IMPACT OF FORECASTING METHOD SELECTION AND INFORMATION SHARING ON SUPPLY CHAIN PERFORMANCE

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Effective supply chain management gains much attention from industry and academia because it helps firms across a supply chain to reduce cost and improve customer service level efficiently. Focusing on one of the key challenges of the supply chains, namely, demand uncertainty, this dissertation extends the work of Zhao, Xie, and Leung so as to examine the effects of forecasting method selection coupled with information sharing on supply chain performance in a dynamic business environment. The results of this study showed that under various scenarios, advanced forecasting methods such as neural network and GARCH models play a more significant role when capacity tightness increases and is more important to the retailers than to the supplier under certain circumstances in terms of supply chain costs. Thus, advanced forecasting models should be promoted in supply chain management. However, this study also demonstrated that forecasting methods not capable of modeling features of certain demand patterns significantly impact a supply chain's performance. That is, a forecasting method misspecified for characteristics of the demand pattern usually results in higher supply chain costs. Thus, in practice, supply chain managers should be cognizant of the cost impact of selecting commonly used traditional forecasting methods, such as moving average and exponential smoothing, in conjunction with various operational and environmental factors, to keep supply chain cost under control. This study demonstrated that when capacity tightness is high for the supplier, information sharing plays a more important role in effective supply chain management. In addition, this study also showed that retailers benefit directly from information sharing when advanced forecasting methods are employed under certain conditions.

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CHAPTER 1

INTRODUCTION

During the past decades, the supply chain literature has focused on strategies such as just-in-time and total quality management to make individual firms efficient and competitive. As the complexity of supply chains increases, managers are realizing that efficiency at each stage of the supply chain does not necessarily lead to optimal supply chain performance. The rule of global competition has shifted from “firm versus firm” to “supply chain versus supply chain.” That is, firms are realizing that a competitive strategy involves making the entire supply chain competitive, both upstream and downstream, and not just the stand-alone firm (Christopher, 2005). Success stories of companies such as Procter & Gamble and Wal-Mart suggest that supply chain management (SCM) is perhaps the single most critical factor determining a firm’s success (Simchi-Levi, Kaminsky, & Simchi-Levi, 2007). In essence, managing the supply chain effectively can improve customer service levels dramatically, reduce excessive inventory in the system, and thus reduce supply chain cost significantly.

Effective SCM is the next logical step toward reduced costs and increased profits. SCM is related to the coordination of products and information flows among suppliers, manufacturers, distributors, retailers, and customers. With effective information sharing and coordination of replenishment and production decisions under demand uncertainty, supply chains can further reduce costs and improve customer service levels. However, a prominent challenge faced by SCM is the bullwhip effect, which is the phenomenon of increased order variability throughout the supply chain. The bullwhip effect potentially leads to serious supply chain inefficiencies that may cost companies millions of dollars via excessive inventory costs, low capacity utilization, excessive freight charges, and loss of sales. Jay Forrester (1958) first discovered this phenomenon and noted its serious consequences.

Industry and academia have researched strategies to synchronize supply and demand to further reduce unnecessary costs due to the bullwhip effect. Among these strategies, lead-time reduction, information sharing, and demand forecasting have proven to be effective in reducing costs and improving system performance. In particular, research has addressed the impact of traditional forecasting methods and information sharing on supply chain performance (Chen, Drezner, Ryan, & Simchi-Levi, 2000a, 2000b; Zhao, Xie, & Lau, 2001; Zhao, Xie, & Leung, 2002; Sohn & Lim, 2008). However, as supply chain complexity evolves and the intensity of competition increases, a better assessment of the impact of forecasting model selection coupled with other operational factors on supply chain performance in a broad, realistic context is required. This study not only considered the operational causes of the bullwhip effect such as demand forecasting and information sharing, but also included environmental factors such as capacity tightness and demand patterns in assessing supply chain performance.

Among the factors that could influence the performance of a supply chain, demand forecasting ranks as one of the critical factors since SCM is “driven by demand” (Stadtler, 2005, p. 580). In reality, retailers and suppliers cannot determine market demand with certainty in advance. Therefore, they must base their inventory decisions and production planning on demand forecasts. Demand forecasting plays an important role in SCM because forecasts generated by the retailers affect not only the retailers’ own performances but also those of other chain members. Overestimating demand forecasts usually leads to excessive inventory and extra production capacity while underestimating forecasts results in stock-out, loss of sales, and poor customer service levels. Ideally, more accurate demand forecasts are preferred.

However, a supply chain usually involves many uncertainties from both the supply side and the demand side. These uncertainties may include highly uncertain product demand, unreliable product yield, and supply chain disruption, all of which make demand forecasting more difficult and make production and inventory planning more challenging. In today's modern economy, companies must be responsive to customers' demands despite these uncertainties. Effective demand forecasting helps firms achieve this goal. Moreover, as a business function of a company, effective forecasting remains an important asset because inefficiencies in the supply chain often result from unreliable forecasts (Zhao et al., 2002). Effective demand forecasting can be realized through proper selection of forecasting methods based on demand patterns and the characteristics of the products. More importantly, managers and practitioners should understand the factors that influence a forecasting method's impact on a supply chain's performance. This knowledge helps minimize the negative impact of uncertainties related to the supply chain system on supply chain performance.

At the executive level, management often lacks knowledge about forecasting issues related to effective SCM. Although forecasting is an ancient activity, it is still an underrated field of research in SCM (Datta, Granger, Barari, & Gibbs, 2007). Recently, forecasting has become more sophisticated as it requires greater expertise and skills on the part of managers and practitioners to use it properly. Although advanced methods are being investigated and are coming into use, they are not popular in practice. Surveys indicate that the moving average and exponential smoothing methods are among the most frequently used forecasting techniques in practice because managers or analysts are familiar and satisfied with these simple forecasting models (Kim & Ryan, 2003).

The use of advanced demand forecasting models does not automatically result in cost reduction for the supply chain. Zhao et al. (2001, p. 3936) reported that "the choice of forecasting model alone did not account for the cost saving achieved. However, the effectiveness of early order commitment in conjunction with different forecasting models was largely determined by the accuracy of the models' demand forecast." In the same vein, Jeunet (2006) showed that improved demand forecast accuracy might not be rewarded if lot-sizing techniques perform equally badly due to forecast error. This raises two questions: "Is it worth the effort to promote advanced forecasting techniques in SCM?" and "Should practitioners continue using the traditional forecasting methods, or should they adopt advanced forecasting methods?" To answer these questions, this dissertation systematically investigates the impact of forecasting method selection on supply chain performance under a variety of conditions in order to provide managerial guidelines on improving the entire supply chain performance.

Foundational Background

This section provides the background information that forms the foundation for this study. The bullwhip effect has prompted research in lead-time reduction, information sharing, earlier order commitment, effective demand forecasting, lot-sizing techniques, and inventory policies to improve supply chain performance. In fact, a stream of literature has developed around the operational causes of the bullwhip effect: lead-time, demand forecasting, batch ordering, gaming and promotions (Lee, Padmandabhan, & Whang, 1997). Focusing on demand forecasting, researchers have taken different approaches and constructed various models to investigate the impact of demand forecasting on the supply chain (Graves, 1999; Chen et al., 2000; Zhao et al., 2002; Alwan, Liu, & Yao, 2003; Dejonckheere, Disney, Lambrecht, & Towill, 2003; Zhang, 2004). These authors reported that forecasting method selection plays an important role in reducing the bullwhip effect in a supply chain. Among them, Zhao et al. (2002) made important contributions in illustrating the significant impact of forecasting model selection on the value of information sharing in a supply chain.

In a series of papers by Zhao et al. (2001, 2002) and by Lau, Xie, & Zhao (2008), the impact of different factors such as information sharing, earlier order commitment, and inventory policies coupled with demand forecasting on supply chain performance were investigated. An important conclusion was that the selection of a forecasting model alone might not account for cost reduction achieved. They showed that information sharing, earlier order commitment, and lot-sizing techniques, coupled with effective demand forecasting, all played a role in achieving significant cost savings for the supply chain. Although the traditional forecasting models in this series of papers generally work well for demand with a relatively stable trend or seasonality, the results of these papers may not hold for demand processes exhibiting time-varying volatility. "It is highly unlikely that the demand for innovative products, durables, or products marketed by a few competitors exhibits the i.i.d. [independent and identically distributed] behavior. In the case of an innovative product, early product diffusion tends to generate highly correlated and varying demand over time" (X. Zhang, 2007, p. 128). In the same vein, F. Zhang (2007) also demonstrated the heteroscedastic nature of demand process in semiconductor supply chain planning and proposed a combinational forecasting method to forecast product demand. In fact, few empirical studies have documented this heteroscedastic effect in the supply chain and operations management literature. It is clear that research in the supply chain literature has paid little attention to this effect despite the fact that recent research has shown that traditional time series forecasting models do not yield satisfactory results for products that exhibit time-varying demand (Sohn & Lim, 2008).

Contributing to this research stream, Datta et al. (2007) theoretically proposed that a generalized autoregressive conditional heteroscedasticity (GARCH) model be used in demand forecasting for a supply chain since a GARCH model is able to capture the time-varying volatility or cluster volatility as it does for financial time series data. Datta et al. (2007) argued that forecasting is needed in almost any operation. However, in general, forecasting methods used in practice are still primitive compared to the progress made by research. Advanced forecasting methods used in predictive analytics in reducing uncertainty and volatile characteristics of global trade are urgently needed. However, little research has been done to empirically demonstrate that the increased accuracy of demand forecasts generated by a GARCH model indeed brings significant benefits to the entire supply chain system.

Moreover, Carbonneau, Laframboise, & Vahidov (2008) investigated the forecast accuracy of both the traditonal methods, such as moving average and mutiple linear regression, and non-traditonal forecasting methods, such as neural networks and support vector machines, by using simulated data and real data (Canadian Foundries orders). The authors reported that, in general, nontraditional methods outperformed traditional methods on real data in terms of accuracy. However, advanced forecasting models did not provide a large improvement over traditional forecasting methods for their simulated data sets. In particular, they did not find that machine learning techniques significantly outperformed multiple linear regression. They also suggested that future resarch should consider the impact of information sharing on forecasting accuracy.

Also examining nontraditional forecasting methods, Aburto & Weber (2007) combined autoregressive integrated moving average (ARIMA) models and neural network models to develop a hybrid intelligent system to forecast demand for a Chilean supermarket. The results showed that the improved forecasting accuracy led to few sales failures and low inventory levels compared with the previous solution. According to F. Zhang (2007, p. 289), "the combinational forecast can increase forecasting accuracy by integrating several separate forecast models when difficulties arise in identifying a single model." When forecasts from different models are averaged, biases among individual models should compensate for one another. As a result, predictions obtained from different forecasting models are expected to be more useful in cases of high uncertainty. Recent research is focusing on how to achieve high accuracy with demand forecasting by employing advanced forecasting techniques. However, it is not certain whether the value of improved forecasting accuracy can be realized in a complex and dynamic business environment.

In short, forecasting methods have been studied in relation to their impact on the bullwhip effect and on supply chain performance under a variety of assumptions and operational settings. Earlier research showed that forecasting models play an important role in reducing the bullwhip effect. It is noted that early research efforts focused on quantifying the bullwhip effect and provided solutions to reduce this effect. However, little research has been conducted to study the cost impact of the bullwhip effect. Zhao et al. (2002) extended the model by Chen et al. (2000) and incorporated different forecasting methods, information sharing, and cost structures into their study to quantify the financial inefficiency resulting from the bullwhip effect. They reported that forecasting method selection greatly impacts the value of information sharing and supply chain performance. However, forecasting method selection by itself may not account for the cost reduction across a supply chain. Thus, the effectiveness of forecasting method selection and its impact on supply chain performance must be evaluated in a broader operational environment.

A limitation of Zhao et al. (2002) is that their results from using traditional forecasting methods assuming relatively stable demand might not hold under a volatile demand process. Another limitation is that traditional forecasting methods may not be able to capture the nonlinear patterns in a demand process. More recent research (Datta, 2007; Aburto & Weber, 2007; Zhang, 2007; Carbonneau et al., 2008) has proposed using advanced forecasting models to cope with demand uncertainty in a supply chain. Unlike Zhao et al. (2002), these authors did focus on demand forecast accuracy, but they did not incorporate other operational factors such as inventory policies and information sharing into their models. Therefore, it is not clear whether advanced methods bring significant improvement to the supply chain's performance since the improved forecast accuracy might not be rewarded if other operational factors such as inventory policy or lot-sizing technique are not properly selected and employed. Moreover, none of these studies specifically investigates the impact of forecasting methods on supply chain performance under temporal demand heteroscedasticity. This dissertation systematically investigates the impact of forecasting models on supply chain performance under different demand patterns including heteroscedasticity.

Finally, ample forecasting techniques are available to practitioners. There are over 70 different time series techniques (Mentzer & Moon, 2005). Even with these forecasting methods on hand, supply chain managers and practitioners may not use the optimal method to forecast demand under certain demand patterns. Instead, they may select simple forecasting methods such as moving average and exponential smoothing because they are comfortable or satisfied with these methods. Limited research has addressed the impact of suboptimal forecasting method selection on the supply chain in terms of costs in a dynamic business environment. With the development of information technology, advanced forecasting methods, and the evolution of the supply chain, there is an urgent need for mangers and researchers to have a better understanding of the impact of forecasting model selection coupled with other operational and environmental factors on the overall supply chain performance. Table 1-1 compiles the major research that forms the foundation of this study and the focus of the previous work.

Table 1-1

Forecasting Methods Investigated in Supply Chain Management

Forecasting Methods	Focus of Study	Demand Pattern	Ordering Policy	Authors
Exponential-weighted moving average	Amplification of demand variability in a single-item inventory model	ARIMA(0,1,1)	Adaptive base-stock policy	Graves (1999)
Moving average, Single exponential smoothing	The impact of forecasting methods on the bullwhip effect (BWE)	AR(1) demand process	Order-up-to policy	Chen et al. (2000a,b)
Naive forecasting, Moving average, Double exponential smoothing, No-trend Winters' method, Winters' three-parameter model	The impact of forecasting methods selection on the value of information sharing in a supply chain	Constant demand, demand with seasonality, demand with seasonality and trend	Economic Order Quantity (EOQ) policy	Zhao et al. (2002)
Minimum mean-squared error (MMSE) forecasting method	The impact of forecasting method on BWE	AR(1) ARMA(1,1)	Order-up-to policy	Alwan et al. (2003)
Moving average, Exponential smoothing	The impact of suboptimal forecasting and limited demand information on the expected inventory costs in a supply chain	AR(1)	Order-up-to policy	Kim & Ryan (2003)

(table continues)

Table 1-1 *(continued).*

Forecasting Methods	Focus of Study	Demand Pattern	Ordering Policy	Authors
Simple exponential smoothing , Moving averages	The impact of forecasting method on BWE using a control theoretic approach	Sine wave demand pattern	Order-up-to policy	Dejonckheere et al. (2003)
Minimum mean-squared error (MMSE) forecasting method, Moving average, Exponential smoothing	The impact of forecasting methods on BWE	AR(1) demand process	Order-up-to policy	Zhang (2004)
Holt's method, Brown's double-exponential smoothing	The impact of forecasting methods and ordering policies on BWE	Demand with trend and random noises	Based on Sterman's model: Generic stock acquisition and an ordering heuristic	Wright & Yuan (2008)
Hybrid demand forecasting ARIMA+Neural Network	Improved supply chain management based on hybrid demand forecasts	Sales data	None	Aburto & Weber (2007)
GARCH model	Use of the GARCH model to forecast demand theoretically	None	None	Datta et al. (2007)
GARCH model	Application of the vector GARCH model in semiconductor demand planning	Sales data	None	F., Zhang (2007)
Naive forecasting, Average, Moving average, Trend, Multiple Linear Regression, Neural Networks, Recurrent Neural Networks, Support Vector Machines	The effectiveness of forecasting distorted demand signals with advanced nonlinear machine learning technique in the extended supply chain	Data set 1: simulation data set (sine wave pattern plus white noise) Data set 2: Foundries data provided by Statistics Canada	None	Carbonneau et al. (2008)

Research Gaps

Gaps exist in the supply chain literature with regard to the impact of forecasting method selection on supply chain performance. First, prior studies concentrated on the impact of the traditional time series forecasting methods on supply chain performance under relatively stable demand patterns. However, none of these studies considered temporal demand heteroscedasticity in their models nor investigated the impact of heteroscedasticity on forecasting method selection and supply chain performance. Even though empirical studies addressing GARCH behavior are numerous in the financial literature, “the operations management community by large has paid little attention to the variability in higher moments of the demand, theoretically or empirically” (Zhang, 2007, p. 141). The good news is that a recent study (Zhang, 2007) has empirically demonstrated that the variability in the higher moments of the demand exists in the supply chain and has argued that it might be associated with the bullwhip effect. Moreover, Datta et al. (2007) theoretically proposed that a GARCH model be used in demand forecasting in SCM because of the variability in the higher moments of the demand and high volume of data available to the supply chain. Motivated by recent research, one of the foci of this dissertation is to investigate the impact of forecasting method selection on supply chain performance under temporal demand heteroscedasticity, which has not been addressed in prior SCM studies.

A variety of time series methods have appeared in SCM literature. Namely, the traditional models have been frequently investigated, usually including moving average, double exponential smoothing, Holt’s, Winters’, and ARIMA. These models work well under the condition that the demand variance (conditional and unconditional) needs to remain homogeneous and constant over time. However, if demand variance is not constant, volatility clustering (Gourieroux, 1997) will cause the predictive accuracy of traditional time series models such as auto-regressive moving average (ARMA) or Holt-Winters' smoothing method to deteriorate considerably because these models do not take it into consideration (Chang & Tsai, 2008). Thus, a question arises as to whether advanced forecasting methods can overcome the limitations of traditional forecasting methods in SCM. Although advanced forecasting models, such as GARCH and neural network, are emerging in the supply chain area, they have not been thoroughly researched. Therefore, an assessment of the impact of these advanced models on a supply chain is needed.

Second, although advanced information technology allows retailers to obtain significant amounts of information on customer demand, many retailers still rely on relatively simple forecasting techniques to forecast customer demand (Makridakis, Wheelwright, & Hyndman, 1998). Relatively little research has addressed the cost impact of suboptimal forecasting methods on a supply chain's performance. Kim & Ryan (2003) is one of the few studies which investigated the impact of suboptimal forecasting methods on system performance. The effect of simple forecast techniques on supply chain performance under different demand patterns, including temporal demand heteroscedasticity, has not been addressed. This research intends to investigate how serious the consequence is if a simple forecasting technique is used by the retailers under different demand patterns.

Lastly, research has been limited in addressing related operational factors and environmental variables that affect demand forecasting's impact on a supply chain's costs. Prior studies have shown that a forecasting method itself may not account for the improvement of supply chain performance. However, a forecasting method, coupled with other operational factors, can greatly improve a supply chain's performance. This dissertation incorporates information sharing, capacity tightness, and environmental factors into the simulation model to evaluate the effect of forecasting methods on system performance so that the results can be generalized to a broader context.

Purpose of Research

The purpose of this research is to investigate the impact of forecasting method selection and information sharing on supply chain performance under different demand patterns, including temporal demand heteroscedasticity, and under different levels of supplier capacity tightness. Traditional forecasting methods and their impacts on supply chain performance have been intensively studied in SCM literature under relatively stable demand patterns. However, recent research has shown that the GARCH error exists in industrial demand, and thus, the influence of advanced forecasting methods on a supply chain needs to be addressed. More importantly, a steady increase in the complexity of supply chains and in the competition among firms makes research examining more effective forecasting techniques and information sharing policies compelling and timely. This research provides an understanding of forecast model selection and systematically studies its impact on a supply chain's performance in a realistic context.

