Inventory Management in an E-Business Environment: A Simulated Study

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Advances in technology have allowed for Internet retailers to share information across the supply chain. As a result, some Internet retailers choose to not hold physical inventories, while others may keep inventory management in-house. In this paper, we identify the factors that may persuade firms to outsource fulfillment capabilities. The results support use of drop shipping by retailers in lieu of holding physical inventories in an e-commerce market.

Keywords: e-business, e-commerce, inventory management, aggregation, simulation, transshipment, virtual inventory, virtual order fulfillment

1. Introduction

Due to the surging popularity of the internet and increasing customer confidence in its security, e-commerce in the retail industry has become more attractive and popular (Ghosh 1997, Guay & Ettwein 1998, Varney & McCarthy 1996). E-commerce is the process of conducting business electronically to satisfy an organizational or individual objective. It provides manufacturers with an increased opportunity to sell and distribute direct to the end customer.

Recent advances in technology have led to new streams of research in inventory management practices and innovative supply chain structures. In an era of unprecedented supply chain network complexity, management must control inventories across these networks. Effective inventory management is the core of supply chain management excellence. While several companies have taken traditional approaches to controlling inventories, new tools and technologies are enabling other companies to manage network inventories in an e-commerce environment. With the advent of new information technologies and information sharing, several new supply chain concepts and practices have emerged in recent years, such as inventory aggregation, transshipping, virtual inventory, virtual warehousing, and virtual order fulfillment.

Inventory aggregation, also known as risk pooling, allows the supplying party to hold inventory in fewer locations until it is needed at a downstream location (Wanke & Saliby 2009). This results in a reduction of costs by decreasing the overall system inventory versus each individual stocking location maintaining their own inventory for order fulfillment. The concept of satisfying customer demand from more than one inventory location, known as virtual inventory, also emerged from information sharing. Customers are each assigned a primary

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distribution site, with backup locations determined by minimal additional cost. The substitution of information for inventory enables inventory from any stocking location to be used to satisfy the order, either by shipping from one of these stocking points, or by cross-shipping (also known as transshipping) inventory from one location to another to fill the order. The expectation is that virtual inventories allow for improved availability with decreased inventory (Ballou & Burnetas 2003). Safety stock reduction offsets the expected increase in cycle stock and transportation costs, and the net effect may be a savings in total cost. Virtual warehousing is an extension of virtual inventory in which single-location consolidated stock is the basis for supply chain management (Cheung et al. 2005). Rather than satisfying customer demand from inventory within the warehouse system, inventory may be shipped directly from the supplier, bypassing the intermediary location altogether. In this arrangement, the upstream supplier may provide all or part of the customer demand. This is sometimes used in stock-out or backorder situations and inventory status information sharing is critical between seller and supplier. Closely related to a virtual warehouse is the concept of virtual order fulfillment, also known as the virtual supply chain (Randall, Netessine & Rudi 2002). As e-commerce sites continue to emerge, many retailers find it difficult to find the best formula for marrying bricks and clicks. Virtual order fulfillment via drop shipping allows e-retailers to ship products through a wholesaler or manufacturer channel without maintaining physical inventories in their own distribution system. In a traditional supply chain, inventory may pass from wholesaler or manufacturer to retailer to customer. In contrast, a virtual supply chain allows inventories to pass directly from the wholesaler or manufacturer to the customer, replacing information for inventory at the retail level. The virtual supply chain could also consist of a hybrid structure in which both strategies are maintained.

This paper is aimed at extending the existing virtual order fulfillment literature to understand the best supply chain structure for a virtual supply chain. It focuses on the topic of virtual order fulfillment, or the satisfaction of consumer demand from a wholesaler’s or manufacturer’s inventory rather than a retailer’s inventory, in contrast to a traditional model in which every level in a supply chain holds finished goods inventory. Although several studies have focused on the analytical impacts of inventory aggregation and transshipments (Anupindi, Bassok & Zemel 2001; Anupindi & Bassok 1999; Ballou & Burnetas 2003; Ballou 1981; Ballou 2005; Chen, Federgruen & Zheng 2001; Dong & Rudi 2004; Eppen 1979; Lee & Whang 1999; Meller 1995; Rudi, Kapur & Pyke 2001; Sieke, Seifert & Thonemann 2006; Wanke 2009; Wanke & Saliby 2009; Zotteri, Kalchschmidt & Caniato 2005; Zotteri & Kalchschmidt 2007), research is still new and many gaps remain in the literature. The analysis of virtual order fulfillment is still in the beginning stages of analytical development (Hovelaque, Soler & Hafsa 2007; Khouja 2001; Netessine & Rudi 2003; Netessine & Rudi 2006), and the understanding of inventory practices in respect to e-commerce is still in the incipient stage. It is only in the last decade that the direct link between inventory management effectiveness and corporate cash flow generation has been well understood. Stocking keeping unit (SKU) proliferation and other factors have put upward pressures on inventory levels, resulting in diminished profitability improvements. Network pressures and supply chain complexities serve as headwinds to inventory reductions, and, as a result, effectively managing inventories at one level of the supply chain is no longer sufficient. Network inventory must be managed holistically, using tools and strategies that reduce inventory while maintaining or improving customer service levels.
Inventory control models have been used widely in research and in practice because they capture real-life situations and they aid in decision making in industry. In general, they are simple to implement and are widely applicable (Hovelaque, Soler & Hafsa 2007). The objective of this paper is determine the best supply chain structure and characteristics for e-retailers when both e-commerce and physical channels exist. Specifically, the following research questions are to be examined: 1) When should e-retailers hold physical inventory and when should they utilize virtual fulfillment via drop shipping, 2) What are the costs and benefits to the e-retailer of using virtual inventory structures versus traditional supply chains, and 3) What conditions allow for the best benefit to the e-retailer under each of the two supply chain structures?

