanlj,sigmalj)-allqty(trialq),0))-gamma*(max(lognrnd(meanl2,sigmal2)-
allqty(trialq),0)),0);
end;
nwprofit=price*nwsales-nwpurchasecost+salvage*nwsalvage-goodwill*nwshortage;
nwprofitar=price*nwsales-nwpurchasecost+salvage*nwsalvagear-goodwill*nwshortage+(price-
cost)*nwbackorder+price*nwbrandswch+price*nwstoreswch;
Expectprofit = mean(nwprofit); Expectprofitar = mean(nwprofitar);
Expectsales = mean(nwsales); Expectshortage = mean(nwshortage);Expectsalvage = mean(nwsalvage);
Expectsalvagear = mean(nwsalvagear);Expectbackorder = mean(nwbackorder); Expectbrandswch =
mean(nwbrandswch);Expectstoreswch = mean(nwstoreswch);
Expectfillr0=Expectsales./(Expectsales+Expectshortage);
Expectfillrar=(Expectsales+Expectbackorder+Expectbrandswch+Expectstoreswch)./(Expectsales+Exp
ectbackorder+Expectbrandswch+Expectstoreswch+Expectshortage);
Stockouts=sum(nwshortage>0);Stockoutsar=sum(nwshortage-nwbackorder>0);CR0real=1-
(Stockouts/maxtrial);CRarreal=1-(Stockoutsar/maxtrial);
end;
[Maxeprofit,indexmax]=max(Expectprofit); [Maxeprofitar,indexmaxar]=max(Expectprofitar);
Maxeqty=allqty(indexmax);Maxeqtyar=allqty(indexmaxar);TAR=alpha+beta+gamma;
MaxCR0real=CR0real(indexmax);MaxCRarreal=CRarreal(indexmaxar);
Maxeqtyfillr0=Expectfillr0(indexmax);Maxeqtyfillrar=Expectfillrar(indexmaxar);
CR0=(price-cost)/(price-salvage); crqty0 = logninv(CR0,meanl,sigmal); CRar=(price*(1-alpha-beta-
gamma)+alpha*cost-cost+salvage*(beta+gamma))/(price*(1-alpha-beta-
gamma)+cost*alpha+salvage*(beta+gamma)-salvage);crqtyar = logninv(CRar,meanl,sigmal);
Maxqtytoartheor=(Maxeqtyar-crqtyar)/(Maxeqtyar);Maxqtytoar=(Maxeqty-Maxeqtyar)/(Maxeqty);
Maxprofitoar=(Maxeprofitar-Maxeprofit)/(Maxeprofit); %AR to CR0 (classic newvsvendor) ratios of
optimal quantities and profit;
nwprofitboth=[reshape(nwprofit,[],1),reshape(nwprofitar,[],1)]; %turn "nwprofit" and "nwprofitar"
each to 1-column array and then join them to combined 2-column array;
p5 = friedman(nwprofitboth,maxtrial,'off');  % maxtrial is number of replicates per cell;
resultofinstance5(instancerow,:)=[price,cost,mcost,salvage,meanl,sigmal,goodwill,meanl2,sigmal2,mea
nlj,sigmalj,alpha,beta,gamma,TAR,Maxeqty,Maxeqtyar,CR0,CRar,crqty0,crqtyar,MaxCR0real,MaxC
Rarreal,Maxeqtyfillr0,Maxeqtyfillrar,Maxeprofit,Maxeprofitar,Maxqtytoartheor,Maxqtytoar,Maxprofit
oar,p5];
instancerow=min(instancerow+1,combinationssize(1));
price=pricec(instancerow);cost=costc(instancerow);mcost=mcostc(instancerow);salvage=salvagec(inst
ancerow);meanl=meanlc(instancerow);sigmal=sigmalc(instancerow);
goodwill=goodwillc(instancerow);meanl2=meanl2c(instancerow);sigmal2=sigmal2c(instancerow);mea
nlj=meanljc(instancerow);sigmalj=sigmaljc(instancerow);alpha=alphac(instancerow);beta=betac(instan
cerow);gamma=gammac(instancerow);
end;
%nonparametric ad-hoc test/ multiple comparison ("resultofinstance3" is exponential distribution - has
one parameter and resultof instance indices)
maxpfactor=[resultofinstance1(:,30)          resultofinstance2(:,30)          resultofinstance3(:,27)
resultofinstance4(:,30) resultofinstance5(:,30)];
maxqfactor=[resultofinstance1(:,29)          resultofinstance2(:,29)          resultofinstance3(:,26)
resultofinstance4(:,29) resultofinstance5(:,29)];
namemulticompare    =    {'factor1','factor2','lowerbound','difference_1_vs_2','upperbound','pvalue'};
%definitions of output for multicompare;names for second table of output below, upper and lower
bounds at default 95% confidence;
[p6,tbl,stats] = friedman(maxpfactor)
```