Scope of Research

This dissertation incorporates the factors illustrated in Table 1-2 and focuses on the impact of forecasting method selection and information sharing on supply chain performance. This study distinguishes itself from prior research in the following aspects. First, different demand patterns, including temporal demand heteroscedasticity, which has barely been addressed in supply chain forecasting literature, are investigated in this dissertation. Second, advanced forecasting techniques, namely the GARCH and neural network models, which have received little attention in supply chain forecasting research, are examined under different market environments and scenarios. Third, the scenario involving non-information sharing is implemented by the supplier using its own forecasting model on aggregated historical orders to plan production. In prior studies, non-information sharing is often implemented by the supplier using only the current retailers' orders. In this study, the supplier's own forecasts are used in a single-item-capacitated lot-sizing rule, in which a fraction of the planning horizon is implemented without further changes. This fraction of the planning horizon is referred to as the frozen period. Finally, this dissertation focuses on the main effects of each factor and on the interaction effects of these factors on supply chain performance as described in Table 1-2 as well. A total of 168 combinations of factor levels are investigated in this simulation study. The findings should assist supply chain managers and practitioners in selecting suitable forecasting techniques and information sharing policies to improve the overall supply chain performance and gain competitive advantages.

Table 1-2

Factors to Be Examined for Effect on Supply Chain Performance

Factors Affecting Supply Chain Performance	Number of Levels	Names of Levels of Factors
Demand Patterns	4	Trend Trend & Seasonality Trend & Seasonality & Heteroscedasticity Trend & Seasonality & Common Disturbance
Forecasting Methods	7	Moving average Double exponential smoothing Winters' method ARIMA SARIMA GARCH Neural networks
Information Sharing	2	No information sharing The sharing of planned orders
Supplier's Capacity Tightness	3	Low (1.33), Medium (1.18), and High (1.05)

Research Questions

Although there are many factors affecting supply chain performance, this dissertation focuses on forecasting method selection and its relationship with information sharing and selected environmental variables such as capacity tightness and demand patterns. Accordingly, the research objectives for this dissertation are as follows.

Research Objective 1: To investigate the impact of traditional and advanced forecasting model selection on supply chain performance along with information sharing under different demand patterns, including temporal demand heteroscedasticity, in a capacitated supply chain.

Research Objective 2: To investigate how operational and environmental factors interact with forecast model selection to influence a supply chain's performance.

Research Objective 3: To provide managers and practitioners with guidelines that provide a framework about forecasting method selection and information sharing options.

To achieve these objectives, this research addresses the following questions:

1. Does the forecasting method selection by the retailers significantly affect the supply chain performance under different levels of information sharing and capacity tightness in a two-echelon capacitated supply chain?
2. Do advanced forecasting methods outperform traditional forecasting methods and bring significant cost reduction to the supply chain under different demand patterns?
3. Are there any significant interaction effects between forecasting method selection, information sharing, and capacity tightness?

The contributions of this dissertation address gaps in the research literature as listed below. First, different demand patterns, including temporal demand heteroscedasticity, which has seldom been addressed in SCM literature, are investigated in this dissertation. Second, this research investigates the impact of nonlinear forecasting methods such as neural network and GARCH models on supply chain performance, which has not been done in previous research in a realistic supply chain setting. Third, this dissertation addresses the impact of simple and commonly used forecasting methods, such as the moving average and double exponential smoothing methods, on supply chain performance to see whether these simple forecasting methods lead to worse supply chain performance. Fourth, in the non-information sharing case, the supplier is assumed in this dissertation to use its own forecasting intelligence to forecast future orders and make its production schedule before orders arrive. Such a situation was not addressed in Zhao et al. (2002). Lastly, interaction effects among forecasting methods, information sharing, demand patterns, and capacity tightness are further investigated.

In this study, a simulation model was used as the basis for an experimental analysis. Due to the uncertainty and complexity inherent in a supply chain, simulation has emerged as a suitable tool for analysis of logistics and supply chain systems (Bowersox & Closs, 1989). Although mathematical models are capable of providing accurate and optimal results, they cannot readily address the computational complexity of the entire SCM problem. Mathematical models require numerous assumptions to make the problem tractable so that an analytical solution can be reached. However, simulation is capable of including stochastic conditions and providing the flexibility to study system behaviors as system parameters and policies are changed (Rosenfield, Copacino, & Payne, 1985). When a supply chain involves more than two echelons, managing the entire supply chain becomes more difficult for mathematical analysis and is usually carried out with the help of computer simulation (Ballou, 1992). Therefore, simulation was employed to investigate the main effect of each critical factor and the interaction effect of these factors in this study.

The next chapter provides a detailed literature review, citing research on the bullwhip effect, forecasting methods, and information sharing. In essence, this research has endeavored to fill some of the gaps in the research associated with forecasting demand, capacity constraints, and information sharing in a dynamic business environment.

CHAPTER 2

LITERATURE REVIEW

The bullwhip effect is a source of supply chain inefficiency, resulting in serious financial consequences for a supply chain. Studies to mitigate the bullwhip effect have extensively researched its causes and have suggested strategies aimed at cost reduction and performance improvement for the supply chain. This chapter reviews three important research streams that motivate the research in this dissertation: the bullwhip effect, forecasting method selection, and information sharing. Research gaps are discussed.

Bullwhip Effect in the Supply Chain

The bullwhip effect refers to the phenomenon that order variation is amplified as orders move upstream in the supply chain. This effect can hurt a supply chain's performance by causing excessive inventory, low capacity utilization and poor customer service. The objective of a large body of research on this topic is to reduce costs and improve supply chain performance by helping management understand how to tame the bullwhip effect. Jay Forrester (1958) first discovered this effect. In the 1960s, the beer distribution game was invented to demonstrate the existence of the bullwhip effect and a number of key principles of SCM. Later on, Lee et al. (1997) mathematically proved the existence of the bullwhip effect, addressed four operational causes of the bullwhip problem, and provided solutions to tame this effect. Much research has been devoted to taming the bullwhip effect and searching for solutions to reduce it.

Causes of the bullwhip effect can be divided into two categories: operational and behavioral causes. Most research on the bullwhip effect has focused on the operational causes. A number of analytical models have been proposed, and solutions have been provided under certain assumptions. However, studies focusing on behavioral causes of the bullwhip effect report that the optimal functioning of a supply chain is often distorted by specific behavior of individual decision makers in the chain. For instance, Croson & Donohue (2003, 2006) demonstrated that the bullwhip effect still persisted even when the commonly cited operational causes noted in Lee et al. (1997) were controlled. More importantly, the behavioral causes responsible for the persistence of the bullwhip effect were identified.

Furthermore, researchers have observed inefficiencies caused by the bullwhip effect in the operations of Campbell's Soup (Fisher, Hammond, Obermeyer, & Raman, 1997), Hewlett Packard and Proctor & Gamble (Lee et al., 1997), and Glosuch (McCullen & Towill, 2000). Due to global competition, increased uncertainty of the supply chain, and higher customer requirements, firms are under greater pressure to tame the bullwhip effect so as to improve supply chain performance. As indicated by Lee et al. (1997), identifying the causes of the bullwhip effect results in strategies for alleviating the detrimental impact of this phenomenon. That is, understanding the root of the bullwhip effect is an important step in attacking the bullwhip problem. This section provides a review of the causes of and remedies for the bullwhip effect.

Using computer simulation models, Jay Forrester (1958) demonstrated that the variance of the order at the upstream end of a supply chain, as in Figure 1-1, may be much greater than the variance of the customer demand at the downstream end. Forrester first observed this phenomenon and asserted that the main cause of the bullwhip effect was irrational behavior at various stages of the supply chain. Since there is a lack of a holistic view of the supply chain, the retailer, wholesaler, distributor, and manufacturer, as displayed in Figure 1-1, may make their order decisions from a myopic point of view, which will lead to order amplification.

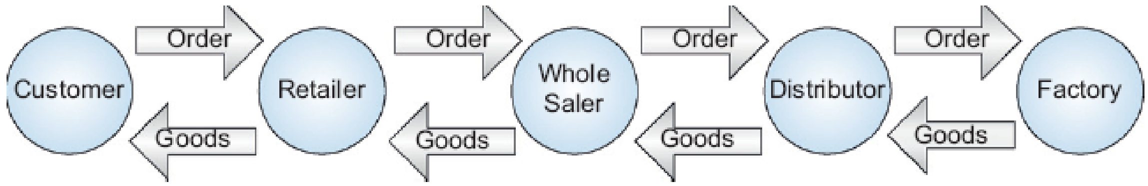

Figure 1-1. Extended supply chain.

Sterman (1989) presented seminal work on the effect of human behavior on the bullwhip effect through a tabletop management game—the so-called MIT beer game. The author reported that individual decisions interacting with the structure of the simulated firm created system dynamics that diverged from optimal behavior systematically and argued that misperception of feedback was responsible for the bullwhip effect. In other words, participants made poor decisions because they had difficulties in evaluating the complex feedback loops in the presence of time delays. Finally, the author proposed an anchoring and adjustment heuristic for stock management to reduce irrationality in determining orders and emphasized that the key to improved system performance lies within the policy used by individuals to manage the system, rather than in the external environment.

Towill (1991) also noted that the bullwhip problem occurred within a supply chain that comprised "the behavior of a very complex system involving many players, whose decision-making procedures may be ill-chosen or who may act upon misinterpretation of true market demand" (Towill , 1991, p.198). The chance of counter-intuitive behavior increases as the supply chain system becomes more complicated. Using the original Forrester (1958) model as a benchmark, the authors showed that demand amplification could be significantly attenuated once the information and material delays were eliminated and that greater benefits could be achieved by encouraging collaboration between all players within the supply chain.

Contrary to the previous studies, Lee et al. (1997) argued that the bullwhip effect was a consequence of rational behavior rather than irrational behavior of the decision makers across the supply chain. These authors mathematically proved the existence of the bullwhip effect and identified five possible causes of this effect: demand forecasting, lead times, batched order, price variations, and rationing game under shortage. The authors made significant contributions in identifying these causes, providing insights into the effect of each cause on the supply chain and suggesting possible strategies to mitigate the bullwhip effect according to the causes identified. More importantly, they identified information sharing as the key to resolving demand distortion.

Croson & Donohue (2003) examined the impact of point of sale (POS) data sharing on ordering decisions in a multi-echelon supply chain through a controlled simulation experiment from a behavioral perspective. In particular, they wanted to investigate how decision makers use their supply and demand lines when POS data are available. They assigned the participants to two groups—a control group and a treatment group. The participants in the control group knew the underlying demand distribution while those in the treatment group knew both the demand distribution and the realized customer demand. They found that participants continued to underweight the supply line in placing their orders in the presence of POS data. However, they did react differently to the demand line when the POS data were known. They observed that the magnitude of the bullwhip effect decreased in the treatment group as compared with the control group. That is, the sharing of POS data mitigated the bullwhip effect in their study.

Croson, Donohue, Katok, & Sterman (2004) demonstrated that the bullwhip effect persists even if all four commonly cited operational causes of this effect are controlled and every participant knows the constant demand. They proposed a new behavioral cause of the bullwhip effect—"coordination risk." That is, participants place excessive orders to protect themselves against the risk that other participants may not behave optimally. They concluded that the bullwhip effect might be mitigated, but the behavioral causes of this effect appear robust.

Croson & Donohue (2006) continued to study the bullwhip effect from a behavioral perspective in a simple supply chain subject to information lags and uncertain demand. They conducted two experiments on two different sets of participants. In one experiment, they found that the bullwhip effect persisted after they controlled all the commonly cited operational causes of this effect (such as batch order, demand forecasting, and price variation). They argued that the "bullwhip effect is not solely a result of operational complications such as seasonality or unpredictable demand trend" (Croson & Donohue, 2006, p. 333). It is also a product of the cognitive limitations, such as underweighting the supply line. In the other experiment, they informed the participants of the inventory status across the supply chain and found that the bullwhip effect and the tendency to underweight the supply line remained. However, the magnitude of the bullwhip effect decreased because the upstream chain members used the inventory information to anticipate and adjust their orders. They showed that the sharing of inventory information helped alleviate the bullwhip effect to some extent.

Gino, Bloomfield, & Kulp (2007) investigated the impact of three factors that were hypothesized to exacerbate the bullwhip effect: durability of products and orders, transit lags, and the nature of demand shocks in experiments in which the operational causes noted in Lee et al. (1997) were controlled. The authors showed that the magnitude of the bullwhip effect was likely to vary with the three hypothesized factors beyond the effects predicted by optimization analyses. In particular, they investigated whether common and consistent errors made by individuals in newsvendor games were responsible for the surprisingly non-optimal phenomena observed in bullwhip games. They found that transit lags exacerbated the demand amplification by interfering with the subjects' ability to correct prior errors.

Nienhaus, Ziegenbein, & Schoensleben (2006) focused on the impact of human behavior on the bullwhip effect using the Online Beer Game. They designed and implemented experiments using human players and computer agents and found that both the human players and computer players performed worse as retailers when compared with the global optimal solution for the retailers. In particular, they showed that human behavior caused the bullwhip effect. If players acting as retailers order more than what they actually need for the sake of being safe, inventory cost at their tier will increase. This, in turn, puts pressure on wholesalers to order more as well. Hence, manufacturers may have to produce more than necessary. Thus, the "safe harbor" strategy employed in one tier has a negative impact on the entire supply chain. Interestingly, another extreme in human behavior is to empty inventory stock before the increase of the consumer demand stops. This action, in turn, results in high penalties for stock-out situations in time periods to come. Nienhaus et al. (2006) aptly demonstrated the role that human behavior plays in causing the bullwhip effect and showed that information sharing helps reduce the bullwhip effect.

Table 2-1

Causes of Bullwhip Effect and Proposed Solutions

Causes of Bullwhip Effect	Proposed Solutions	Comments and Contributions	Authors
Irrational behavior at various stages of the supply chain	1) Better understanding of the supply chain dynamics	System dynamics leads to diverge from optimal behavior.	Forrester (1958)
Misperceptions of feedbacks, Supply line underweight	1) Anchoring and adjustment heuristic to reduce irrationality	The suboptimal performance often results from misperceptions of feedback.	Sterman (1989)
Information and material delays	1) Eliminating information and material delay 2) Collaboration	Just-in-time strategy and the echelon removal strategy proved to be the most effective in mitigating the bullwhip effect.	Towill et al. (1992)

(table continues)

Table 2-1 *(continued)*.

Causes of Bullwhip Effect	Proposed Solutions	Comments and Contributions	Authors
Lead-times, demand signal forecasting, ordering batching, gaming, and promotions	1) Information sharing 2) Lead-time reduction 3) Echelon-based inventory	Rational behavior rather than irrational behavior causes the bullwhip effect.	Lee et al. (1997)
Underweighting supply line in the presence of POS data	1) POS data sharing	POS data doesn't affect how subjects react to the supply line, but it does affect how they react to customer demand. POS data sharing mitigates the bullwhip effect.	Croson et al. (2003)
Coordination risk (the uncertainty about the actions of other decision makers)	1) Holding additional on-hand inventory 2) Informing the participants of the optimal policy	Behavioral causes of the bullwhip effect appear to be robust.	Croson et al. (2004)
Cognitive limitation such as supply line underweight	1) Inventory information sharing	Information sharing can mitigate the bullwhip effect, but it cannot eliminate it.	Croson et al. (2006)
"Safe harbor" behavior and "panic" behavior	1) Information sharing beyond passing on orders among chain members	Impact of human behavior on the bullwhip effect is demonstrated using the Online Beer Game.	Nienhaus et al. (2006)
Product durability, transit lags, and nature of demand shocks	None	The magnitude of the bullwhip effects is likely to vary with product durability, transit lags, and the nature of demand shocks beyond the effects predicted by optimization analyses.	Gino et al. (2007)

Table 2-1 summarizes both operational and behavioral causes of the bullwhip effect. Lee et al. (1999) recommended solutions to the bullwhip effect from operational causes: lead-time reduction, effective demand forecasting, and information sharing and coordination among chain members. Gino et al. (2007) and prior research recommend that behavioral aspects of the bullwhip effect be addressed since "decision makers systematically deviate from optimality in their inventory ordering choices" (p. 23). Suboptimal performance has been shown to result from misperceptions of feedback (Diehl & Sterman, 1995; Sterman, 1989). More recently, Croson et al. (2003, 2004, and 2006) illustrated that the persistence of the bullwhip effect, resulting from suboptimal decision making, may be due to cognitive limitation. In the same vein, Nienhaus et al. (2006) argued that the role that human behavior plays in causing the bullwhip effect is still underestimated. If the behavioral causes of the bullwhip effect are at least as important as the operational causes, then the current strategies or techniques focusing on reducing the operational causes are at best incomplete solutions.

This literature review indicates that the role of human behavior in affecting bullwhip is not as well addressed in literature as the role of operational causes. The system dynamics of a supply chain cause members to deviate from optimal decisions. Sterman (1989) argued that the key to improved supply chain performance depends on the policy that individuals use to manage the system, not on the external environment. Thus, awareness of the behavioral aspects of the bullwhip effect would assist managers in making proper decisions to improve supply chain performance. Whether strategies can be effective in mitigating the bullwhip effect resulting from human behavior is beyond the scope of this dissertation. The problem of interest in this dissertation is the impact of possible suboptimal decision-making regarding forecasting method selection and information sharing on supply chain performance. In the previous research mentioned above, most analytical and simulation models in this area would suggest the optimal forecasting models based on forecast accuracy. That is, under different demand patterns, suitable or optimal forecasting methods are established. Then the entire supply chain performance is evaluated.

A criticism of this approach is that these models ignore the impact of human behavior on supply chain performance. Sterman (1989, p. 336) states that "even a perfect forecast will not prevent a manager who ignores the supply line from over ordering." Another criticism of this approach is that practitioners might ignore the nature of the demand pattern and choose basic traditional forecasting methods to forecast demand simply because they are comfortable with them. In addition, little research has addressed the impact of subjective forecasting method selection by practitioners in terms of cost in a supply chain. In this study, a series of traditional and advanced forecasting models are investigated across a variety of demand patterns to examine the impact of suboptimal forecasting method selection on supply chain performance, thus filling a gap in the supply chain literature. This study provides useful insights for managers and practitioners on the importance of improving supply chain performance by using effective demand forecasting.

The Impact of Forecasting Method on Supply Chain Performance

SCM is "driven by demand" (Stadtler, 2005, p. 580). Demand forecasting is important to inventory, production, and capacity planning for firms in a supply chain. It is no wonder that industry and academia have given much attention to demand forecasting and modeling. If properly used, forecast modeling is an effective tool in taming the bullwhip effect. Paik (2003) identified demand forecasting as a significant variable in controlling the bullwhip effect. Miyaoka & Hausman (2004) confirmed that improved forecasting models might reduce fluctuations in manufacturing production level. Zhao et al. (2002) demonstrated that forecasting methods, coupled with information sharing, can help achieve greater savings for the supply chain under certain conditions.