Previous inventory research is heavily focused on analytical optimization models, with some limited empirical validation of these models. Drop shipping is still considered a developing strategy, and the previous studies are limited overall. In practice, mathematical models are heavily influenced by computational limitations, necessitating simplistic, well-defined models. This may prove to be restrictive. While some models may be considered quite accurate, this is usually based on practice and validation. Without this level of validation, it may be dangerous to use a mathematical optimization model to draw direct conclusions. Analytical models may give useful lower bounds, but more complex models that arise in practice may prove to be intractable, limiting solutions to sub-optimal, rather than optimal. For these models to be useful in practice, they must be experimentally and empirically validated. In reality, most real-world systems are too complex to allow realistic models to be evaluated analytically. Simulation provides a method to evaluate models numerically and to estimate the desired characteristics of the models.

Simulation and empirical studies to validate the analytical models have been limited in the research of virtual inventory models. The motivation for this paper is to address this gap in the research, offering an important first step in providing information to e-retailers on what supply chain structures are best suited for the growing e-commerce market.

This paper is organized as follows. Section 2 provides an updated review of the literature on virtual supply chains, followed by model development and design in section 3. The results are discussed in section 4, followed by the conclusion and identification of future research needs in this new research stream in section 5.

2. Literature Review

Two streams of literature in e-commerce will be reviewed: inventory aggregation/virtual inventory and virtual warehousing/virtual order fulfillment. The past three decades have focused on inventory consolidation and aggregation, and their impact on total costs and profits.

The objective of virtually all inventory control models is to minimize costs (Rinnooy Kan & Zipkin 1993). The earliest models can be traced to Harris (1915) who studied the basic tradeoffs that need to be made when making inventory control decisions. In this work, he derived the first economic order quantity (EOQ) model. Beginning in the 1950s, important scholars undertook more advanced analyses of various inventory problems and developed
simple mathematical inventory models. Bellman, Glicksberg and Gross (1955) discussed how methods of dynamic programming could be used to obtain structural results for a simple version of the periodic review stochastic demand problem of a single product. Single product models dominate the literature and are most frequently used in practice (Rinnooy Kan & Zipkin 1993). Arrow (1958) developed a collection of sophisticated mathematical models and discussed the motivation of firms to hold inventory, with the main three motives being transaction, precautionary, and speculative. The work provided the basis for much of the mathematical extensions of the single location model (Dvoretzky, Kiefer & Wolfowitz 1952; Dvoretzky, Kiefer & Wolfowitz 1953; Whitin 1953). Silver, Pyke and Petersen (1998) discussed most of the single location and single product models in detail, including those that consider other factors and constraints.

The single product and single location models provided a basis for further extensions of the EOQ model, including multi-stage systems. The past 20 years has seen a shift to close-to optimal, versus full-optimal, policies of simple structures (Silver, Pyke & Petersen 1998). These are generally easier to compute and implement. Accurate and easily computable approximations of system-wide costs have also been developed for used in design studies (Silver, Pyke & Petersen 1998).

2.1 Inventory Aggregation and Virtual Inventory

The earliest studies on inventory aggregation demonstrate the effects of demand consolidation on inventory costs. Eppen (1979) analytically demonstrated that centralization can reduce both inventory holding and penalty costs in a system. Without sophisticated systems, implementing aggregation methods was complicated. Ballou (1981) provided a simple regression technique to estimate aggregate inventory levels at multiple locations, balancing complex costs and service level requirements. This simple model provided a method that could be used to set target inventory levels across the network. Although the model was a basis for inventory auditing, execution without advanced systems was difficult. An early simulation study examined the relationship between aggregate safety stock levels and component part commonality, concluding that component part commonality increases inventory pooling and decreases uncertainty and safety stock levels, resulting in decreased inventory holding costs (Collier 1982).