multicomparisonp1 = multcompare(stats,'CType','dunn-sidak','Display','off')%multiple comparisons to find out which groups of the factors inside [..] are significantly different; type of critical value for nonparametric Post-hoc tests is either Dunn-Sidak (less conservative)or Bonferroni;
multicomparisonp2 = multcompare(stats,'CType','bonferroni','Display','off')
multicomparisonp12 = [multicomparisonp1;multicomparisonp2];
outputtablenonparametr1 = array2table(multicomparisonp12,'VariableNames',namemulticompare);
[p7,tbl,stats] = friedman(maxqfactor)
multicomparisonq1 = multcompare(stats,'CType','dunn-sidak','Display','off')%multiple comparisons to find out which groups of the factors inside [..] are significantly different; type of critical value for nonparametric Post-hoc tests is either Dunn-Sidak (less conservative)or Bonferroni;
multicomparisonq2 = multcompare(stats,'CType','bonferroni','Display','off')
multicomparisonq12 = [multicomparisonq1;multicomparisonq2];
outputtablenonparametr2 = array2table(multicomparisonq12,'VariableNames',namemulticompare);
sprintf('(i) rows = total number of instances = %d ;(ii) columns = number of parameters in each instance = %d ; (iii) total number of elements = %d.', combinationssize(1), combinationssize(2), allcombinations) %display needed values on screen
%if results of each table is needed in Matlab table form, enter (for example of 1st table) "outputtablenp1 = array2table(writetable(outputtablenonparametr1,'algonparametr.xls')";
xlswrite('nonparametr.xlsx',resultofinstance1,'normal'); %export several variables to the same Excel file in separate sheets, then make pivot table;
xlswrite('nonparametr.xlsx',resultofinstance2,'uniform');
xlswrite('nonparametr.xlsx',resultofinstance3,'exponential');
xlswrite('nonparametr.xlsx',resultofinstance4,'gamma');
xlswrite('nonparametr.xlsx',resultofinstance5,'lognormal');
writetable(outputtablenonparametr1,'algonparametr.xls');
writetable(outputtablenonparametr2,'algonparametr.xls','Sheet',2); %export 2 tables to one excel;
%sprintf('(i) rows = total number of instances = %d ;(ii) columns = number of parameters in each instance = %d ; (iii) total number of elements = %d.', combinationssize(1), combinationssize(2), allcombinations) %display needed values on screen

LIST OF PUBLICATIONS

Refereed journal papers

1. Ovezmyradov, B., Kurata, H., 2018. Effects of customer response to fashion product stockout on holding costs, order sizes, and profitability in omnichannel retailing. *International Transactions in Operational Research* (forthcoming).[1]

2. Kurata, H., Ovezmyradov, B., Meuthia, Y., 2017. Stocking decision and supply chain coordination under the occurrence of backlogging, brand switching, and store switching. *The Journal of Japan Industrial Management Association*, 68(2E).

Conference proceedings papers

1. Ovezmyradov, B., Kurata H., 2016. Active response of strategic consumers to stockout. *Asia Pacific Industrial Engineering and Management Systems Conference*, 2016, Taipei, Taiwan.

2. Ovezmyradov, B., Kurata, H., 2015. Effects of active response of consumers to stockout on performance of fashion supply chain. *Asia Pacific Industrial Engineering and Management Systems Conference*, 2015, Ho Chi Minh City, Vietnam.

3. Kurata H., Ovezmyradov B., 2014. Stockout management: how does customer's brand and store loyalty influence supply chain performance? *Proceedings of Decision Sciences Institute*, 2014 Annual Meeting, Tampa, Florida, USA.

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[1] This dissertation is mostly based upon this paper.