Chen et al. (2000a) presented seminal work in quantifying the impact of demand forecasting on the bullwhip effect in a two-stage serial supply chain, in which downstream retailers used a moving average model to forecast demand. They considered an AR (1) demand process and analytically derived a simple lower bound on the bullwhip effect. Chen et al. (2000b) extended their work to a multistage supply chain under a more complex demand pattern with trend and correlated demand, in which retailers employed exponential smoothing to predict future demand. The authors demonstrated that order variation was always higher than demand variation, and they provided a lower bound on the variance of the orders. Moreover, they reported that improperly applied forecast modeling causes the bullwhip effect. Reinforcing this conclusion, Dejonckheere et al. (2003) demonstrated that the bullwhip effect is always there in order-up-to systems when forecasting is necessary. However, in general, the smoother the demand forecast, the smaller the bullwhip effect.

A summary of the major findings of Chen et al. (2000a, 2000b) are as follows:

- The nature of the demand process and forecasting technique determines the magnitude of the bullwhip effect. The authors demonstrated that under both moving average and exponential smoothing, forecasting a demand process with a linear trend would result in more variable orders than forecasting an i.i.d. demand process.
- Lead-time also plays an important role in affecting the magnitude of the bullwhip effect. Longer lead-time induces greater order variability for the upstream chain members. In other words, short lead-time helps reduce the bullwhip effect. Given longer lead-time, a retailer has to use more demand data in order to reduce the bullwhip effect.

- Centralized customer demand information can significantly reduce the bullwhip effect, but it cannot eliminate it.

Despite all these interesting findings, it is not clear whether the results obtained are still valid if retailers use other forecasting methods to forecast customer demand. For example, Chen et al. (2000b) stated that “the exponential smoothing may not be the ‘optimal’ forecasting tool for the demand process considered in this paper.” Thus, future research should consider different forecasting methods and demand patterns. Furthermore, Chen et al. (2000b) did not consider the cost structure such as inventory cost, ordering cost, and production setup cost in the supply chain. Researchers must investigate the cost impact of the bullwhip effect so that practitioners can obtain insights from a financial perspective.

Kim & Ryan (2003) presented a supply chain model similar to that considered in Chen et al. (2000a, 2000b) and quantified the impact of suboptimal forecasting methods and limited demand information on the expected inventory costs in the supply chain. Kim & Ryan (2003) concluded that choosing the optimal value of the smoothing constant alpha can significantly reduce the expected cost experienced by a retailer who uses an exponential smoothing model under an AR (1) demand process. However, when alpha is not chosen optimally, the expected costs experienced by a retailer may show strange and unexpected patterns. In addition, they demonstrated that manufacturers could benefit from the demand information shared by the retailer. However, the benefits of shared demand data are limited when a manufacturer can use a large number of previous orders placed by the retailer to forecast demand.

Kim & Ryan (2003) made a significant contribution in evaluating the impact of suboptimal forecasting methods on inventory costs in a simple supply chain. Kim & Ryan (2003, p. 400) reported that “these observations are contrary to our standard expectations, which are derived under the assumptions that the retailers know the exact demand and use the optimal inventory policy for the given demand process." In reality, many supply chain members do not operate optimally due to a variety of factors such as demand uncertainty or a myopic view of the supply chain. Thus, understanding the role of suboptimal decision making by supply chain members in influencing the supply chain performance is important. This kind of research provides practical suggestions to the practitioners regarding how to efficiently reduce supply chain costs and improve system performance.

The study examined by Kim & Ryan (2003) has limitations. Areas for further research regarding their study are as follows:

- This supply chain model is a simple chain consisting of one retailer and one supplier which has unlimited capacity. It can be extended to a supply chain model with one capacitated supplier and multiple retailers. It would be interesting to see whether the conclusions obtained are still valid for the extended model.
- This study investigated two commonly used time series forecasting models under an AR (1) demand pattern. However, the impact of these two forecasting models on supply chain performance under other demand patterns is not clear.
- This study only examined the sharing of demand information. Additional types of information sharing, such as the sharing of demand forecast and inventory policy, should be explored further.

Zhao et al. (2002) extended the work by Chen et al. (2000b) to a supply chain consisting of one capacitated supplier and multiple retailers in a simulation study. These authors investigated the effects of demand forecasting, order decisions by the retailers, and production decisions by the supplier under different demand patterns and capacity tightness. They demonstrated that forecasting model selection, information sharing policy, demand patterns faced by the retailers, and capacity constraints faced by the supplier significantly influence the overall supply chain performance. In particular, they focused on the effect of forecasting method selection on the value of information sharing. Their study showed that the value of information sharing increases considerably as forecast accuracy increases, and greater improvement in supply chain performance can be achieved via information sharing under certain demand patterns and at the level of medium capacity tightness. However, they also demonstrated that the total cost and service might worsen under certain demand patterns and a low level of capacity tightness.

The study examined by Zhao et al. (2002) provided considerable insights into a variety of factors affecting system performance. The contributions of this study are as follows:

- Unlike prior research, they incorporated the cost structures into the study to quantify the cost impact of the bullwhip effect in a dynamic business environment in which different demand patterns and capacity tightness levels were considered. The findings provide valuable insights for supply chain managers and practitioners in selecting proper forecasting methods and information sharing policies to improve system performance in terms of cost and service level.
- Unlike prior research, their study focused on the sharing of forecast-driven demand data such as net requirements and planned orders from the retailers to the supplier. Previous research concentrated on the effects of sharing of demand data between supplier and retailers on supply chain performance. However, retailers usually do not know the demand in advance. They make their order decisions based on demand forecasts, as is the usual practice in the real world. Since demand forecasting is one of the important drivers for production and inventory

planning decisions, their study has important implications for supply chain managers in selecting proper forecasting methods to reduce supply chain cost and improve customer service level.

- The authors systematically studied several traditional forecasting methods under different demand patterns including trend and seasonality. They found that forecasting method selection alone might not bring significant benefits to the supply chain. However, accurate demand forecasting, coupled with information sharing, can greatly improve performance for the entire supply chain. Moreover, they demonstrate that environmental factors such as demand patterns and capacity tightness significantly affect supply chain performance through the operational factors mentioned above. Therefore, it is of great practical value for practitioners to understand the importance of the effects of forecasting method selection on supply chain performance under other operational factors.
- These authors not only examined several forecasting methods but also investigated the interaction effect among operational factors. More importantly, they illustrated that supply chain performance depends on the complex interaction of critical factors such as forecasting method and information sharing. In essence, they evaluated the effectiveness of forecasting methods in a more realistic and broad context while similar research in this area concentrated exclusively on forecasting accuracy.

Although Zhao et al. (2002) made significant contributions toward understanding the role that forecasting method selection plays in reducing the bullwhip effect and supply chain cost, their study has limitations. Possible extensions and future research directions for their study are as follows:

- Would their results be generalizable to a demand process which exhibits time-varying volatility? Although this study provided useful insights regarding forecasting method selection and its impact on supply chain performance under relatively stable demand processes, it is not clear whether the results hold for the case of unstable demand processes.
- Is it worth the effort to promote advanced forecasting methods in SCM? How do advanced methods affect supply chain performance? It is clear that traditional forecasting methods lack the ability to capture nonlinear behavior in demand processes exhibiting time-varying volatility. Recent research shows that advanced forecasting methods such as neural network models and GARCH models can overcome the limitations of traditional forecasting to generate accurate forecasts. However, few studies have addressed how these advanced forecasting methods affect the supply chain performance in a broad, realistic context.
- What are the effects of simple forecasting methods on supply chain performance? Previous studies suggested that forecasting method selection should depend on the demand pattern. Under certain demand processes, improper forecasting methods might exacerbate the bullwhip effect. Consequently, inaccurate forecasts might add unnecessary costs to the supply chain. For example, if a demand process exhibits trend and does not exhibit heteroscedastic behavior, then exponential smoothing might be the appropriate method to forecast demand. When the demand process exhibits both trend and seasonality, Winters' three parameter

model is often recommended. However, sophisticated forecasting methods require expertise in order to use them properly. In practice, managers and practitioners might choose the forecasting methods with which they feel comfortable to forecast demand. Indeed, Makridakis et al. (1998) reports that users are less familiar and less satisfied with sophisticated methods such as Box-Jenkins, but they are most familiar and most satisfied with simple forecasting models such as moving average, exponential smoothing, and regression. Under these circumstances, practitioners might select suboptimal forecasting models to forecast demand. Clearly, previous research has seldom addressed the impact of the "misspecified" forecasting models on supply chain performance.

In an effort to extend previous contributions, Wright & Yuan (2008) modified Sterman's (1989) model to investigate how different ordering policies and forecasting techniques can be used to reduce the bullwhip effect. Using Sterman's (1989) ordering heuristics rule, by selecting different smoothing constants α and β to simulate the effect of different ordering policy space, they identified a range of ordering policies for which the bullwhip effect can be alleviated by using either Holt's or Brown's forecasting method. They found that the bullwhip effect could be substantially reduced, by up to 55%, by selecting an appropriate ordering policy and forecasting method. In particular, they showed the potential benefit of the sophisticated forecasting methods such as Holt's or Brown's forecasting method. However, they emphasized that these forecasting methods must be used in conjunction with an appropriate ordering policy in order to achieve improved system performance. In particular, they claimed that the supply chain could be stabilized by using Holt's or Brown's forecasting technique coupled with appropriate ordering policy. Compared to the moving average and exponential smoothing methods, Holt's and Brown's forecasting methods are more effective in taming the bullwhip effect.

Wright & Yuan (2008) demonstrated that sophisticated forecasting methods, along with proper ordering policies, significantly reduce the bullwhip effect in a modified beer game model. They simulated the ordering policy space based on Sterman's (1989) ordering heuristics rule. It is unclear whether ordering policies used in practice coupled with proper forecasting techniques will generate the same results. Thus, a fruitful area for future research is investigating the impact of more sophisticated models along with commonly used ordering policies on system performance in a capacitated supply chain.

Sohn & Lim (2008) studied the impact of forecasting method selection and information sharing on system performance in a two-echelon supply chain, in which a supplier provides two generations of a high-tech product to the market. They demonstrated that the proper selection of the information sharing policy and forecasting model significantly influences the supply chain performance. Furthermore, they found the optimal combination of the information sharing policy and forecasting method, which can maximize the profits and service level for the supply chain. Consistent with what Zhao et al. (2002) concluded, they argued that a forecasting method alone does not necessarily account for the improved supply chain performance. However, the proper selection of the information sharing policy along with the proper forecasting method under certain market conditions will greatly improve supply chain performance.

Sohn & Lim (2008) made significant contributions in demonstrating the impact of forecasting model selection along with information sharing in a two-echelon supply chain, in which one supplier produces two generations of one high- tech product and distributes them to four retailers. They pointed out those traditional forecasting methods such as the exponential smoothing, Holt's model, and ARIMA methods have been frequently used in SCM. However, these methods do not yield satisfactory results for a product whose demand is extremely volatile. Thus, they used three models— Winters' model, Norton and Bass's model, and Speece and Maclachlan's model—to forecast future demand for the high-tech product. They investigated the effect of these forecasting methods under different levels of information sharing and different market conditions. They inferred that absolutely shared information sharing does not always produce the best performance in a supply chain and concluded that forecasting method selection and information sharing should be used together to produce the best supply chain performance.

The studies by Sohn & Lim (2008) and Zhao et al. (2002) have some important differences. Although these two studies investigated the effect of forecasting method selection and information sharing in a supply chain having a single capacitated supplier and four retailers, these two studies have significant differences, which are as follows:

- Zhao et al. (2002) systematically studied traditional time series forecasting methods under different demand patterns (relatively stable demands). However, Sohn & Lim (2008) focused on the impact of forecasting method and information sharing under volatile demand pattern for a high-tech product. In the case of high volatile demand, traditional forecasting methods may fail to produce satisfactory results. Thus, it is reasonable to use sophisticated forecasting models to forecast demand under this circumstance.
- Both studies investigated the value of information sharing under different forecasting methods. However, the types of information sharing are quite different. In Sohn & Lim (2008)'s model, the retailers share their net sales with the suppliers, and with these data, the suppliers forecast their future sales and

make production decisions. While Zhao et al. (2002) let retailers forecast customer demand, the retailers pass either their net requirements or planned orders to the supplier which uses these data to make its production decisions.

- Although both studies investigated the impact of capacity tightness on supply chain performance, the implementation of the capacity constraints is quite different in the two studies. Zhao et al. (2002) implemented the single-item capacitated lot-sizing algorithm (Chung & Lin, 1988) to figure out production quantity and production periods to minimize the total cost for the supplier according to the cost structure. However, Sohn & Lim (2008) did not use the lot-sizing rule to determine the production plan for the supplier despite the fact that they assumed fixed capacity for the supplier using the same capacity tightness parameters as used in Zhao et al. (2002).

Despite the differences between the Zhao et al. (2002) and Sohn & Lim (2008) studies, they arrived at similar conclusions. In particular, forecasting method selection alone might not account for most of the cost reduction achieved in a supply chain. However, proper forecasting method selection, along with information sharing, significantly influences the entire supply chain performance. Although the results provide useful insights for supply chain managers into the proper use of forecasting methods, several limitations exist, and several issues need to be explored further, including those that follow:

- The quick changing of customer demand requires nontraditional forecasting methods for demand forecasting in a supply chain, especially when demand patterns become more volatile. So far, little research has been done to investigate the impact of advanced forecasting methods such as the GARCH model on the overall supply chain performance in a dynamic business environment despite the fact that the GARCH model is an effective tool for forecast financial time series data.

- Investigating whether nontraditional forecasting methods outperform traditional forecasting methods in terms of supply chain cost (rather than in terms of forecast accuracy) is worthwhile.
- Interaction effects between nontraditional forecasting methods and other operational factors such as information sharing and inventory policy need to be addressed in future research.

To explore the effectiveness of advanced forecasting methods for SCM, Aburto & Weber (2007) developed a hybrid-intelligent-system, which combines ARIMA models and neural network models for demand forecasting and was used in a proposed replenishment system for a Chilean supermarket. The authors demonstrated that improvement in forecasting accuracy by using hybrid demand forecasting leads to few sales failures and low inventory levels when compared with the previous solution.

Datta et al. (2007) proposed modifications of the GARCH model and its applications to SCM to forecast demand from a theoretical point of view. GARCH models have been widely used in forecasting financial data to capture the volatility of the financial time series. However, few papers have considered the potential of GARCH models in forecasting demand in SCM. Datta el al. (2007) theoretically showed that a GARCH model could be used to model the volatility (bullwhip effect) associated with a supply chain. They argued that a GARCH model could generate accurate forecasts to reduce operational inefficiencies in SCM.

Charbonneau et al. (2008) emphasized the value of forecasting techniques for firms that usually do not have full information regarding other members' demands in a supply chain. They investigated the impact of both traditional and nontraditional forecasting methods on the performance of the supply chain by using simulated data and real data (Canadian Foundries orders). They demonstrated that sophisticated methods such as neural network, recurrent neural networks, and support vector machines outperform the traditional forecasting methods such as moving average and exponential smoothing in term of forecasting accuracy. Advanced forecasting methods do well in forecasting demand because of their ability to capture the nonlinear activities in a demand process. However, the circumstances under which advanced forecasts significantly improve supply chain performance are not clear.

This literature review indicates that most studies have concentrated on traditional forecasting techniques such as moving average and exponential smoothing. While these studies offer a number of useful implications for supply chain practitioners, they do not provide all the information required as none of these studies considered heteroscedasticity in their models. Traditional techniques "rely on the historical data and assume the validity of the past demand patterns for the near future" (Bayrajtar et al., 2008, p. 195). Moreover, they assume a linear relationship between the dependent and independent variables. As customer demand becomes more complex and volatile, these assumptions may not hold anymore, and traditional forecasting methods might become inappropriate. Thus, the search for new forecasting methods and applications of nonlinear models associated with demand forecasting is under intense investigation. Recent research (Aburto & Weber, 2007; Carbonneau et al., 2008; Au et al., 2008) demonstrated that nonlinear machine learning techniques outperform the traditional forecasting methods under certain demand processes which exhibit significant levels of nonlinearity. Therefore, it is reasonable to investigate the effectiveness of the advanced methods in a broad and realistic supply chain setting to see whether these forecasting techniques can significantly improve supply chain performance in terms of cost.

Moreover, although research in SCM has made significant contributions towards understanding the role of forecasting method selection in reducing the bullwhip effect and in improving performance, none of the studies examined the effect of the coupling of suboptimal forecasting methods and information sharing on supply chain performance. In the area of forecasting, an “optimal” forecast model is often referred to as that forecast model which can generate the minimum mean square forecast errors. In reality, practitioners might not use the optimal forecasting methods because the implementation of the optimal forecasting model is more difficult than that of the simple smoothing methods when parameters are not known (Alwan, Liu, & Yao, 2008). In fact, moving averages and exponential smoothing are widely used in supply chain forecasting due to their simplicity and ease of implementation. However, under certain demand patterns or certain parameters, these simple forecasting methods become suboptimal forecasting methods. However, the impact of using suboptimal forecasting methods on supply chain performance is seldom studied. In addition, research focusing on the behavioral aspect of the bullwhip effect shows that supply chain members might deviate from optimal decision-making because of supply chain dynamics, which provides support for the relevance of this study. Thus, this dissertation investigates the impact of both optimal forecasting methods and suboptimal forecasting methods coupled with information sharing on supply chain performance. The ramifications of using suboptimal forecasting methods with regard to supply chain performance are reported in this dissertation, and these findings fill a gap in the literature.

The Impact of Information Sharing on Supply Chain Performance

Information sharing is another research stream that is closely related to the questions addressed in this dissertation. A literature review indicates that information sharing is one of the key approaches for taming the bullwhip effect. In fact, information sharing has been a cornerstone of recent initiatives such as Vendor Managed Inventory (VMI) and Quick Response (QR) in SCM. Although information sharing can help improve supply chain performance in most cases, it may not generate the desired results under certain circumstances. Thus, substantial research has investigated the value of information sharing under various conditions. This section provides a review of the literature on information sharing related to this study.

Lee et al. (1997) is the seminal work demonstrating that the sharing of end-consumer demand within a supply chain reduces the bullwhip effect and improves supply chain performance. That is, the sharing of demand information improves a supplier's ordering decisions and thus results in inventory reduction and cost savings. The authors specifically studied the impact of lead times and underlying demand processes on the bullwhip effect and reported that information sharing may reduce supply chain costs by about 23% on average.

Gavirneni, Kapuscinski, & Tayur (1999) studied the value of information sharing for a finite capacity supplier facing demand from a single retailer, in which the retailer uses an (s, S) model and the supplier employs a modified (s, S) inventory model. They demonstrated the benefits of sharing a retailer's ordering policy with a supplier and found that information sharing is most valuable when capacity is not constrained and when the supply chain system is flexible enough to respond to the information. However, they also reported that when a supply chain faces capacity constraints, the value of information and information sharing tends to decrease. Gavirneni et al. (1999) is one of the few studies which investigated the value of information sharing in a capacitated supply chain setting. Their study provided valuable insights for supply chain managers in selecting the type of information to be shared and the proper information sharing policy for real world applications since most manufacturing systems have limited capacity.

Cachon & Fisher (2000) investigated the value of sharing demand and inventory data in a supply chain consisting of one supplier and multiple (N) identical retailers under an (R, nQ) inventory policy and stationary stochastic demand. They stated that firms are able to share demand and inventory data quickly and less expensively due to the development of information technology and demonstrated that both lead time and batch size reductions lead to substantial savings for the supply chain. However, they were not able to demonstrate significant benefits to the sharing of demand information in their models. They further rationalized that the value of sharing demand data was not significant because the retailer's orders provided a substantial portion of the information that the supplier needed in making its replenishment and allocation decisions.