The 1990s brought an increase in the number of studies pertaining to inventory aggregation. Several analytical studies addressed inventory centralization versus decentralization in single and multi-echelon supply chains. Most of these studies concluded that physical inventory centralization decreases overall costs and increases profits for the retailers. Researchers then began challenging the basic assumptions of inventory aggregation. Previous EOQ models assumed constant demand, whereas new models investigated system profitability as a function of the number of stocking points and overall demand (Meller 1995). Models were also expanded to include multiple decision-makers. Although centralization always benefits the retailers, it is not always beneficial for the wholesaler or manufacturer (Anupindi & Bassok 1999). Also, multiple players in a supply chain need to align incentives to maximize profits (Cachon & Lariviére 1999; Cachon & Zipkin 1999; Lee 1999; Anupindi, Bassok & Zemel 2001; Cachon 2001; Chen, Federgruen & Zheng 2001; Cachon 2004). Based on these analytical studies, full cooperation among partners leads to lower system inventories.
Transshipments occur in situations where one location has ample inventory while another incurs a stock-out. Surplus stock from one location may be shipped to the other location to satisfy demand. Krishnan and Rao (1965) first analytically modeled transshipment cost for emergency situations, followed by a stream of literature examining the impact and cost structures of transshipments (Lee 1987; Tagaras 1989; Axsater 1990; Kukreja, Schmidt & Miller 2001). Usually, a decision to maximize one’s own profits does not increase overall system profits (Rudi, Kapur & Pyke 2001).

Improvements in information systems have allowed businesses to treat multiple locations as one, also known as virtual inventories (Ballou & Burnetas 2003). Although the inventory may be lower at the individual stocking locations, service levels will increase by transshipping the unfilled demand from another location. In addition, cycle stocks tend to increase in a virtual inventory system; however, this increase is generally offset by a decrease in safety stock inventories, resulting in an overall reduction of costs (Ballou & Burnetas 2003). Other variables, such as wholesaler costs (Dong & Rudi 2004) and demand correlations (Dong & Rudi 2004; Wanke & Saliby 2009), may also impact the degree of virtualization.

Table 1 provides a general evolution of the literature, identifying the major streams and representative studies in each of these streams. The newness of virtual warehousing and virtual fulfillment produces major gaps in all streams.
## Table 1: Research streams

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<th>Research Stream</th>
<th>Inventory Aggregation and Virtual Inventory</th>
<th>Virtual Warehousing and Virtual Fulfillment</th>
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<td><strong>Theoretical Studies/Case Studies</strong></td>
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<td>Chopra &amp; Meindl (2007)</td>
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<td>Gunasekaran et al. (2002)</td>
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<td><strong>Simulation Studies</strong></td>
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<td>Cheung et al. (2005)</td>
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<td><strong>Simulation Models</strong></td>
<td>(Context of this study)</td>
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<td><strong>Empirical Models</strong></td>
<td>Patil &amp; Divekar (2014)</td>
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<td>Rabinovich, Rungtusanatham &amp; Laseter (2008)</td>
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<td>Randall, Netessine &amp; Rudi (2002; 2006)</td>
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### 2.2 Virtual Warehousing and Virtual Fulfillment