Cachon & Fisher (2000) contributed to the literature by demonstrating that solely sharing demand and inventory data among supply chain members is not sufficient for cost reduction. In their models, great cost savings for the supply chain are mainly due to the implementation of information technology, which significantly influences supply chain performance by smoothing and accelerating the physical flow of goods, not to the sharing of demand data. That is, the implementation of information technology helps reduce lead-time and batch size and, consequently, achieves reduction in the bullwhip effect and supply chain costs.

Additional research is needed to assess information sharing with non-identical retailers. Most supply chain models assume identical suppliers and retailers for modeling simplicity.

Better procedures need to be introduced to tackle the “non-identical” case. Different retailers may face different demand patterns and distribute in different regions. Under these conditions, results obtained from previous studies based on multiple identical retailers may not hold. Therefore, a need exists for future research to assess the value of information sharing with non-identical retailers. In addition, the effects of different types of information sharing, such as the sharing of inventory status and production yield, and the effect of the extent of information sharing need to be explored further.

Lee et al. (2000) investigated the value of information sharing within a two-stage supply chain consisting of a retailer and a manufacturer. The authors quantified the benefits of information sharing to the supply chain, and they argued that the characteristics of the demand process and the replenishment lead-time significantly affect the benefits of information sharing for the manufacturer. Finally, they concluded that information sharing leads to significant inventory reduction and cost savings for the manufacturer and, in particular, that information sharing achieves larger cost reduction to the manufacturer when the demand process is highly correlated over time, when it is highly volatile, or when the lead-time is long, whereas the retailer primarily benefits from lead-time reduction. However, they also reported that the value of information sharing decreases if the manufacturer uses historical order information to forecast demand. Consistent with this finding, Raghunathan (2001) demonstrated that the value of information sharing decreases and converges to zero over time under a negatively autocorrelated AR(1) demand process.

Although this research provides useful insights for chain members when evaluating an information sharing program, certain issues remain. Further issues requiring exploration include the following.

- Most prior studies demonstrate that information sharing can help firms carry appropriate inventory and operate at the right level of capacity to meet customer demand more efficiently, which results in cost reduction and performance improvement for a supply chain. Some other studies state that the value of information sharing decreases in some cases. However, none of these studies demonstrate the circumstances under which the different types of information sharing programs are not necessary. Future research should explore this area further.
- The sharing of additional types of information, such as demand forecasts and inventory status, should be explored to determine whether different types of information sharing affect supply chain performance differently.

Chen et al. (2000) modeled a serial supply chain in which firms at each stage use the same forecasting method and the same inventory policy (order-up-to policy) under an autocorrelated demand process. Then the impacts of demand forecasting on the bullwhip effect under information sharing (centralized demand information) and non-information sharing were compared. The authors concluded that both forecasting method and demand patterns determine the magnitude of the bullwhip effect. They also demonstrated that centralized demand significantly reduces the bullwhip effect. More importantly, their study provided the foundation for later research such as Zhao et al. (2001, 2002) to further investigate the impact of forecasting method selection and information sharing on supply chain performance in a realistic context.

Zhao et al. (2001) demonstrated that information sharing and order coordinating among chain members help improve system performance through simulation study. Retailers were assumed to use the moving average method to forecast demand. Based on the demand forecast, retailers could share their net-requirements or planned orders with the supplier in addition to the orders placed. They argued that information sharing significantly affects the supply chain performance. In particular, sharing future order information with the supplier is more beneficial than sharing only the future demand information. More importantly, earlier order commitment usually improves the system performance. However, it is not clear whether benefits gained through information sharing still hold under other forecasting methods and demand patterns.

Zhao et al. (2002) further evaluated the value of information sharing under a variety of traditional forecasting methods and demand patterns. They implemented the same information sharing scheme as in Zhao et al. (2001). The authors showed that demand pattern, forecasting method selection, and capacity tightness significantly influence the value of information sharing and system performance. The authors also demonstrated that accurate forecasts alone might not help improve supply chain performance if the retailers choose not to share information with the supplier. However, when information sharing is shared, the accurate demand forecast usually increases the value of information sharing. In particular, greater improvements in system performance can be achieved by sharing information with the supplier when retailers face identical demands with trends and/or with medium capacity tightness, resulting in total supply chain cost reduction as high as 60% under some conditions.

Although the findings from Zhao et al. (2002) provided useful insights to practitioners about forecasting method selection and the value of information sharing, limitations exist. Several research issues that need further examination include the following:

- Their study demonstrated the value of sharing demand forecast information between chain members under relatively stable demand patterns. However, it is unclear whether the results obtained still hold under highly volatile customer demand. Thus, future research needs to explore this area further.

- A few traditional forecasting models were used to generate the demand forecast under different demand patterns on a rolling forecasting horizon in this study. Whether the sharing of demand forecast produced by advanced forecasting methods such as neural network models or GARCH models can significantly improve supply chain performance is another research venue that needs to be investigated.
- Their study focused on the impact of forecasting method selection and information sharing on supply chain performance. However, they did not investigate the impact of the suboptimal forecasting method selection on system performance. Further research needs to determine whether suboptimal techniques and polices perform well or poorly relative to the optimal techniques and policies. Thus, practitioners would be better able to manage a supply chain based on the practical suggestions recommended by this type of study. In addition, research focusing on the behavioral aspects of the bullwhip effect provides support for the need to take account of the suboptimal decision-making in evaluating supply chain performance.
- Most research has focused on the impact of information sharing on system performance in a two-stage make-to-stock supply chain. Further research is needed to determine whether previous research results can be generalized to a scenario involving a multiple echelon supply chain in a make-to-order environment.

- Their study did not investigate the case in which the supplier used its own forecasts to plan a production schedule when no information was shared. The results of their study considered only the case in which the supplier only used the current orders from the retailers when no information was shared.

Sahin & Robinson (2005) demonstrated that a distinct difference exists between make-to-stock and make-to-order supply chains. The authors analyzed the manufacturer's ordering policies, transportation activities, and the vendor's manufacturing and order fulfilment processes under five alternative integration strategies in a make-to-order supply chain. In their models, the value of sharing MRP generated orders and net requirements between vendor and manufacturer was investigated. They reported that information sharing helps reduce supply chain costs to some extent, but it does not account for the large percentage of cost savings achieved in the supply chain. They concluded that coordinated decision-making generates main economic gains rather than information sharing. Moreover, they demonstrated that the benefits from information sharing and coordination are not equally distributed among supply chain members.

Although Sahin & Robinson (2005) made significant contributions in investigating the impact of information sharing and system coordination in a make-to-order supply chain, some limitations exist. Futher research issues include those which follow.

- In this study, the vendor used Wagner-Wihtin (WW) lot- sizing rule to make production decisions when information was shared. The WW lot- size rule is not applied in industry due to its complexity and computational disadvantage in comparison with other rules (Wemmerlov et al., 1984). Therefore, addtional research based on different lot-size rules is worthwhile.

- Although this study addressed an important managerial issue in information sharing and system coordination between a supplier (vendor) and a manufacturer and provided insights to help managers in selection of information sharing policies and coordination strategies, capacity constraints were not considered in the model. Capacity constraints should be included in future research since most suppliers and manufacturers face capacity constraints in reality.

Choi (2008) investigated the impact of information sharing and information errors on system performance in a two-stage supply chain. In this study, the author considered both upstream and downstream information sharing along the supply chain. Upstream information sharing refers to the sharing of inventory data and demand information from the retailer to the supplier, while upstream information sharing refers to the sharing of production yield and advanced shipping notice from the supplier to the retailer. Choi (2008) demonstrated that upstream information sharing is more beneficial when a supplier's yield variance is high and when customer demand fluctuation is low. Downstream information sharing is more valuable when demand fluctuation is high or when the supplier's penalty to holding cost ratio becomes higher. In general, the presence of errors in both upstream and downstream information reduces the benefits of sharing such information. In particular, the impact of errors becomes greater when yield variance is low and demand is relatively stable, and thus it is better not to share information under these situations.

Choi (2008) estimated the benefits of information sharing and provided guidance to maximize the benefits under certain supply chain conditions. The author also pointed out that sharing erroneous information can nullify the benefits of information sharing. Choi (2008) made the first attempt to add an error component to the information sharing process and investigated the impact of information errors on system performance. This study provides useful insights for supply chain practitioners about when information sharing could benefit the supply chain and when it could hurt system performance.

Table 2-2

Information Sharing in Supply Chain Management

Information Sharing Type	Supply Chain Structure	Comments and Contributions	Authors
Sharing sales and inventory data with the supplier	One supplier – one retailer	Identified causes and counter-measures of the bullwhip effect and claimed that information sharing is the key to tame BWE. However, supplier's production decisions and cost structures are not considered in their model.	Lee et al. (1997)
Sharing a retailer's ordering policy with the supplier	One capacitated supplier – one retailer	Demonstrated that information sharing is most valuable when capacity is not constrained and when the system is flexible to respond to customer demand.	Gavirneni et al. (1999)
Sharing demand and inventory data with the supplier	One supplier – multiple identical retailers	Demonstrated that the implementation of information technology (resulting in both lead time and batch size reductions) leads to substantial savings for the supply chain. However, the benefits of information sharing are not significant.	Cachon & Fisher (2000)
Demand data	One supplier – one retailer	Concluded that information sharing leads to significant inventory reduction and cost savings to the manufacturer. However, the value of information sharing decreases under certain demand patterns.	Lee et al. (2000)
Centralized demand data	One supplier – one retailer	Demonstrated that centralized demand information could significantly help reduce the bullwhip effect, but it cannot eliminate it.	Chen et al. (2000)
Sharing demand forecast data (such as net requirements and planned orders) with the supplier	One capacitated supplier – four retailers	Information sharing and coordinating replenishment and production decisions help further reduce costs and improve system performance. Retailers use moving averages to forecast future demand.	Zhao et al. (2001)

(table continues)

Table 2-2 *(continued).*

Information Sharing Type	Supply Chain Structure	Comments and Contributions	Authors
Sharing demand forecast data (such as net requirements and planned orders) with the supplier	One capacitated supplier – four retailers	Demonstrated that accurate forecasts might not help improve supply chain performance significantly if the retailers choose not to share information with the supplier. However, under information sharing schemes, accurate demand forecast achieves great cost savings for the supply chain.	Zhao et al. (2002)
Sharing MRP generated orders and net requirements with the supplier	One supplier – one manufacturer	Demonstrated that information sharing helps reduce supply chain costs to some extent. However, it does not account for the large percentage of cost savings achieved in the supply chain. Coordinated decision-making generates main economic gains.	Sahin & Robinson (2005)
Sharing net sales with the supplier in a high-tech industry where two generations of the same product coexist	One capacitated supplier – four retailers	The results obtained were consistent with Zhao et al. (2002). They also pointed out that the information sharing degree is hard to control in reality. Thus, searching for the optimal forecasting method with a proper capacity to improve system performance is necessary.	Sohn & Lim (2008)
Sharing upstrem information (production yeild and advanced shipping notice) with the retailer, Sharing downstream informaiton (inventory and demand data) with the supplier, Information sharing with error	One supplier - one retailer	Demonstrated that sharing either upstream or downstream information benefits the supply chain. However, sharing erroneous information can nullify the benefits of information sharing.	Choi (2008)

It is clear that the extant literature has extensively analyzed the value of information sharing on supply chain performance under a variety of conditions and assumptions. A summary is provided in Table 2-2. The literature indicates that information sharing helps reduce the bullwhip effect and lower supply chain costs. In particular, information sharing plays an important role in coordinating activities between strategic partners in a supply chain. In practice, more and more supply chain members have come to rely on strategic alliances and are coordinating their efforts on important issues such as demand forecasting, production planning, and capacity management in order to manage the supply chain efficiently.

Despite the fact that information sharing is significant in reducing the bullwhip effect and improving supply chain performance under certain circumstances, there are still some inconsistent results. Surprisingly, Steckel, Gupta, & Banerji (2004) found that sharing POS information is unambiguously beneficial only in Sterman's step-up demand pattern. When the demand pattern was S-shaped (with or without error), POS sharing actually hurts system performance. This is in stark contrast to theoretical literature that suggests the reverse (Lee et al., 2000; Raghunathan, 2001). In addition, Lin (1998) demonstrated that different supply chain structures benefit from different types of information sharing, and information sharing actually hurts supply chain performance under certain circumstances.

Thus, in order to have a better understanding of the value of information sharing in SCM, the following issues require further research:

1) Previous studies showed that the reported benefits of information sharing differ considerably from one study to another. One explanation is that findings obtained from one problem environment may not apply to another with dissimilar operational characteristics (Cachon & Fisher, 2000). Although there are many supply chain settings in reality, a lot of research has focused on the simple serial supply chain, and most of it has been done in a simple setting with a single supplier and a single retailer. Future research should explore more complex and realistic supply chain settings

beyond the dyadic level of analysis between the supplier and the retailer.

2) Although different types of information sharing have been investigated in the literature, the impact of sharing planning information across a supply chain has not been explored extensively. Planning information usually refers to the demand forecast and order schedule. The demand forecast contains future demand information while the order schedule specifies order quantity of each coming time period in advance. In reality, many production managers are overwhelmed with forecast and demand data generated by MRP systems and find it difficult to transform this data into information. Thus, it is worthwhile to investigate the impact of sharing MRP generated data (planning information) with other chain members on system performance. In other words, how to make better use of these data to improve overall supply chain performance is an important question for future research to answer.

3) Although great progress has been made in this area, the value of information sharing and the impact of production control strategies on supply chain performance have been studied separately. Despite the fact that MPS drives the material requirements planning (MRP) system and provides the link between the demand forecasting, order entry, and production planning activities, research has paid little attention to the value of sharing MRP generated orders and net requirements since most research does not consider a manufacturer's production decision. To our knowledge, Sahin & Robinson (2005) is the only work which has investigated the value of sharing the MRP generated orders and net requirements in a two-stage make-to-order supply chain. Additional research on the value of sharing planned orders and net requirements is worthwhile as long as the manufacturer is included in the supply chain, and the

research is not limited to a make-to-order supply chain.

4) Most previous studies consider information sharing from downstream to upstream along the supply chain or vice versa and use traditional non-information sharing as the base case to gauge the value of information sharing. However, even in the case of non-information sharing, a supplier can forecast future orders to improve its own performance, which may eventually improve the entire supply chain performance. Future research should further investigate the value of information sharing when a supplier is assumed to use his own intelligence to forecast future orders from the retailers.

CHAPTER 3

RESEARCH DESIGN

This chapter presents the conceptual model and methodology that were used to address the research objectives as defined in Chapter 1. The methodology employs a comprehensive experimental design approach using supply chain costs obtained via a simulation study. The forecasting models, the types of demand patterns, the supplier's capacity constraints, and information sharing schemes are selected so as to systematically examine their effect on a supply chain's performance.

Conceptual Model

Supply chain performance not only depends on the proper choice of operational policies, such as forecasting methods and information sharing policies, but also relies on the complex interactions of operational policies and external factors such as demand patterns and cost structures, which cannot be controlled by supply chain managers. This study considers a supply chain consisting of one capacitated supplier and four retailers as described in Figure 3-1. This model has been used for a series of papers (Zhao et al., 2001; Zhao et al., 2002; Lau et al., 2008; Sohn & Lim, 2008).

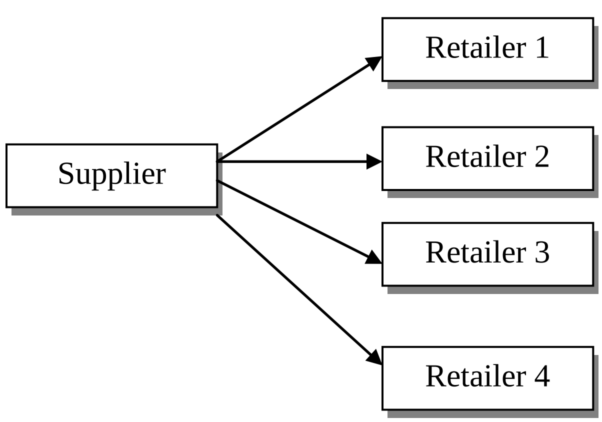

Figure 3-1. Conceptual model.

The purpose of this dissertation is to extend the scope of Zhao et al. (2002). The following research issues are investigated as they have not been adequately addressed in prior research:

1. This study includes stable and heteroscedastic demand. Although the demand pattern has a significant impact on the predictive accuracy of the selected forecasting methods and on the supply chain performance, prior research focused on relatively stable demand patterns. None of these prior studies considered temporal demand heteroscedasticity in investigating the impact of heteroscedasticity on demand forecasting and supply chain performance. This study incorporated a heteroscedastic component in the demand generation process by using a GARCH (1, 1) pattern to account for conditional variance and simulate volatile demand behavior for innovative products or products which exhibit time-varying demand. More importantly, the impact of forecasting method selection coupled with information sharing on supply chain performance was investigated under different demand patterns including temporal demand heteroscedasticity.
2. This study includes traditional and advanced forecasting models. Despite the fact that a variety of time series forecasting methods have been used in SCM literature, traditional forecasting methods face problems such as volatility clustering and overshoot problems, which have occurred in time series prediction from time to time. More recent research has investigated the application of nontraditional forecasting methods in SCM and shown that nontraditional advanced forecasting methods outperform traditional forecasting methods in terms of forecast accuracy. However, it is not clear whether advanced forecasting

methods such as neural network or GARCH models outperform traditional forecasting methods in terms of cost in a realistic supply chain setting with demand forecast being done in a rolling time horizon. Thus, this research intends to explore the impact of advanced forecasting methods on supply chain performance.

3. This study includes information sharing and capacity constraints for a supplier in conjunction with the traditional and advanced forecast models used by retailers. The retailers can either place only the current orders with the supplier or share the future planned orders with the supplier. If the retailers pass only the current orders to the supplier, then the supplier always uses double exponential smoothing to forecast future orders. If the planned orders of the retailers are shared with the supplier in addition to the current orders, then the supplier uses these values instead of its own forecast values to determine its production schedule. The supplier's capacity tightness levels are low, medium, or high.
4. Finally, this dissertation examines the impact of simple forecasting methods (most likely suboptimal forecasting models) on supply chain performance under a variety of conditions involving information sharing and capacity constraints.

Research Hypotheses

Hypothesis I: Forecasting method selection by the retailers will significantly influence supply chain performance by interacting with the policy of information sharing.

Hypothesis II: Demand patterns faced by the retailers will significantly influence the supply chain performance.

Hypothesis III: Advanced forecasting models will significantly improve a supply chain's performance relative to traditional, simple forecasting methods.

Hypothesis IV: The supplier's capacity tightness will significantly influence the impact of forecasting method selection and the value of information sharing on supply chain performance.

Dependent and Independent Variables of the Experimental Design

As discussed in Chapter 1 and Chapter 2, the types of factors that affect the supply chain performance can be classified into two categories: operational factors and environmental factors. This study focuses on a few critical factors as indicated in the literature review section. The independent variables in this simulation experiment include two operational factors (forecasting method and information sharing) and two environmental factors (demand patterns and capacity tightness). The environmental factors of the supply chain are those factors which cannot be controlled by supply chain managers but affect the system performance through operational factors. The main effect of each factor and the interaction effects of these factors are the major focus of this dissertation.

Dependent Variables

The performance measures of the supply chain are the dependent variables, and they reflect the cost across the supply chain. Three categories of performance measures are considered: total cost for the retailer, total cost for the supplier, and total cost for the entire supply chain.

- The total cost for the supplier (TCS) is the sum of the production setup cost, production backorder cost, production costs per unit item, transportation cost, and inventory carrying cost.

- The total cost for the retailer (TCR) is the sum of the ordering cost (including transportation cost), backorder cost, and inventory carrying cost for the retailer.
- The total cost for the entire supply chain (TC) is simply the sum of the TCS and TCR.

Independent Variables

The independent variables in this simulation experiment are operational factors and environmental factors. The operating conditions of the supply chain system are forecasting model (FM) and information sharing policy (IS). Although supply chain managers have control over these operational factors, environmental factors cannot be ignored by the supply chain managers since they indirectly affect system performance through the operational factors. In this study, we consider demand pattern (DP) and capacity tightness (CT) as the environmental factors. The independent variables for the experiment are described below.

- Forecasting methods (FM)

  A variety of time-series demand models have appeared in the literature of SCM. Among these methods, moving average, double exponential smoothing, Winters' three parameter, and ARIMA methods are used to forecast demand. Previous research has shown that these methods work well under relatively stable demand. However, none of the prior studies investigates how these time series models perform under more volatile demand patterns including temporal demand heteroscedasticity. Furthermore, when demand exhibits time-varying behavior, the predicative accuracy of traditional forecasting methods might deteriorate considerably. Thus, advanced forecast models such as the GARCH model and neural networks, which can overcome those limitations, are investigated to see how these models perform and how they affect supply chain performance. The forecasting methods used in this study are listed below.

- Moving average: The moving average forecasting method works well when demand is stable over time. The only parameter required for the moving average forecasting model is the number of past periods used to average the demand, and this is determined by minimizing the mean absolute deviation (MAD) of the forecasting errors. In this study, the moving average model averages the historical demand of the most recent 7 time periods. This number coincides with the cycle length selected in the simulation study. Other numbers were experimentally used for this parameter but did not materially reduce the forecast error. As one of the most simple and popular forecasting models in practice, the moving average model has proved to perform well when forecasting error is used as the measurement of the model performance (Zhao, Xie, & Zhang, 2002).
- Double exponential smoothing: Exponential smoothing has proven to be very useful in many forecasting situations such as inventory control and production planning. In 1957, Charles C. Holt first developed this model and used it for non-seasonal time series showing no trend. He then later developed a procedure (1958) that does handle trend, which is double exponential smoothing. This model is good at forecasting the trend component but not the seasonality components in a time series. Therefore, if a time series contains

seasonality components, systematic error will exist. SAS ETS 9.2 recommends using an ARIMA(0,2,2) model as an approximation for an optimal double exponential smoothing model. This ARIMA model was used in the simulation study as a proxy for the double exponential smoothing model.

- Winters' three parameter trend and seasonality model: This model is an extension of double exponential smoothing by Winters in 1965. This seasonally-adjusted and trend-enhanced exponential smoothing model is usually used for data that exhibit both trend and seasonality. Because this model can forecast both the trend and seasonality components in a time series, systematic errors in the forecast will be very small. The details of the double exponential smoothing and Winters' models can be found in Makridakis et al. (1998). SAS ETS 9.2 recommends using ARIMA(0,1,1)x(0,1,1)s as a good approximation to an optimal one parameter Winters' model. For this simulation, an ARIMA model was used as a proxy for the Winters' model.
- ARIMA model: ARIMA represents an autoregressive integrated moving average and was developed by George Box and Gwilym Jenkins (Box & Jenkins, 1976). It can handle a wide variety of time series patterns and has proved to be useful in representing both stationary and nonstationary time series (Liu, 2006). ARIMA models are often used as the baseline for forecasting comparison. When forecasts are generated under a more complicated model such as neural network, they are often compared with those obtained by an ARIMA model. If the forecasts obtained under an

ARIMA model are still more accurate than the forecasts obtained under a more complicated model, it often indicates misspecification in the more complicated model or the existence of outliers in the series (Liu, 2004).

- SARIMA model: Despite the fact that ARIMA models are able to deal with a wide variety of time series, they do not include seasonal time series which exhibit periodic behavior patterns. In order to handle seasonal time series, seasonal components need to be included in the ARIMA model. It was Box and Jenkins (1976) who extended the ARIMA model to seasonal ARIMA (SARIMA), which greatly increased the flexibility and usefulness of the models (Liu, 2004). The components of the ARIMA models are denoted by the P, D, and Q values in the notation ARIMA$(P, D, Q)_s$ and represent the autoregressive, integrated, and moving average components, respectively. The "s" at the end of this notation indicates the order of periodicity for seasonality. For the simulation study, an ARIMA(7,1,0) was used to fit the generated data as this model generally resulted in a good fit when seasonality was present.
- Neural network (NN): Neural networks are biologically-inspired semi-parametric models which have been used to capture complex nonlinear relationships between dependent and independent variables. "Neural networks have been widely used as a promising method for time series forecasting" (Zhang & Qi, 2005, p. 501). NN modeling represents a different paradigm compared to the traditional linear paradigm, which assumes a linear relationship between input and output variables. Thus, NN forecasting models can provide more accurate and robust solutions for problems where traditional

methods cannot be applied. In fact, an NN model with proper configuration can generate forecasts for data with very challenging and complex characteristics. It is often used when the true distribution of the demand is unknown, especially when the demand process exhibits nonlinear activities. Although neural networks have been used for several decades in different areas and disciplines, the complexity of these models has increased significantly since their development. Fortunately, with advances in computing power, the network training time has been greatly reduced, which further increases the attractiveness and applicability of such an advanced forecasting technology in demand forecasting. In practice, the performance of neural networks depends on the number of hidden layers and the number of nodes in each hidden layer. Cybenko (1989) demonstrated that one hidden layer with the sigmoid function is sufficient for most neural network learning problems. Thus, in this study, two types of feed-forward neural network, each with one hidden layer, were configured. The first neural network uses 7 input neurons to catch the input patterns, one hidden layer (Multi-Layer Perceptron design) with 7 neurons to propagate the intermediate signals, and one output layer with 1 neuron to display the computed results. In addition, a hyperbolic tangent activation function is applied as the activations in both the hidden layer and the output layer. The second neural network is configured the same as the first neural network except that the number of input neurons is 12. We purposely included the second neural network in the simulation model to investigate how the minor change of neural network structure affects its forecasting performance.

- GARCH model: The generalized autoregressive conditional heteroscedasticity (GARCH) model was designed to deal with the problem of volatility clustering in time series and extends the ARCH model by imposing an ARMA (autoregressive and moving average) structure on the conditional variance of the process error (Bollerslev, 1986). "GARCH includes past variances in the explanation of future variances and allows users to model the serial dependence of volatility" (Chang & Tsai, 2008, p. 928). Under a demand process which exhibits heteroscedastic behavior, the GARCH model is expected to generate more accurate forecasts by minimizing forecast error compared to other traditional forecasting methods. Since their development, these models have found numerous applications in the finance and economics fields and have proved particularly valuable in modeling time series with time-varying volatility. However, temporal heteroscedasticity has not been incorporated into supply chain demand forecasting, and the application of advanced forecasting models such as the GARCH model in SCM has not attracted much attention. More importantly, the impact of advanced forecasting models on supply chain performance is not clear under temporal demand heteroscedasticity. This research purposely included a GARCH model to investigate how it would perform under different demand patterns including temporal heteroscedasticity.

- Information Sharing

Demand forecast plays an important role in production and inventory planning decisions.

The sharing of demand forecast data with the upstream supplier is implemented in this simulation study. Two schemes of information sharing are investigated in this study.

a. No information sharing (NIS): Traditional information policy (non-information sharing) refers to the process in which retailers make their own inventory replenishment decisions based on their demand forecast and place orders to the supplier (manufacturer) one at a time. Thus, the supplier has to make its production plan based on the retailers' orders on a lot-for-lot basis. Researchers usually use this scheme as the baseline to compare with other information sharing schemes to determine the benefits of using information sharing. However, in practice, it is reasonable for the supplier to forecast future orders using historical order information to make its production schedule and better utilize its resources. Raghunathan (2001) demonstrates that the supplier is still able to estimate the demand process and the related parameters using some forecasting models in the case of non-information sharing. In this dissertation, the supplier is allowed to use double exponential smoothing to forecast future orders to plan its production before receiving any orders. It is noted that the so called "non-information sharing" in this study is not the same as the "traditional non-information sharing" in which the supplier simply responses to retailers' orders on a lot-for-lot basis. In this study, based on the forecasted order information, the supplier uses a single-item-capacitated lot-sizing model (Chung and Lin, 1988) to solve the lot-sizing problem and get an optimal production schedule. This model is implemented using the mixed integer programming model in SAS/OR's proc

LP. Only the production schedule in the frozen interval will be executed. Other schedules will be subject to change when new orders from retailers become available. Figure 3-2 illustrates the case of non-information sharing in this study.

b. Planned order information sharing (OIS): In this case, the retailers share their planned orders with the supplier. First, retailers forecast future demand within the forecast horizon. After considering the inventory, the retailers apply the EOQ policy to calculate the order quantity and their planned orders, and then they place current orders to the supplier and inform the supplier of their planned orders in the future as well. After the supplier receives these orders, he uses planned orders as the gross requirements to solve the lot-sizing problem in order to get a feasible production schedule by using an SAS LP version of the capacitated lot model. Figure 3-3 illustrates the scenario of information sharing in this study.

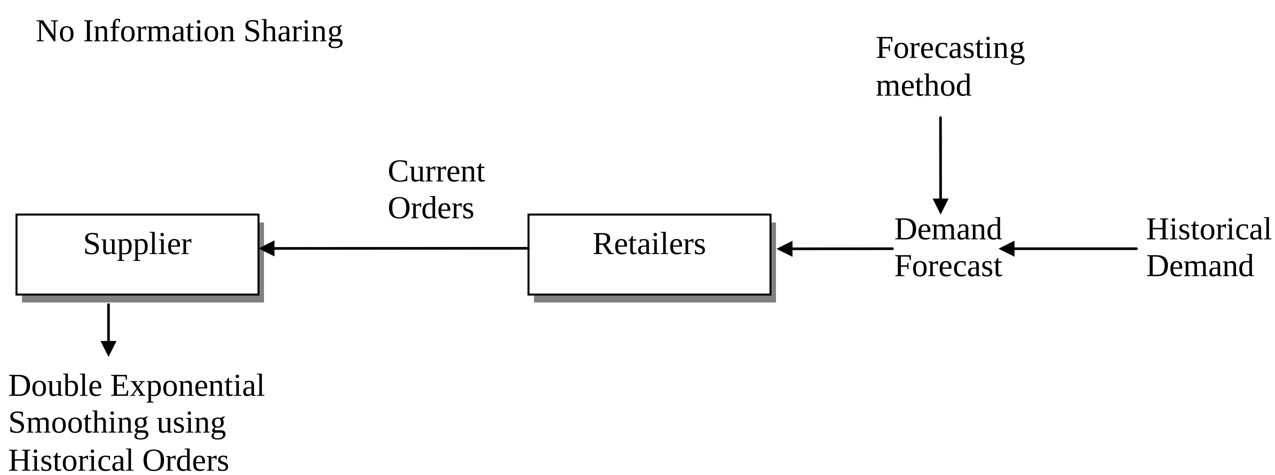

Figure 3-2. No information sharing between the retailers and the supplier.

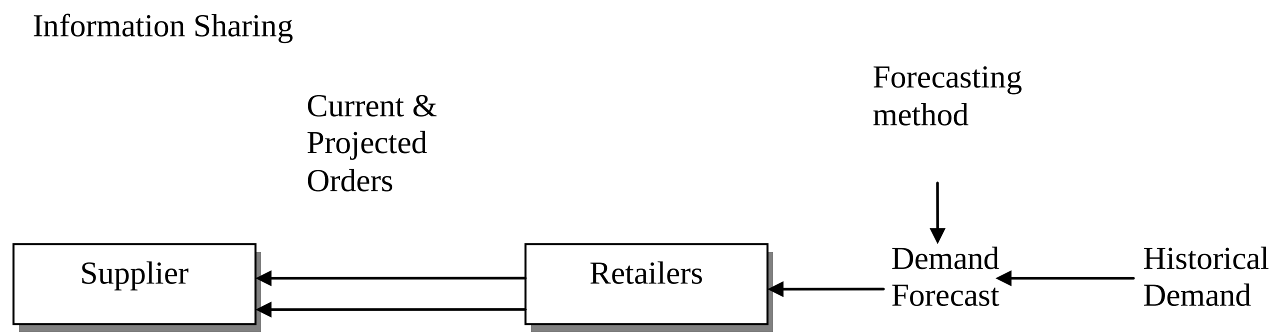

Figure 3-3. The sharing of planned orders between the retailers and the supplier.

- Demand Pattern (DP)

Demand pattern is an important environmental factor that significantly influences supply chain operation and its performance. In this study, temporal demand heteroscedasticity is included in the demand generation process. Different types of demand patterns are generated using the following formula and are listed in Table 3-1.

$$\mathrm{Demand}_t = \mathrm{base} + \mathrm{slope} * \mathrm{t} + \mathrm{season} * \sin\left(\frac{2\pi}{\mathrm{SeasonCycle}} * \mathrm{t}\right) + \mathrm{noise} * \mathrm{error} \quad (1)$$

Demand_t here represents the demand in period t (t=1, 2 … 400). SeasonCycle is chosen to be 7 for all demand patterns except for the demand pattern with only trend. As to the "noise*error" component in the demand generation process, two types of variance for this component are considered— one is a constant value for the noise parameter to generate a constant variance, and the other is a value for this parameter to generate a heteroscedastic pattern. SAS's standard normal random number generator, snormal(), is used to generate the normal disturbance for the i.i.d. error term. Denoting the term labeled "error" in equation (1) by ε, the noise parameter for the heteroscedastic pattern is expressed as h_t in equation (2) and is

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (2)$$

which is a function of the lagged error and the lagged noise parameter. Generating this pattern of heteroscedasticity will allow a GARCH(1,1) model to fit the generated data. In addition, the parameters (base, slope, season, and noise) that appear in the demand generator equation are characteristic parameters for a demand process. Different values of these parameters can be chosen to generate demand patterns with different trend, seasonality, and random variation components.

Because there is either a normal variant or a GARCH (1, 1) error component in the demand generation process, a negative demand value might conceivably occur. However, when a reasonably large base parameter was selected, this possibility did not occur in the simulation. In Table 3-1, the value of the slope was selected as 2, the same as in Zhao et al. (2002) for increasing trend. Only the increasing trend is considered in this study. Zhao et al. (2002)'s simulation results showed that information sharing was not particularly beneficial for retailers unless all retailers face demand with trends. For the demand pattern with common error, 80% of the "noise*error" component for each retailer was identical for each time period. When noise components for the retailers are not identical, it is more likely that some of the positive and negative error components will cancel each other out.

Table 3-1

Characteristics of Demand Patterns Used in This Study

DP	Base	Slope	Season	Noise
Trend & Heteroscedasticity	500	2	200	α_1 = .33, β_1=0.66 , and α_0=100
Trend & Seasonality	500	2	200	100
Trend	500	2	0	100
Trend & Common Error	500	2	200	100 80% of noise component identical for all 4 retailers

- Cost Structure

Cost structure is another environmental factor that can significantly affect supply chain performance. Table 3-2 describes the cost parameters for the supplier and retailers in this simulation study. Similar cost parameters have been used in previous studies (Zhao & Lee, 1993; Ebert & Lee, 1995; Zhao, Lee, & Goodale, 1995; Zhao et al., 2002).

Table 3-2

Cost Structure for the Supplier and the Retailers -- Source: Zhao et al. (2002)

Supplier/retailer	Supplier	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Ordering costs($/order)	500 (Set-up costs)	30.00	30.00	30.00	30.00
Transportation costs ($/truck)	N/A	450.00	255.00	331.00	553.00
Production costs per unit item	.05	N/A	N/A	N/A	N/A
Backorder costs ($/unit/period)	0.30	0.40	0.40	0.40	0.40
Inventory costs ($/unit/period)	0.03	0.04	0.04	0.04	0.04

Note: Production costs per unit item is not mentioned in Zhao et al. (2002)but is used for the single-item-capacitated lot sizing rule in Chung and Lin (1988).

- Capacity Tightness (CT)

Capacity constraint on the supplier is another important environmental factor that can significantly influence supply chain performance. Although many factors could have been selected as affecting the flow of goods in the supply chain, such as a supplier's yield uncertainty or supply chain disruptions, this study selected constraints on a supplier's capacity tightness because of the importance given to this factor in the literature. By definition, capacity tightness (CT) is used to measure the tightness of the supplier's production capacity relative to the total demand (the ratio of the total capacity available to the total demand to be met). Intuitively, as capacity becomes tighter, more backorders will occur for the supplier, which in turn will increase the costs for the supplier and decrease the supplier's service level. Three levels of capacity tightness, i.e. low (1.33), medium (1.18), and high (1.05) are used in this study, all of which were also used in previous studies (Zhao et al., 2002; Sohn et al., 2008).

Single Item Capacitated Lot Size Problem

Single item capacitated lot size problem (CLSP) formulation (Chung & Lin, 1988) is as follows:

$$\text{Min } Z = \sum_{t=1}^{T} (K_t \delta(x_t) + p_t x_t + h_t I_t) \tag{3}$$

Subject to: $I_{t-1} + x_t - r_t = I_t$, $t = 1, 2, \dots T,$

$0 \le x_t \le C_t$, $t = 1, 2, \dots T,$

$I_0 = 0,$

$I_t \ge 0, t = 1,2, \dots T,$ where

$\delta(x) = 0$ if $x = 0$ and $\delta(x) = 1$ if $x > 0$

C_t =production capacity in period t, where $C_t \geq 0$.
x_t = production quantity in period t , where $0 \le x_t \le C_t$.
I_t = inventory level at the end of period t.
r_t = demand in period t.
K_t= production setup cost in period t, where $K_t \geq 0$.
p_t = unit cost of production in period t , where $p_t \geq 0$.
h_t = cost of holding one unit in inventory in period t , where $h_t \geq 0$.
T = the periods of forecasting horizon

This problem is known to be nondeterministic polynomial-time hard (NP-hard), but there exist special cases that can be solved in polynomial time. For the CLSP with non-increasing setup costs, general holding costs, non-increasing production costs, and non-decreasing capacities over time, Chung & Lin (1988) developed an $O(T^2)$ algorithm while Heuvel &

Wagelmans (2006) proposed a more efficient $O(T^2)$ algorithm to get the optimal solution. However, both of the algorithms need to preprocess the demand in order to obtain feasible solutions. That is, the demand has to be modified to satisfy the condition that “the sum of the demand till period t” is less than or equal to “the sum of the capacity till period t” for every t period in the forecasting horizon. If this condition is not satisfied, the demand in period t will be reduced, and the backorder will be put into the next period’s demand. Due to this limitation, we decided to use SAS/OR’s proc LP procedure to get the optimal solution. This SAS procedure not only provides exactly the same result as the programs based on the above algorithms but also saves us a lot of time in programming and validating the results of an alternative algorithm.