In a traditional supply chain structure, inventory is often held at several levels in a supply chain. Customers typically place orders with retailers, and occasionally, directly with upstream manufacturers. Retailers place orders with the manufacturer or wholesaler to replenish stock, which may ship via intermediary warehouses. In virtual supply chains, information still passes from the customer to the retailer, but physical inventories are maintained solely at the manufacturer or wholesaler, who ships directly to the customer, bypassing the retailer altogether. The manufacturer or wholesaler may also use intermediary warehouses. These two models are shown in figures 1 and 2.
As e-commerce sites emerge, the choice between the two supply chain structures involves a complex tradeoff of costs and benefits. Despite the claim that virtual structures provide the e-retailer with reduced inventory and transportation costs and increased product variety and fill rates, profit margin and control over orders and customer lists may decrease (Randall, Netessine & Rudi 2002). Several conditions must be evaluated when choosing an effective structure. A purely traditional approach is likely never the best solution for an e-commerce company. Successful companies may use either a pure virtual fulfillment or hybrid structure, dependent on business conditions (Randall, Netessine & Rudi 2002; Netessine & Rudi 2003; Netessine & Rudi 2004; Netessine & Rudi 2006).
Chopra and Meindl (2007) categorized the various distribution networks available to e-businesses into six models: 1) manufacturer storage with direct shipping, 2) manufacturer storage with direct shipping and in-transit merge, 3) distributor storage with package carrier delivery, 4) distributor storage with last mile delivery, 5) manufacturer/distributor storage with customer pickup, and 6) retail storage with customer pickup. The first model, manufacturer storage with direct shipping, ships product directly from the wholesaler or manufacturer to the end customer, bypassing the retailer. It is best used with items of high value and low, unpredictable demand. The second model, manufacturer storage with direct shipping and in-transit merge, combines portions of the order from various manufacturing sites into one shipment to the final customer. As with drop shipping, the ability to aggregate inventories and postpone product customization is a significant advantage in this model. The third design, distributor storage with package delivery, maintains inventories at an intermediate warehouse rather than at the manufacturer or wholesaler. The retailer then transports the product via package delivery to the end customer, requiring a higher level of inventory due to demand uncertainty. Distributor storage with last mile delivery, is similar to model three with the exception that the product is delivered to the customer’s home rather than using a package carrier. Aggregation with this model is low, thus inventories are high. In manufacturer/distributor storage with customer pickup, inventories are stored at the manufacturer or wholesaler. Customers place orders electronically with the retailer, and inventory is then shipped to customer pickup points as needed. Aggregation is high with this model, thus inventories are lower. Finally, in the sixth model, retail storage with customer pickup, inventory is stored locally at retail locations. Aggregation in this model is low and, thus, inventories are higher than with any other model. Gunasekaran et al. (2002) also conceptually discussed the impact of e-commerce on the supply chain. They concluded that e-commerce promises to become a mainstay of modern business and a competitive necessity; however, few useful frameworks exist in literature to understand its potential. Lawrence et al. (2001) discussed the issues that must be addressed before implementing a specific supply chain model. In regards to inventory management, when a manufacturer is selling directly to a customer, the tradeoff between forecast accuracy and inventory reduction must be assessed. Lee and Whang (2001) outlined five approaches to e-fulfillment: logistics postponement, dematerialization, resource exchange, leveraged shipments, and clicks and mortar. They provided guidelines on successful implementation of each of these strategies. None of these models were based on any analytical modeling or validation. This paper serves to explore these models, in particular manufacturing storage with direct shipping and a traditional model similar to a combination of distributor storage with package carrier delivery and retail storage with customer pickup.

Khouja (2001) introduced one of the earliest mathematical models to design the optimal mix of drop shipping by optimizing profits. He found that drop shipping has significant advantages over holding physical inventories, including decreased holding and obsolescence costs. He also concluded that drop shipping causes fragmentation, resulting in a mixed strategy of drop shipping and physical inventory. Hovelaque, Soler & Hafsa (2007) used a newboy order policy model to compare the advantages of three organizational models: store-picking, dedicated warehouse-picking, and drop shipping. They examined, via a simple exploratory model, how inventory holding policies effect supply chain efficiency. They found that when considering to choose either a drop-shipping or store-picking model, the retailer must take into account two effects. The store-picking alternative makes it easier to handle demand
fluctuations with one single stock, while drop-shipping transfers the risk of shortage to the supplier. Netessine and Rudi (2004; 2006) analytically compared the traditional and virtual supply chain structures from the e-retailer and wholesaler perspectives. They modeled both channels as two-stage supply chains with one wholesaler and multiple identical retailers. They found that the e-retailer trades off increased wholesaler prices for decreased inventory risks, while the wholesaler trades off margin versus inventory risk. They modeled the dual strategy problem as a non-cooperative game in which the retailers and wholesalers compete for demand and for inventory allocation. The authors identified conditions that lead to equilibrium, and conducted sensitivity analysis based on changes in wholesale price, drop ship markup, and transportation cost parameters. They also explored the different channels using numerical experiments and found that as the number of e-retailers increased, the virtual channel, or a hybrid approach, is more profitable. Netessine and Rudi observed that drop ship markup and transportation costs are the main drivers impacting the supply chain structure. Their analytical findings concluded that both drop shipping and a hybrid structure have potential to be Pareto-optimal choices, while the traditional channel does not, indicating that e-retailers should strive to not hold any physical inventories. Their results supported the empirical findings of Randall, Netessine & Rudi (2006).

Patil and Divekar (2014) used survey and secondary data to study the challenges and risks involved in inventory management. They provided various strategies to mitigate the risk associated with inventory management of online retailers. Rabinovich, Rungtusanatham and Laseter (2008) empirically studied the impact of drop shipping on margins and customer distribution. The authors concluded that a cost leadership competitive strategy is not the only viable alternative for e-commerce. They evaluated both speed and profits as performance variables. Randall, Netessine and Rudi (2006) empirically studied the conditions that favor the choice of one supply chain structure over another, and the financial impacts of this choice. The authors concluded that several factors, including gross margin, firm age, product variety, demand variability, number of retailers, and product size all impact the structure choice. Finally, they tested two alternative views of how a company’s supply chain structure can impact its economic performance. The first view assumes that one structure is dominant and will lead to better firm performance. The second states that performance is a function of fit between structure choice and the firm’s competitive strategy, controlling for other performance-related variables. They found support for basing supply chain structure decisions on strategy.

Prior research has laid the foundation for the study of the relationship between traditional and drop ship inventory models. With more than one third of retailers relying primarily on drop shipping (Randall, Netessine & Rudi 2006), this inventory strategy has become increasingly common in e-commerce. Our simulation model extends the analytical and empirical findings of the previous e-commerce studies, analyzing the impact of various factors on firm performance. Unlike most of the analytical models, our research looks beyond just profits to include firm success factors such as fill rate, costs, and customer satisfaction. While mathematical models may provide an approximation of optimality, they must then be examined to see how they can be used to answer the question of interest about the inventory system they represent. Our simulation model provides a means of validating some of these mathematical models developed in literature.
3. Model Development and Design

3.1 Theoretical Model

Based on the theoretical model developed by Netessine and Rudi (2006), we assumed a single product, with the wholesaler/manufacturer distributing the product to the retailer in weekly deliveries based on a calculated period order quantity (POQ) in the traditional model (Model T) or shipping directly to the customer, based on actual demand, in the virtual model (Model D). The model used a single period model, but it is possible to extend the results into a multi-period model. We also assumed that customers will wait for product to be available for shipment. There were n identical (same demand distribution function, same pricing) retailers. All demands were random variables with identical distributions. Each retailer sold the product at an exogenous price (which includes all handling and shipping charges from the retailer or from the wholesaler to the customer) and purchased the product from the wholesaler at a specified price. The assumption of exogeneity had the following impact: the addition of retailers to the model did not result in cannibalization of demand, but rather, it merely increased total demand. This is reasonable, assuming that each retailer has a different customer base, and additional retailers are considered as new entrants into the channel, perhaps moving from an alternate channel. This assumption is especially appropriate if the retailer/market size ratio is small (Netessine & Rudi 2006). Retailers have requested the wholesaler to drop ship the product in Model D, in which case the wholesaler charged the retailer an additional drop ship markup to compensate for additional shipping and handling costs, as well as the risk of holding inventory. The model assumed the wholesaler charged the same price to each retailer. The analysis also ignored fixed costs. Transportation costs varied, based on level of the supply chain. In Model T, shipments from the wholesaler to the retailer were shipped in full truckload quantities, assuming optimization of shipments. The same inventory was then shipped from the retailer to the customer in single units. In Model D, the wholesaler shipped direct to the customer, typically in unit quantities, hence eliminating any inbound transportation costs to the retailer.

3.2 Conceptual Model

Existing literature shows that high demand variability increases supply chain costs by increasing the mismatch between supply and demand (Ramdas 2003; Cachon & Terwiesch 2004; Randall, Netessine & Rudi 2006). Product availability depends on the retailer’s ability to forecast demand. Aggregating demand allows for increased forecast accuracy, leading to decreased stock-outs and safety stocks. Pooled demand smooths variations, which should translate to higher service levels (Randall, Netessine & Rudi 2002) and mitigates risk (Eppen 1979). In the virtual supply chain, rather than stocking inventory in each retailer location, inventory is solely stocked at the wholesaler and drop shipped to the customer, which allows pooling of demand and reduction of variability.

Hypothesis 1: Demand variability is positively related to the use of drop shipping.

Although pooled demand should result in mitigation of demand fluctuation, the extent of this reduction in variability depends on the number of retailers. The traditional channel does not benefit from pooling of demand because each retailer has their own demand distribution;
however, as the number of retailers increases, the less effective uncertainty the wholesaler faces (Randall, Netessine & Rudi 2006), and thus, the use of drop shipping increases. According to Netessine and Rudi (2003), each additional retailer added to the virtual model increases profits for all supply chain members; however, the inventories become insensitive to the differences when the number of retailers is greater than ten. They reach this conclusion by plotting the optimal sticking levels as a function of the number of retailers in the channel. In both the traditional and in the virtual model, the plots level out as the number of retailers approaches ten, indicating that the benefits of risk pooling have already been achieved.

**Hypothesis 2:** The number of retailers is positively related to the use of drop shipping.

As drop shipping becomes more expensive, retailers may prefer to hold inventory rather than use drop shipping via the wholesaler. At some point, inventory costs should be less expensive than incurring high wholesaler markups for each customer order that is drop shipped. An increase in wholesaler markup could have two effects. The retailer may opt to increase inventories, thus reducing drop shipping, or the wholesaler may increase inventories, assuming higher profitability per order. Overall, we assume, without collaboration, as wholesaler markup increases, system inventories increase. Thus, we expect that retailer profit will decrease. The wholesaler markup is one of the main driving forces affecting retailer channel decisions (Netessine & Rudi 2006).

**Hypothesis 3:** Wholesaler markup is negatively related to the use of drop shipping.

In the traditional channel, the retailer will typically pool shipments to the customer into truckload quantities to reduce transportation cost per unit. Pricing in our model is based on truckload (TL) or less than truck load (LTL) rates. In the virtual channel, the wholesaler will typically ship via parcel delivery since the shipment sizes are smaller. Even if the wholesaler is able to ship via LTL, the smaller load results in a higher piece rate. It may be hypothesized that as transportation costs increase, drop shipping may become less desirable.