Simulation Procedures

The underlying assumptions are that the supply chain operates in a make-to-stock environment, the supplier faces capacity constraints and produces a single product for the retailers, and one unit of the resource is required to produce exactly one unit of each finished product. Production lead time is assumed to be zero, which means that the supplier processes the retailers’ orders immediately once it receives orders from the retailers. However, transportation lead time is assumed to be one period. Retailers face customer demand and are assumed to be using an EOQ policy to replenish their inventories. The replanning periodicity (the number of periods between replanning cycles) is set to be one period, and the number of frozen periods in the planning horizon is chosen to be 4 for the supplier in this study. During each replanning period, the parameters of the forecasting models are re-estimated, and planned schedules within the non-frozen interval of the forecasting horizon are revised as more order information becomes available.

At the beginning of each period, the four retailers use historical demand data to forecast demand within the forecasting horizon, which is 20 periods. After the retailers get demand forecasts, they calculate their EOQ order quantities and place their current period's orders to the supplier. After submitting their orders to the supplier, the retailers receive the delivery shipped by the supplier one period previously. At the end of each period, when customer demand is realized, the retailers satisfy their customer's demand including any backorders using on-hand inventory. If on-hand inventory is insufficient, any shortages will become backorders.

The orders placed by the retailers become the demand for the supplier, and the supplier makes its production schedule using the same planning horizon as the retailers. Based on the orders from retailers, the supplier performs local optimization to find feasible production schedules using the CLSP formulation in equation (3). The supplier makes its production schedule depending on the information sharing scenarios. In the case of non-information sharing, the supplier forecasts future orders based on historical order data using the double exponential smoothing method because no information is shared between the supplier and the retailers. That is, the order forecasts and current orders are the only data that the supplier can get before production begins. Then the supplier uses the capacitated lot-sizing rule to determine its production plan for the forecasting horizon.

In the case of information sharing, the retailers not only submit their orders to the supplier but also share their planned orders with the supplier. Thus, the supplier can use both the placed orders and the planned orders as gross requirements to make its production schedule according to the capacitated lot-sizing rule. The first 4 periods of the production schedule within the planning horizon are frozen, and other planned production schedules in the unfrozen interval will be subject to change when new orders from the retailers arrive. The current period's production schedule is executed. After the production for the current period is completed, the supplier makes shipping decisions from its on-hand inventory. If sufficient on-hand inventories are available, the supplier fills the retailers' orders and any backorders from previous periods. Otherwise, the supplier will fill the retailers' orders as much as it can, and any orders that are unfilled become backorders. Finally, shipments are made from the supplier to the retailers by truck, it is assumed that the truck load is sufficient so that a single truck can deliver the orders which the retailers have placed. The party to whom the transportation cost will be billed depends on whether the retailers place an order to the supplier in the current period or not. If the retailers place an order to the supplier in the current period, then the retailers will pay for the transportation fee. Otherwise, if the shipment is used only to deliver backorders to the retailers, then the transportation cost will be charged to the supplier.

Customer demands are generated for 420 periods using demand generation functions with different trend, seasonality, and random variation components. Demand for the first 50 periods is used to estimate initial parameters for the forecasting methods. During each replanning period, the parameters of the forecasting method will be re-estimated when more demand data is available. The final performance measures for the retailers, the supplier, and the entire supply chain are based on 350 simulation periods. The last 20 periods were used to avoid termination effect. In order to avoid possible backorders for the retailers due to transportation lead time at the beginning of the simulation, four retailers are assumed to have initial inventory at 1000, 1500, 1800 and 2000 units respectively. As in Zhao et al. (2001), Zhao and Lee (1996), and others, in order to reduce the effect of random variation, five replications are generated using the associated values of cost for each combination of the factor levels.

In summary, the simulation process includes the following: generation of the demand pattern, retailers' making ordering decisions and the supplier's making production and delivery decisions. The simulation procedure continues until ordering, production, and delivery decisions are developed for all 350 periods. At the end of each period, costs for the retailers and the supplier are computed by considering the inventory cost, production unit cost, order cost, setup cost, backorder cost and transportation cost. Once the simulation is done, the total costs for the retailers, the supplier, and the supply chain are computed and used to measure the supply chain performance.

The simulation program was written in SAS since SAS has numerous built-in procedures for all forecasting methods investigated in this study. Moreover, SAS/OR's proc LP procedure was used to solve the capacitated lot-size problem. A bottom-up testing approach was used to verify and validate the results of the simulation program. That is, as each submodule was implemented, testing data sets were used to examine the results. Consistency of results for replicated output from the simulation program was analyzed to determine if the output was in an acceptable range.

CHAPTER 4

RESULTS OF STATISTICAL ANALYSES

This simulation study was designed so that a factorial experiment could be used to test the influence of the following four factors on a supply chain's performance: forecasting method selection, information sharing, demand pattern, and the supplier's capacity tightness. To investigate the research objectives proposed in Chapter 1 and test the hypotheses presented in Chapter 3, an analysis of variance (ANOVA) and Duncan's multiple range tests were performed using the following dependent variables: total cost for the supply chain (TC), total cost for supplier (TCS), and total cost for retailer (TCR) on the data set. A natural log transformation was used on these dependent variables to meet the assumptions of ANOVA. This chapter presents the results of the statistical analysis.

Selected ANOVA results, namely the *F* tests and significance levels, are presented in Table 4-1 for a complete factorial model consisting of main effects and two-way, three-way, and four-way interactions. The results of this ANOVA table reveal that for TC, all the main effects and interaction effects are significant at the 5% level of significance with the exception of the three-way interaction between forecasting method, information sharing and capacity tightness. For the dependent variables TCS and TCR, all the main and interaction effects are statistically significant at the 5% level of significance. That is, all the factors being investigated in this study significantly affect the supply chain performance. In particular, the main effect for capacity tightness has a dominant effect with F values of 21703.3, 34642.4, and 11185.4 for TC, TCR, and TCS, respectively. Such a substantial main effect suggests that the dependent variables are readily separable across the three capacity tightness levels for the supplier. This result is consistent with the belief that higher capacity constraints generate higher costs for a supply chain.

The next term in the factorial experiment that has a very large effect is information sharing. The values of the *F* statistic for this main effect are 1896.72 and 3129.19 for TC and TCS, respectively. These large values indicate that the type of information sharing policy plays a substantial role in increasing or decreasing costs. For TCR, the values of the F statistic, other than for capacity tightness, were not very large. The next two large values of the F statistic, 94.87 and 94.76, were for the effects of the demand pattern and the forecasting model. These values indicate that demand patterns and forecasting models significantly affect the retailers' performances. Moreover, the interaction effects between information sharing and the above two factors are also statistically significant. Another very large F statistic value is the one for the interaction of information sharing and capacity tightness. For TC and TCS, the values of this statistic are 526.41and 690.21, respectively. These substantial F statistic values indicate that the effect of information sharing is dependent on the level of capacity tightness. The results of this study demonstrate that information sharing plays a more important role in affecting the supply chain performance as capacity tightness increases.

Although the *F* statistic values of the interaction effects are not as prominent as those of the main effects mentioned above, the two-way, three-way, and four-way interactions contribute to the supply chain's costs as well. Interpreting the results of this simulation study is particularly difficult due to the presence of these interactions. The interpretation of each main effect must be explained by examining its effect on the different combinations of levels of the other main effects. That is, forecasting methods employed by the retailers, the demand pattern faced by the retailers, information sharing policy adopted between the supplier and the retailers, and capacity tightness faced by the supplier significantly jointly affect the supply chain performance in term of cost. In particular, the interaction effects among these factors have important implications for supply chain managers. Thus, in order to achieve cost reduction, supply chain managers should jointly consider all the critical factors in this study in selecting the appropriate forecasting method coupled with other operational factors under different scenarios so as to improve the supply chain performance.

Table 4–1

Selected ANOVA Results for Factors Affecting Supply Chain Costs, Retailers' Costs, and Supplier's Costs

Source	Dependent variables					
	TC		TCS		TCR	
	F value	Pr >F	F value	Pr >F	F value	Pr >F
IS	1896.72	0.0001	3129.19	0.0001	5.77	0.0165
DP	96.14	0.0001	74.28	0.0001	94.87	0.0001
IS*DP	28.50	0.0001	17.34	0.0001	46.72	0.0001
FM	123.73	0.0001	110.15	0.0001	94.76	0.0001
IS*FM	18.19	0.0001	12.40	0.0001	40.61	0.0001
DP*FM	7.30	0.0001	6.90	0.0001	5.63	0.0001
IS*DP*FM	6.43	0.0001	6.43	0.0001	5.23	0.0001
CT	21703.3	0.0001	11185.4	0.0001	34642.4	0.0001
IS*CT	526.41	0.0001	690.21	0.0001	11.32	0.0001
DP*CT	13.77	0.0001	8.19	0.0001	22.17	0.0001
IS*DP*CT	6.73	0.0001	5.85	0.0001	6.68	0.0001
FM*CT	2.94	0.0005	3.02	0.0004	2.32	0.0066
IS*FM*CT	1.45	0.1403	2.56	0.0026	2.30	0.0071
DP*FM*CT	1.96	0.0008	1.67	0.0092	2.21	0.0001
IS*DP*FM*CT	2.90	0.0001	2.70	0.0001	2.88	0.0001

The Impact of Forecasting Methods on Supply Chain Performance

As stated in Chapter 1, the first research objective was to investigate the impact of forecasting model selection, coupled with information sharing under different demand patterns including temporal demand heteroscedasticity, on supply chain performance in a capacitated supply chain. Examples of the demand patterns investigated in the simulation study are displayed in Figures 4-1 through 4-4. By examining these figures, it is easy to determine that the demand patterns have reasonably constant error variance about a general trend in all but one graph, in which the data with a heteroscedastic term in the error increases in volatility. The demand pattern with 80% common error has larger swings. These four patterns represent different types of volatility about the same trend line.

To examine the impact of forecasting methods on the performance of the supply chain, Figures 4-5 through 4-11 illustrate the performance of each forecasting model across these demand patterns under different levels of information sharing and capacity tightness. Examination of these figures shows that higher capacity tightness will result in higher supply chain costs. When CT is high, the supplier usually has to use most of its capacity to produce in order to meet customer demand, and it seems that forecast accuracy does not matter much since the supplier does not have enough resources to respond to customer demand. However, when CT is medium or low, supply chain performance improves because the supplier can better utilize its capacity based on the demand forecasts.

According to prior research (Zhao et al, 2002; Sohn & Lim, 2008), when capacity tightness is low or medium, information sharing is usually beneficial to the supply chain under certain circumstances compared to the traditional non-information sharing case used by most previous research. Thus, when capacity tightness is not high and planned order information is shared, retailers should select a forecasting model with high forecast accuracy. Results from this study differ somewhat from those of the previous research. This difference may be due to the assumption that the supplier forecasts future orders based on historical order information when no information is shared by retailers. That is, the supplier may obtain forecasts from its historical order information that are at least as beneficial as information being passed on from the retailers to the supplier. Another possible explanation is that temporal demand heteroscedasticity was included in this study. This demand pattern may make the retailers' EOQ policies less effective, which in turn affects the supply chain performance in a negative way.

Examination of Figures 4-5 through 4-11 reveals that NIS performs better than OIS under most scenarios. The results indicate that information sharing is not always beneficial to the supply chain. These results are consistent with the results from some prior studies, but not all. Graves (1999) reported that there is no value from information sharing as firms can utilize their own business intelligence to forecast demand. Cachon & Fisher (2000) concluded that the value of sharing demand data was not significant due to the fact that the retailer's historical orders provide a substantial portion of the information that the supplier needs in making replenishment and allocation decisions. In addition, Kim & Ryan (2003) also demonstrated that the benefits of shared demand data are limited when a manufacturer can use a large number of previous orders placed by the retailer to forecast demand.

The results of this simulation identified scenarios in which the supply chain can benefit from information sharing. In some situations, information sharing lowers the supply chain costs when capacity tightness is medium or high under certain demand patterns. It is interesting to compare our results with the conclusions of Zhao et al. (2002). Zhao et al. (2002) considered three information sharing schemes: non-information sharing, sharing of net requirements, and sharing of planned orders. They observed that "sharing future order information with the supplier is more beneficial than sharing only future demand information. Total cost savings for the entire supply chain are substantial under most conditions" (Zhao et al., 2002, p. 343). This dissertation illustrates conditions in which forecasting orders by the supplier without information sharing can achieve significant cost reduction for the entire supply chain. This result has practical implications for SCM. In practice, there are some circumstances in which retailers are not willing to share their demand and future order information with the supplier due to the fact that information sharing usually generates more benefits to the supplier than to the retailer under most circumstances. Other issues, such as security and confidentiality of the companies' data, also prevent the retailers from sharing their demand and planned order information with the supplier. For instance, "retailers are reluctant to share information with the manufacturer because of fear (lower bargaining power, information leakage, etc.)" (Tang, 2005, p. 477). Thus, it is reasonable for the supplier to forecast future orders and plan its production schedule in advance so as to improve the entire supply chain performance.

Figures 4-5 through 4-11 provide a comparison of forecasting model performance across demand patterns and under different levels of information sharing and capacity tightness. This study does not compare the accuracy of the forecasts of these methods under different demand patterns. Instead, performance of the supply chain is compared across scenarios in terms of costs. Since there is a strong interaction between capacity tightness and information sharing, the results in these figures reveal that as capacity tightness increases, the value of information sharing increases relative to the case of non-information sharing.

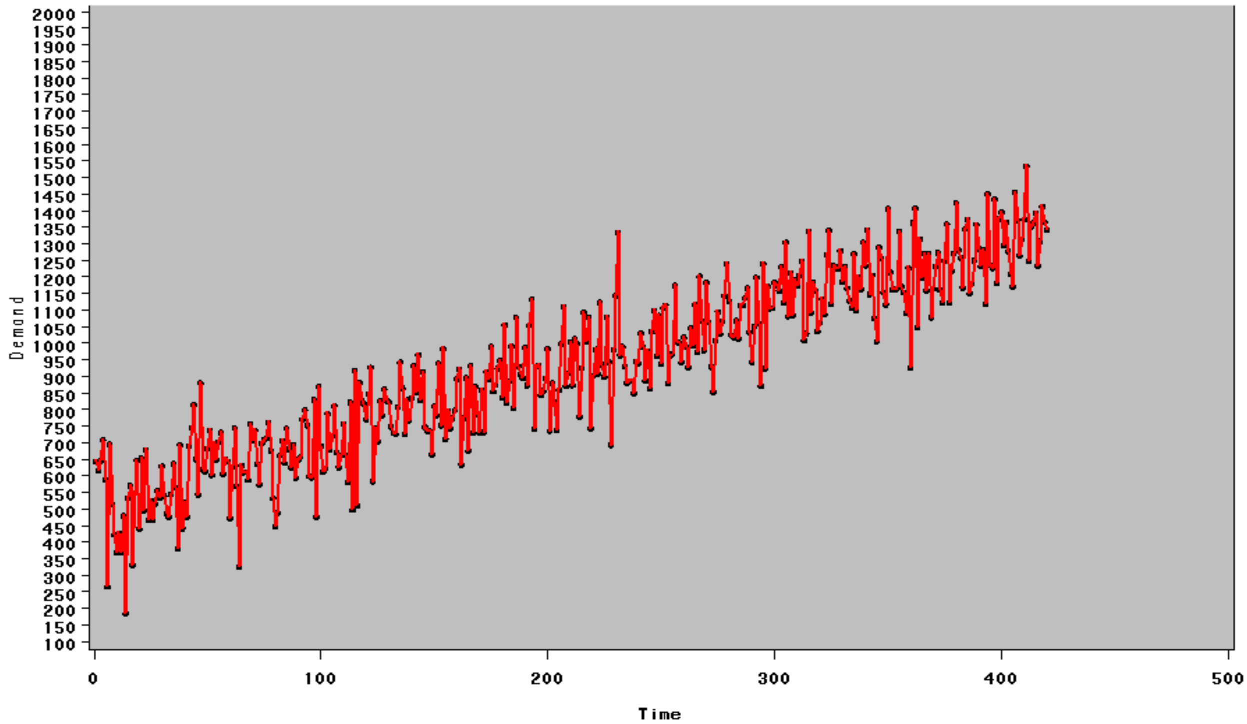

Figure 4-1. Demand data generated using only trend.

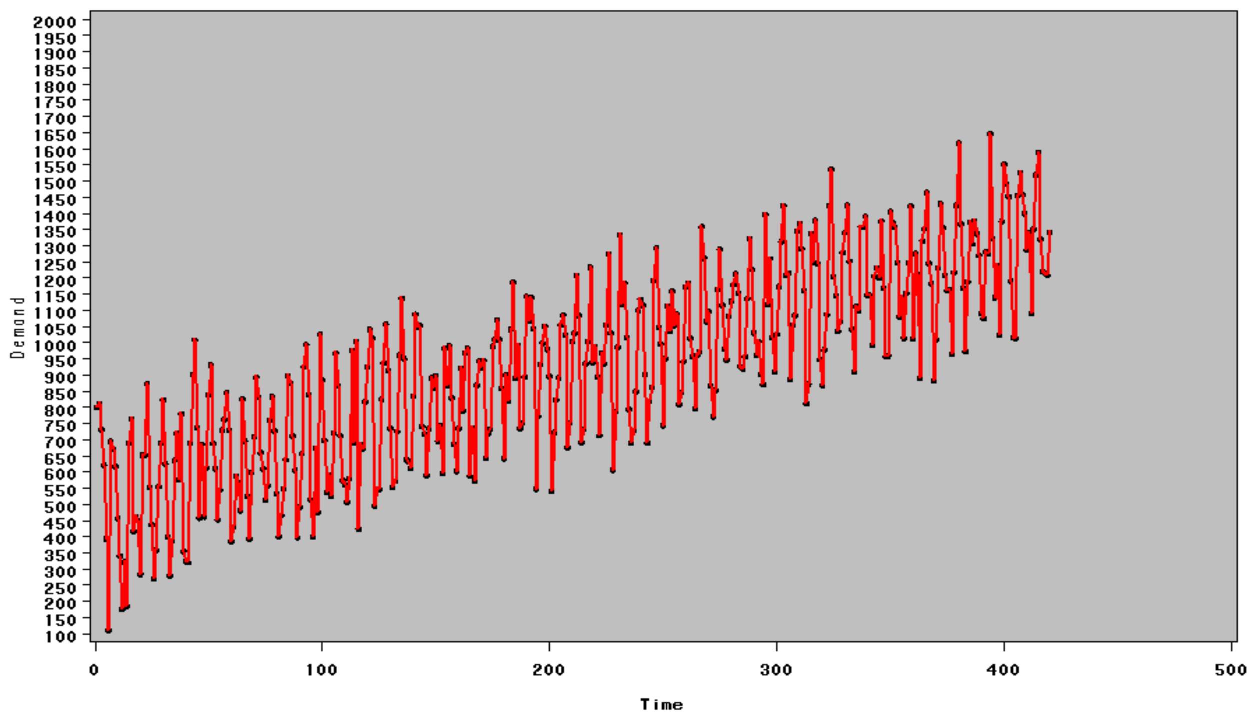

Figure 4-2. Demand data generated using trend and seasonality.