**Hypothesis 4a:** Transportation costs from retailer to customer are negatively related to the use of drop shipping.

In the traditional channel, wholesalers ship in TL quantities to retailers, who in turn ship in TL or LTL quantities to retailers. Even though these shipments from the wholesaler to the retailer are eliminated in the virtual model, overall, due to the increased piece rate in the virtual model, drop shipping should result in increased system transportation costs.

**Hypothesis 4b:** Drop shipping is positively related to system transportation costs.

Inventory exists because the supply chain is inherently inefficient (Lawrence et al. 2001). Because retailers cannot forecast demand with certainty, they must hold stock to cover the variability in demand. Retailers with smaller demand must order in large quantities and have higher carrying costs. As customer demand varies at the retailer level, it becomes further advantageous for retailers with smaller demands to not hold physical inventories. It is assumed that the reduction in retailer inventory costs brought by drop shipping will compensate for the higher costs at the supplier level.
Hypothesis 5: Demand imbalance among retailers is positively related to the use of drop shipping.

As demand variability is smoothed and inventory is pooled at the wholesale level, customers should experience higher service levels due to fewer stock-outs. The real-time information delivered in e-commerce environments decreases variability and reduces forecast error.

Hypothesis 6: Drop shipping is positively related to customer fill rates.

Pooling inventories at the wholesale level and eliminating duplicate inventories at each retailer should result in a lower system inventory in the virtual model versus the traditional model. Forecast error and process variability, both information dependent, are decreased with a virtual inventory environment. Bypassing the intermediaries and their related processes speeds the progress of information and reduces error.

Hypothesis 7: Drop shipping is negatively related to retailer cycle inventory cost.

Drop shipped inventories direct from the wholesaler to the customer should result in a decrease in order cycle time from customer order date to customer delivery date. Even though retailers may be located physically closer to the customer, the ability to pool demand and smooth out demand variations allow wholesalers to respond to demand in a more efficient time frame than a retailer who must forecast individual demand and rely on supply orders from the wholesaler. While Chopra and Meindl (2007) argued that drop shipping may also adversely affect other aspects of customer experience, we measure customer experience to be on-time performance and time in the system.

Hypothesis 8: Drop shipping is positively related to customer experience (total time and on-time performance).

3.3 Simulation Experiment

The preceding hypotheses were tested with a simulation experiment to establish performance differences of the two models. In this section, we first will review how simulation logic was developed to replicate e-commerce activity in both a traditional and a virtual environment. Second, the simulation experimental procedures are discussed. Third, the dependent variables are explained and justified. Finally, the experimental results are described and discussed.

To examine the differences between Model T and Model D, and to test hypotheses one through seven, two conceptual, discrete event simulation models were developed. To analyze the potential advantages of one model over another, the order fill rate, transportation costs, inventory costs, time in system, and on-time delivery were calculated. Total costs were also captured. The simulation model was developed using Arena® and simulates the flow of goods and information in a traditional model and in a virtual model. Figure 3 graphically displays the conceptual framework for the simulation model.
Mathien & Suresh

Figure 3: Simulation flow

The experimental model examined the ordering, distribution, and shipment of one product between a customer, various retailers, and a wholesaler/manufacturer. Independent variables included demand variability, demand imbalance, number of retailers, transportation costs, and wholesaler markup. A fractional factorial design was carefully chosen to exploit the sparsity-of-effects principle, indicating that little statistical difference was seen with the addition of other combinations of variables to the model.

Demand variability was characterized by varying the standard deviation within the same probability function. Demand imbalance was captured by distribution of independent demand evenly or unevenly among the standard ten retailers. Retailers were varied from one to ten. Based on literature, there is little impact on the system beyond ten retailers (Netessine & Rudi 2003). Transportation cost ratios between truck load and less than truck load were taken from actual history and assumed to be constant. Due to the advantage of economies of scale, traditional retailers were assumed to order in full truck load quantities, and pooling of outbound inventory was also assumed. The virtual inventory model assumed no inbound transportation and less than truckload outbound shipments. Wholesaler markups were only applied to the virtual model.

In both models, the retailer order processing was triangularly distributed with a mean of one hour because batch order processing in many firms occurs at the top of the hour. In turn, the retailer would ship the product to the customer with a triangular distribution with a mean of 24 hours. The time it takes customers to receive their orders was assumed to be triangularly distributed, with a mean of one hour.

In the traditional model, the manufacturer or wholesaler was assumed to process orders with a triangular distribution with a mean of 24 hours. Inbound inventory was scheduled weekly for each retailer based on average weekly demand, using a POQ principle. The EOQ was divided by the mean demand to compute the time between orders (TBO) of approximately one week.
Mathien & Suresh

The model was then set to order inventory in weekly-scheduled deliveries to the retailers to cover exactly one week of demand.

Table 2: Model parameters (times listed in minutes)

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<thead>
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<th>Parameter</th>
<th>Values/Measurement</th>
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<tbody>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Demand variability</td>
<td>Beta [1, 5, 10, 15, 30, 60, 120]</td>
</tr>
<tr>
<td>Demand balance among retailers</td>
<td>10% each, 30/25/15/6/4%, 55%/5% balance, 73%/3% balance</td>
</tr>
<tr>
<td>Number of retailers</td>
<td>1, 2, 5, 10</td>
</tr>
<tr>
<td>Transportation cost (T/D ratio)</td>
<td>1/5, 10/50, 20/100, 50/250, 100/500, 200/1000, 500/2500</td>
</tr>
<tr>
<td>Wholesaler markup (D only)</td>
<td>10, 20, 50, 75, 100, 150, 200</td>
</tr>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Fill rate</td>
<td>% orders complete</td>
</tr>
<tr>
<td>System transportation cost</td>
<td>Total inbound/outbound cost</td>
</tr>
<tr>
<td>Average system inventory</td>
<td>Total holding cost</td>
</tr>
<tr>
<td>Customer experience</td>
<td>Total time, % orders shipped on-time</td>
</tr>
</tbody>
</table>

3.4 Simulation Runs

The simulation experiment corresponded to a batch means procedure with a one-month warm-up period, following by ten one-year sub runs, with no intervening gap between each sub-run. This procedure allows for batch means that are considered to be independently distributed as long as each run is sufficiently long (Hamister & Suresh 2008). Each run consisted of a one-month period in which no statistics were captured, followed by 11 months of data capture. This ensured independence of operations. A one-month period warm-up, determined via the Welch graphical procedure, was found to be adequate using graphical procedures with five initial replications. A linear congruential generator (LCG) was used to generate a sequence of random integers, with a specific seed identified as the starting point for random number generation. The same random number seed was used for each of the two models to reduce variance between the two models. Standard procedures to avoid transient bias and auto-correlated outputs were also employed (Law & Kelton 1982).

The independent variables were changed for each run to compare the impacts of these variables on the dependent variables (see table 2 for details). The dependent variables were fill rate, system transportation cost, average system inventory cost, and customer experience (on-time delivery and time in system). Fill rates were measured by the percentage of orders that were delivered in full. System transportation costs consisted of both inbound costs to the retailer, if applicable, and outbound costs to the customer. Average system inventory costs were the holding costs associated with the average inventory held at the retailer. Since no inventory is assumed to be held in the virtual model, inventory holding costs were only assumed to apply to the traditional model. Finally, customer experience was measured by the percentage of orders that were delivered by the customer’s request date. If inventory was not available to fulfill a shipment, the order was delayed until it could it could be shipped in full. Data were collected on each of these variables to compare the performance of the two models.
4. Results and Discussion

To test the individual hypotheses, the results were analyzed using a separate univariate analysis of variance (ANOVA) test for each response variable, comparing the traditional model to the drop ship model. Hypotheses 1 through 5 were partially supported, indicating that retailers prefer to drop ship rather than hold inventory. In all cases except wholesaler markup (H3) and transportation cost (H4a, H4b), drop shipping influenced average transportation costs and customer experience (time, but not late shipments); however, there was no impact on fill rates or average inventory. In the case of H3, drop shipping also impacted average inventory costs, and in H4a and H4b, the average transportation cost was insignificant.

Because there was more than one dependent variable, multivariate analysis of variance (MANOVA) was conducted for each of the dependent variables to determine if performance differed between the traditional and the virtual models. MANOVA was used to determine if changes in the independent variables have significant effects on the dependent variables, and to determine what the interactions are among the dependent variables and among the independent variables. The results differed from the above analysis using separate univariate ANOVAs for each response variable. The univariate ANOVA does not produce multivariate results utilizing information from all variables simultaneously. In addition, separate univariate tests are generally less powerful. The multivariate test of differences between groups using the Wilks Lambda criteria was statistically significant (F (32, 145.42) = 16.52; p<.0001). The results of the simulation are presented in table 3.

Hypothesis 6 was not supported, indicating that there was no difference in fill rates between the traditional model and the drop ship model. This may be due to orders of one product in order quantities of one. The model was also developed to not allow stock outs, thus, this likely impacted time in the system versus fill rate. In the simulation results, there were few instances of shortages overall.

Hypotheses 7 and 8 were partially supported. The only parameter that impacted inventory costs was wholesaler markups, indicating that as wholesaler markups for drop shipping increase, the use of drop shipping by retailers decreases, supporting the claim by Netessine and Rudi (2006). Customer experience was measured by two factors, time in system and percentage of late orders. While percentage of late orders was insignificant, the time in system was significant for every parameter measured.