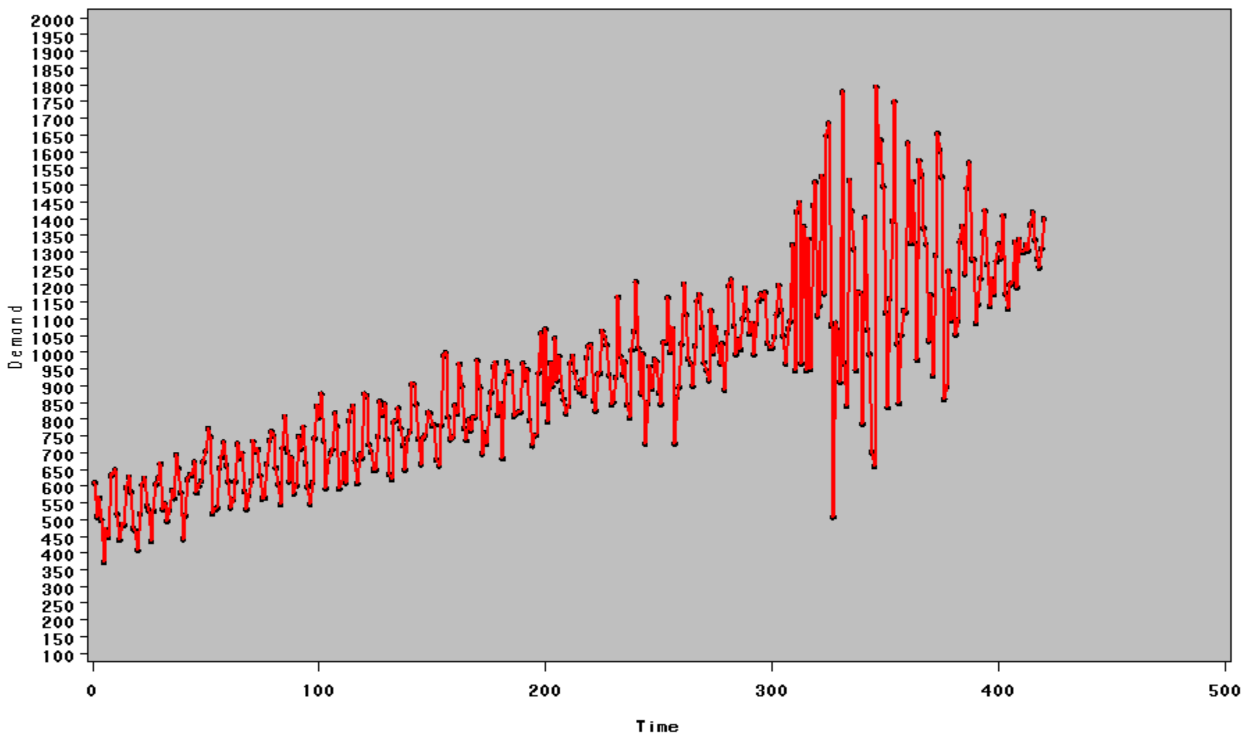

Figure 4-3. Demand data generated with heteroscedasticity – GARCH(1,1) error.

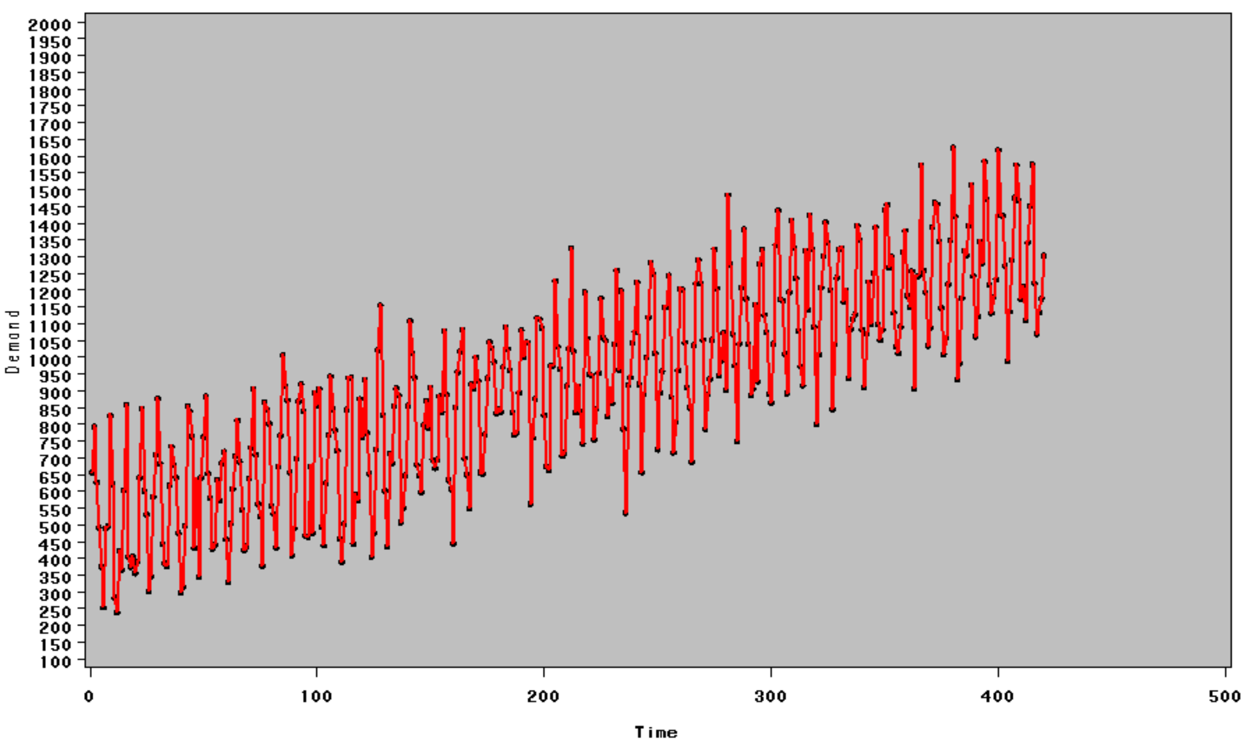

Figure 4-4. Demand data generated using trend, seasonality and common error.

Figure 4-5 shows how the GARCH model performs under different scenarios. Demand patterns with common error or with heteroscedastic components are more volatile than the other two demand patterns being investigated. Figure 4-5 indicates that the GARCH model generates the lowest cost for the supply chain under the temporal demand heteroscedasticity when capacity tightness is low and information is not shared, which may be due to the fact that the GARCH model was designed to deal with time-varying variance. However, when information is shared, the supply chain cost increases dramatically, especially for the demand pattern with heteroscedasticity. The GARCH model behaves quite differently between the two information sharing cases. When information is shared, this model generates the highest supply chain cost among the four demand patterns. This unexpected result may be due to the fact that temporal demand heteroscedasticity makes the retailers' EOQ policies less effective, which indirectly influences the supply chain's performance negatively. As capacity tightness goes up, information sharing plays a more important role in affecting the supply chain performance. When capacity tightness is medium, the GARCH model with information sharing under two of the demand patterns (demand with trend and demand with trend and seasonality) can help the supply chain reduce cost to some extent. However, under more volatile demands (demand with common error and demand with heteroscedastic component), the supply chain performance is better off without information sharing if retailers use the GARCH model to forecast demand. As the capacity tightness reaches the highest level under the GARCH model, the difference between supply chain performances become smaller. At least, the supply chain's performance with information sharing is as good as that without information sharing when capacity tightness is high. In other words, the value of information sharing increases as capacity tightness increases.

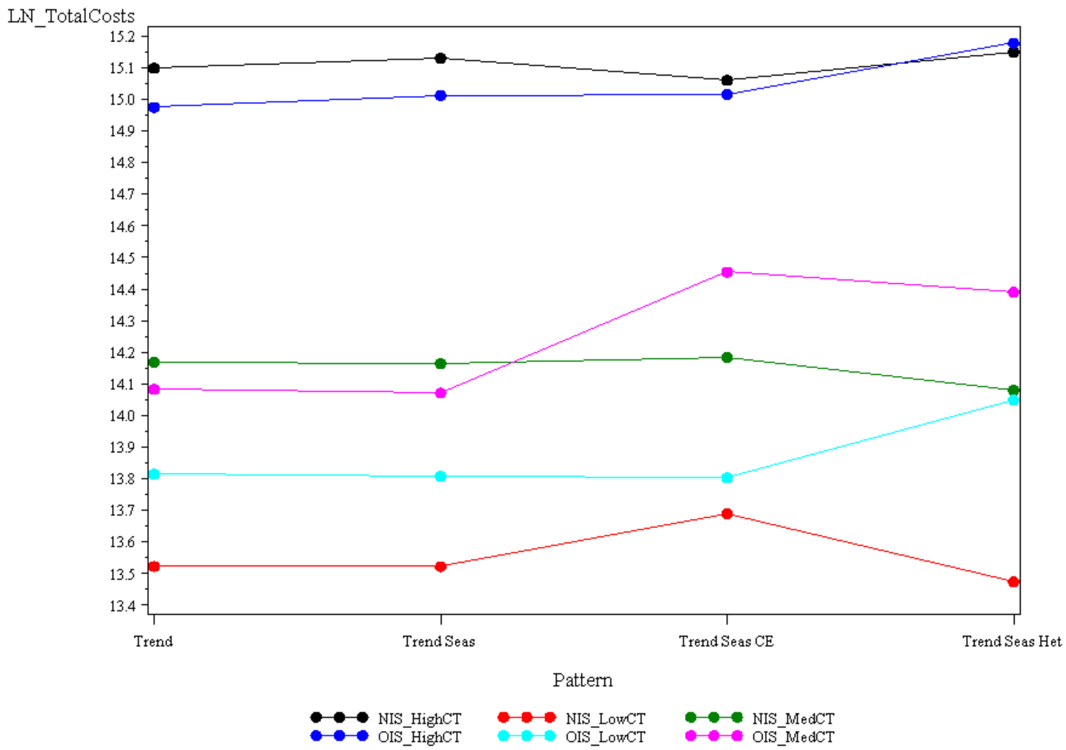

*Figure 4-5.*GARCH forecasting model's effect on supply chain's costs.

Figure 4-6 presents the results for the additive Winters' forecasting model under different scenarios. Winters' model was designed to forecast time series with trend and seasonality. This model does best when capacity tightness is low and information is not shared. However, the supply chain cost tends to increase slightly under the demand pattern consisting of common error. The supply chain cost increases as capacity tightness increases. With capacity tightness being high, the difference in the supply chain cost between the two cases of information sharing becomes smaller. In general, Winters' model performs worse under information sharing except in a few cases.

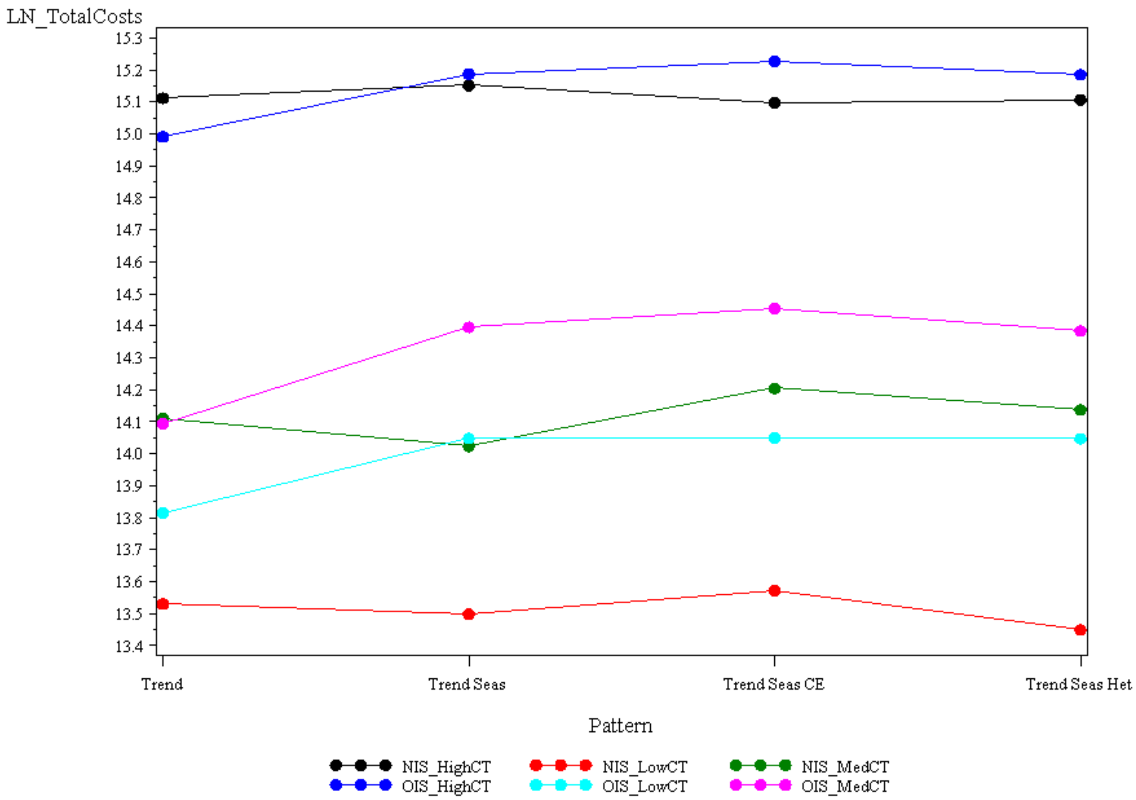

Figure 4-6. Additive Winters' forecasting model's effect on supply chain's costs.

Figure 4-7 shows how the neural network model with 7 inputs performs under different scenarios. In the case of non-information sharing, the performance of NN7 is not significantly different across all the demand patterns with capacity tightness being low, and this model generates lower costs across different scenarios. When information is shared, NN7 results in higher supply chain costs with low capacity tightness, especially under the demand pattern with heteroscedasticity. As the supplier's capacity becomes tight, the effect of information sharing becomes noticeable. For example, with medium capacity tightness, although the supply chain is still better off without information sharing, the cost difference of the supply chain becomes smaller under the two information sharing cases. The performance of NN7 tends to be worse under the demand pattern with heteroscedasticity, with information being shared and capacity tightness being high.

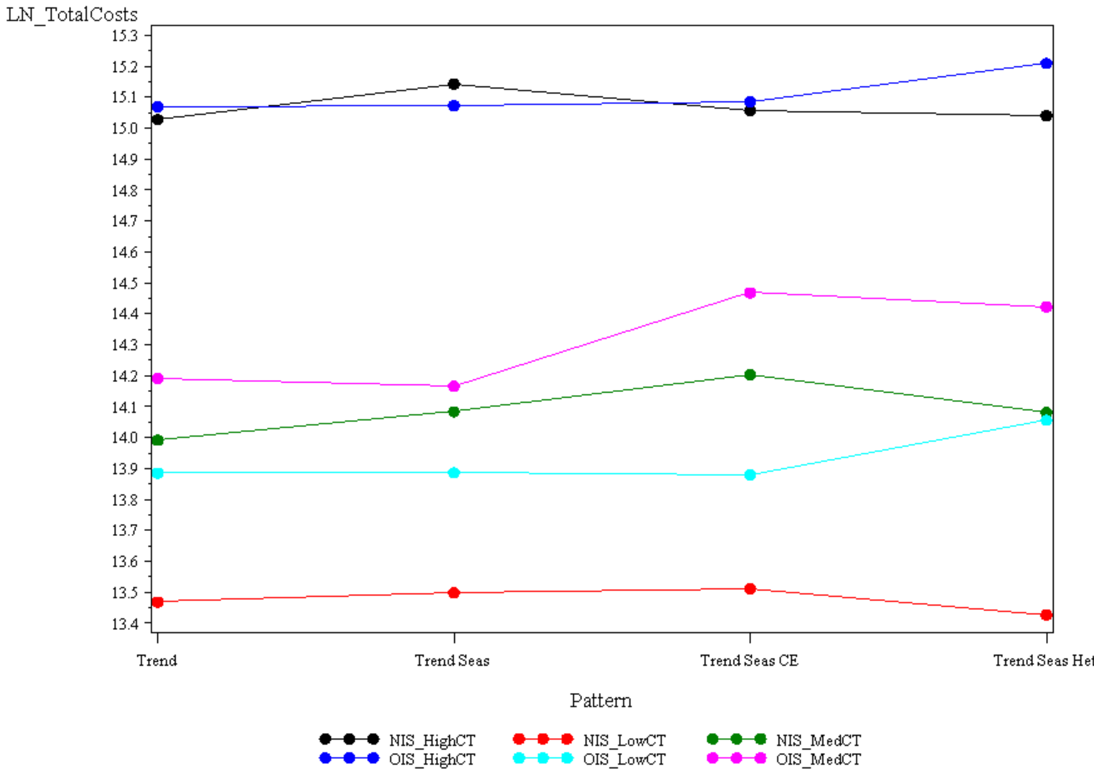

Figure 4-7. Effect of neural network model with 7 inputs on supply chain's costs.

Figure 4-8 illustrates how neural network with 12 inputs performs under different scenarios. The supply chain costs tend to differ only slightly across the demand patterns for NN12. When information is shared, NN12 consistently performs worse compared to the non-information sharing case. As capacity tightness goes up, supply chain costs increase because of setup cost, backorder cost, or stock-out cost occurring more often. However, information sharing does not seem to bring any benefit to the supply chain when NN12 is used. Compared with Figure 4-10 and Figure 4-11, the performances of the NN12 model under different scenarios are similar to those of the moving average and the double exponential smoothing models in most cases. The configuration of the NN12 models may be responsible for the poor performance of this model.

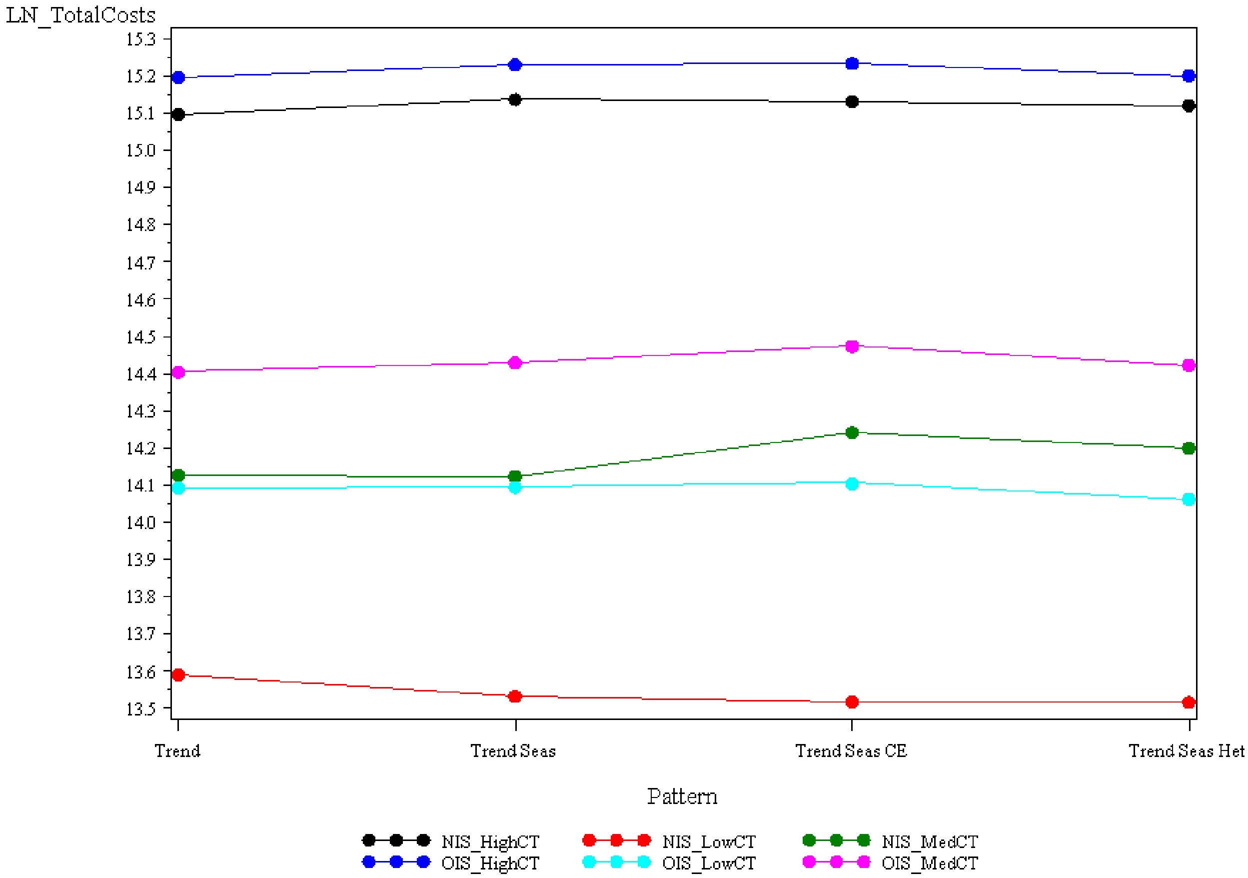

*Figure 4-8.*Effect of neural network model with 12 inputs on supply chain's costs.