The results do not support several of the previous studies that indicate that drop shipping results in reduction of total costs, and thus improves retailer profits; however, some individual factors do impact average transportation costs and customer experience. Overall, a virtual inventory management strategy will improve customer experience, in support of Rabinovich, Rungtusanatham and Laseter (2008). The findings also support the claims of Netessine and Rudi (2004; 2006) in that the main drivers of drop shipping performance are wholesaler markup and transportation costs. Thus, retailers should adopt a drop ship model as demand variation, the number of retailers, and demand imbalance increase, being sensitive to the increased costs due to wholesaler markups and system transportation costs.
### Table 3: Simulation results (F values, *10%, **5%, ***1%, ****<1%)

<table>
<thead>
<tr>
<th></th>
<th>Fill</th>
<th>Avg Transp</th>
<th>Avg Inventory</th>
<th>Time</th>
<th>Late</th>
<th>Ttl Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multivariate Contrast</td>
<td>0.75</td>
<td>2.55*</td>
<td>1.48</td>
<td>603.95****</td>
<td>0.00</td>
<td>1.48</td>
</tr>
<tr>
<td>Demand Variability</td>
<td>0.00</td>
<td>111.18****</td>
<td>3.16</td>
<td>562.79****</td>
<td>0.00</td>
<td>3.98*</td>
</tr>
<tr>
<td># Retailers</td>
<td>0.00</td>
<td>1134.36****</td>
<td>3.16</td>
<td>353.93****</td>
<td>0.00</td>
<td>3.14</td>
</tr>
<tr>
<td>Wholesaler MU</td>
<td>0.00</td>
<td>12.50**</td>
<td>440.57****</td>
<td>379811.00****</td>
<td>0.00</td>
<td>561.88****</td>
</tr>
<tr>
<td>Transport Cost</td>
<td>0.00</td>
<td>0.71</td>
<td>13073.20</td>
<td>1959160.00****</td>
<td>0.00</td>
<td>12.59***</td>
</tr>
<tr>
<td>Demand Imbalance</td>
<td>0.00</td>
<td>111.18****</td>
<td>4.04*</td>
<td>2272.60****</td>
<td>0.00</td>
<td>3.98*</td>
</tr>
</tbody>
</table>

### 5. Conclusions and Limitations

The increasingly popular practice of drop-shipping is rather new to literature. In our paper, we further advance the study of drop-shipping by validating previous mathematical models, including traditional and drop-ship supply chains. The use of simulation modeling to test analytical and empirical findings is an important next step in validating the conclusions of mathematical approximations of complex systems. It also allows for control and manipulation of variables that cannot be readily tested in a live environment. We compared the two channel alternatives and found that drop-shipping can be a viable choice for both the retailer and the wholesaler. In summary, we determined that the drop ship channel often offers advantages to both retailers and the wholesaler, in support of the analytical and empirical studies. By comparing the e-commerce supply chain alternatives, we provide managers with specific guidelines for choosing an appropriate channel structure for e-commerce retailing. Our findings are in line with the results of Netessine and Rudi (2004; 2006), who found that several variables impact channel choice and firm performance. The performance measurement focus of this paper goes beyond the financial measurements of most previous studies, to also include customer satisfaction measures of on-time and in-full deliveries. This research offers insights into managerial decisions of channel choice, and in specifying the relevant managerial trade-offs.

This study has several limitations. The first limitation is the exclusion of several other factors that may impact the analysis. Previous studies (Randall, Netessine & Rudi 2002; Netessine & Rudi 2003; Netessine & Rudi 2004; Netessine & Rudi 2006; Randall, Netessine & Rudi 2006) have introduced some of these factors, although not all have been included in this simulation study, and none have been previously tested via simulation. Due to the increasing complexity of the models used in this study, several of these factors were omitted. Second, the analysis does not consider stock outs or backorders. Fill rates in this model were directly impacted by this exclusion, and the modeling of stock outs and backorders may have had very different results, especially in the measurement of customer experience. Another limitation is that the models did not measure bullwhip effect, which could have been a significant dependent variable in measuring supply chain effectiveness. Measuring variability at the various points in the supply chain could have extended this study into the plethora of literature available in this area. The final limitation of this study is that the models were developed for a pure traditional structure and a drop ship structure. Previous analytical studies determined that a hybrid approach may often be the best model for an e-commerce retailer.

These limitations suggest several avenues for further research on this topic. First, the set of parameters should be explored more fully to better generalize the model. A third model could also be developed to represent a hybrid model in which some physical inventories are held.
Mathien & Suresh

This paper suggests that drop shipping supply chains outperform traditional supply chains in an e-commerce market. This research will lead to many new lines of analysis in the new inventory management research arena.

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Mathien & Suresh


Mathien & Suresh


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