Figure 4-9 shows how seasonal ARIMA performs under different scenarios. SARIMA was designed to deal with time series consisting of seasonality. Without information sharing, SARIMA helps reduce the costs for the supply chain significantly across all the demand patterns when capacity tightness is low. However, when information is shared, the supply chain cost dramatically increases, especially under the demand pattern with heteroscedasticity. As capacity tightness increases, the value of information sharing increases. That is, the difference between supply chain costs under the two information sharing schemes becomes smaller as capacity tightness becomes tight. The supply chain cost is lower under information sharing than that under non-information sharing in most cases when capacity tightness is high.

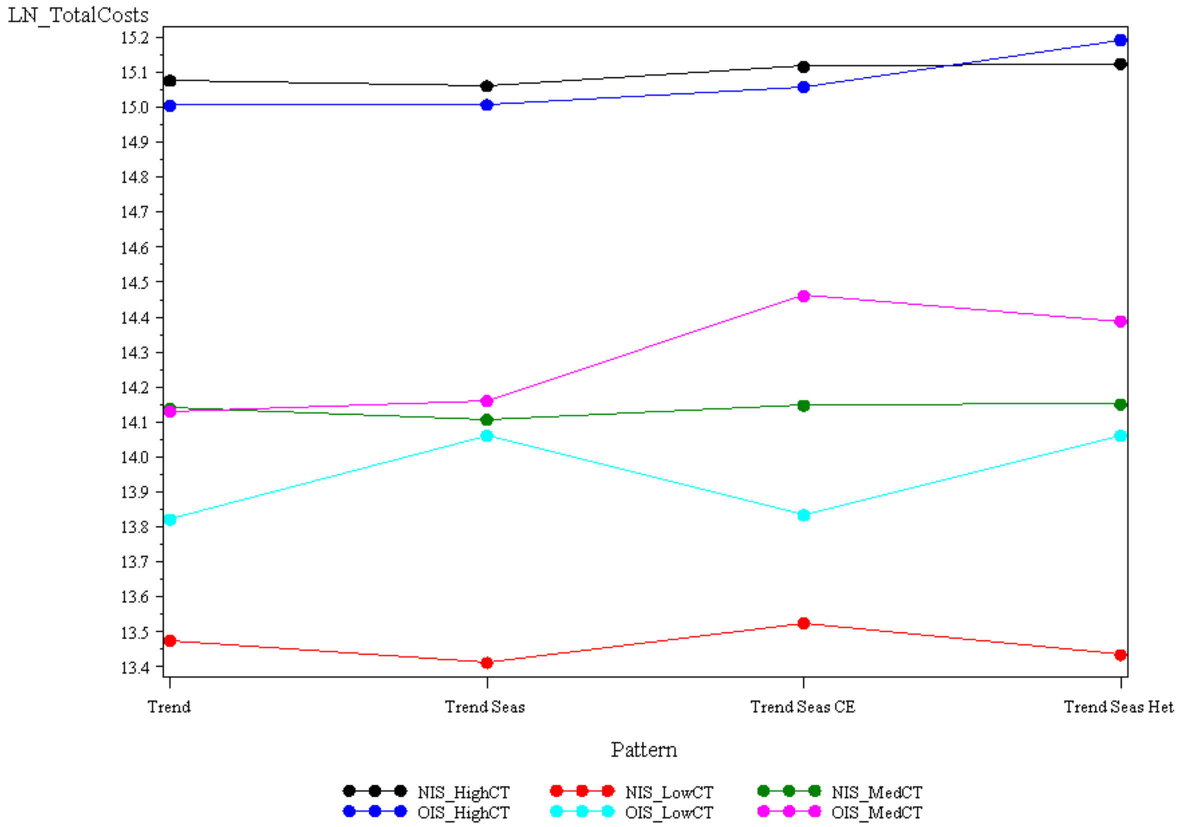

Figure 4-9 .SARIMA forecasting model's effect on supply chain's costs.

Figure 4-10 describes how the moving average method performs under different scenarios. The results demonstrate that the moving average method performs best under a trend demand pattern with non-information sharing and low capacity tightness. As the demand pattern becomes more volatile, the cost of the supply chain increases for low capacity tightness with no information sharing and for medium capacity tightness with information sharing. It is also noticeable that the moving average method always exacerbates the supply chain costs under information sharing. Therefore, the moving average method should be avoided when information sharing policy is implemented. As mentioned previously, capacity tightness also plays an important role in affecting the supply chain cost. As capacity tightness increases, the differences of supply chain costs under both information sharing schemes become smaller because the supply chain does not have enough capacity to respond to retailers' orders.

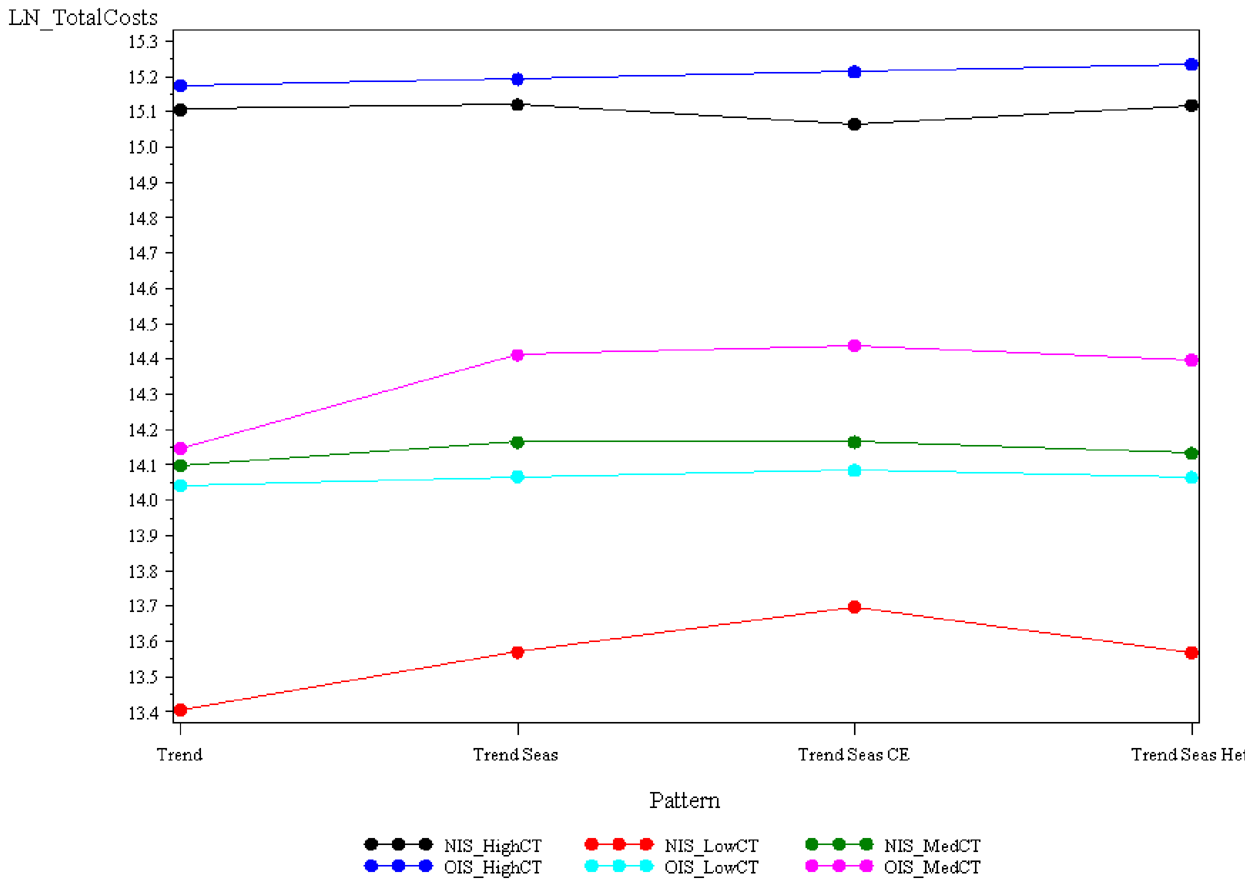

Figure 4-10. Moving average forecasting model's effect on supply chain's costs.

Figure 4-11 shows how the double exponential smoothing method performs under different scenarios. Double exponential smoothing results in lower costs under the trend demand pattern. However, it was not designed to handle seasonality. Systematic error exists when double exponential smoothing is used to forecast data consisting of seasonality. Supply chain costs dramatically increase under demand patterns showing seasonality. Double exponential smoothing performs even worse when information is shared. For demand patterns other than the trend demand pattern, the double exponential smoothing method is misspecified. The supply chain costs are higher when the planned orders are shared with the supplier. Thus, it can be concluded that double exponential smoothing should be avoided, especially for the case of information sharing and when seasonality is present.

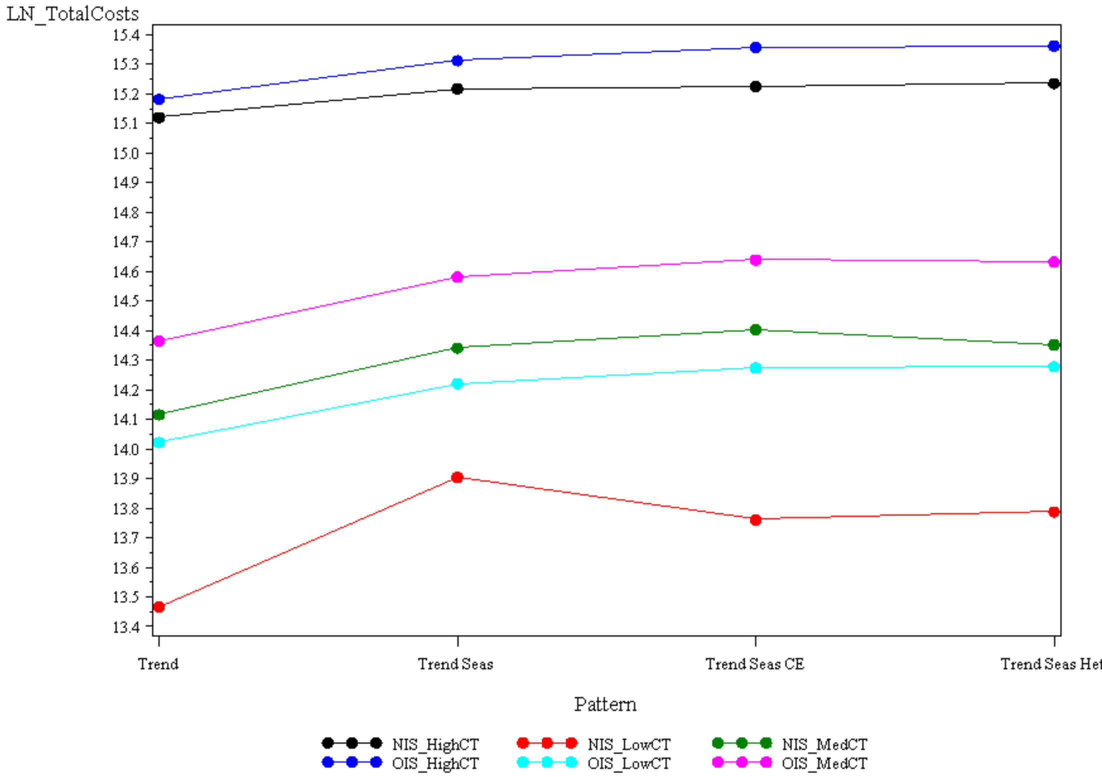

Figure 4-11.Double exponential smoothing forecasting model's effect on supply chain costs.

The Interaction Effect of Information Sharing, Capacity Tightness, and Forecasting Method on Supply Chain Performance

As stated in Chapter 2, the second research objective is to investigate how operational and environmental factors interact with forecast model selection to influence a supply chain's performance. The ANOVA results from Table 4-1 clearly show that all interaction effects are statistically significant at the 0.05 level of significance except for the interaction effect among information sharing, forecasting method, and capacity tightness for the supply chain (TC). To illustrate which combinations of forecasting method and information sharing policy significantly affect a supply chain's performance, an analysis of these methods is presented under each level of the environmental factors, capacity tightness and demand patterns, because of their significant interactions. Duncan's multiple range tests were used to display the combinations of the operational factors which significantly differed. Tables 4-2 through 4-13 present the results.

As demonstrated in Table 4-2,when the demand pattern consists of trend, seasonal, and heterogeneous components with low capacity tightness, the total costs for the supply chain, the supplier, and the retailers (TC, TCS, and TCR) are significantly lower for models with non-information sharing as compared to models with order information sharing. This result is due to the fact that the supplier uses exponential smoothing on historical orders to forecast future orders and plan its production schedules to avoid possible backorders or more production setups.

Table 4-2

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend, Seasonality, and Heteroscedasticity with CT= Low

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	14.279	OLD	A	13.974	OLD	A	12.930	OLD
B	14.065	OLM	A, B	13.826	OLS	B	12.528	OLN12
B	14.063	OLN12	A, B	13.824	OLM	B	12.522	OLM
B	14.062	OLS	A, B	13.820	OLN7	B, C	12.511	OLG
B	14.057	OLN7	A, B	13.820	OLN12	B, C	12.509	NLD
B	14.050	OLG	B	13.811	OLW	B, C, D	12.498	OLS
B	14.047	OLW	B	13.808	OLG	B, C, D	12.497	OLN7
C	13.788	NLD	C	13.457	NLD	B, C, D, E	12.487	OLW
D	13.569	NLM	D	13.186	NLM	C, D, E	12.420	NLW
D, E	13.517	NLN12	D, E	13.114	NLN12	C, D, E	12.419	NLM
D, E	13.475	NLG	D, E	13.054	NLG	D, E	12.407	NLN12
E	13.450	NLW	E	13.006	NLW	D, E	12.406	NLS
E	13.435	NLS	E	12.989	NLS	D, E	12.406	NLN7
E	13.428	NLN7	E	12.977	NLN7	E	12.400	NLG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

Advanced forecasting methods such as neural network models, GARCH, and seasonal ARIMA appear in the group that is not significantly different from the scenario with the lowest cost. With information sharing, the forecasting models are not significantly different with the exception of double exponential smoothing. The double exponential smoothing model with information sharing performs significantly worse than all the other models for TC and TCR. As mentioned previously, the cost to the supplier may be lower with non-information sharing because the supplier's own forecasts are for all four retailers' aggregated historical orders, and these smoothed values may be more useful for future planning than the retailers' individual forecasts.

Zhao et al. (2002) revealed that information sharing generally yielded better supply chain performance. In particular, more substantial cost savings can be achieved when the retailers share future orders with the supplier than in the cases in which the retailers share demand forecasts. Moreover, Zhao et al. (2002) showed that the supply chain performances were better in the case of both information sharing schemes than that in the case of non-information sharing. As a caveat, Zhao et al. (2002) did not use the same version of non-information sharing as used in this study. The result of this dissertation shows that the supplier's using its own forecasts is more efficient than the sharing of planned order information, especially when demand becomes more volatile. To some extent, our results are consistent with those of the previous study (Huang, Lau, Wang, & Humphreys, 2008, p. 47), which states that "sharing information may not necessarily improve supply chain performance in a turbulent market manifested in the seasonal demand pattern." In the case of a demand pattern with heteroscedasticity, as specified in this simulation study, information sharing is not of much benefit to the supply chain and in fact may yield worse supply chain performance.

As shown in Table 4-3, when the demand pattern consists of trend and seasonal components with low capacity tightness, the total costs for the supply chain and the supplier are significantly lower for models without information sharing as compared to models with order information sharing, except for the double exponential smoothing model. Similar to the results for the demand pattern with trend, seasonal components, and heterogeneity, low capacity tightness makes information sharing less important than when capacity tightness is higher, particularly for TC and TCS. With information sharing, the two best forecasting models for TC, TCS, and TCR consist of the neural networks model with 7 inputs and the GARCH models. These two models are not significantly different. For TC and TCS, the double exponential smoothing model with non-information sharing is not significantly different from these two models.

Table 4-3

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend and Seasonality with CT= Low

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	14.222	OLD	A	13.960	OLD	A	12.750	OLD
B	14.095	OLN12	A, B	13.844	OLN12	B	12.586	OLN12
B	14.067	OLM	B	13.823	OLM	B	12.582	NLD
B	14.062	OLS	B	13.818	OLS	B, C	12.538	OLM
B	14.048	OLW	B	13.805	OLW	B, C	12.531	OLS
C	13.905	NLD	C	13.651	OLN7	B, C, D	12.514	OLW
C	13.887	OLN7	C	13.595	NLD	C, D, E	12.481	NLM
C	13.808	OLG	C	13.560	OLG	D, E	12.437	NLN12
D	13.571	NLM	D	13.154	NLM	D, E	12.437	NLS
D	13.533	NLN12	D	13.123	NLN12	E	12.428	NLW
D	13.523	NLG	D	13.119	NLG	E	12.421	NLG
D, E	13.499	NLW	D	13.084	NLN7	E	12.411	NLN7
D, E	13.499	NLN7	D	13.076	NLW	F	12.326	OLN7
E	13.412	NLS	E	12.938	NLS	F	12.293	OLG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

For TCR, information sharing is beneficial as the neural network model with 7 inputs and the GARCH models are significantly better than the other models. The double exponential smoothing model with information sharing performs significantly worse than all other models under most scenarios. Double exponential smoothing often does not perform well in the presence of seasonality. For the retailers, not all of the models without information sharing are significantly better than the models with information sharing as they are for the supplier or the overall supply chain. This study shows that retailers benefit directly from information sharing when advanced forecasting models, namely, the neural network model with 7 inputs and the GARCH model, are used, resulting in significant cost savings for the retailers.

As demonstrated in Table 4-4, when the demand pattern exhibits trend with capacity tightness being low, the overall cost of the supply chain (TC) is significantly lower for models with non-information sharing as compared to models with order information sharing. This may be due to the fact that the supplier uses its own forecasting intelligence to forecast future orders and plan its production schedule ahead of time. The supply chain performance under non-information sharing scenarios is significantly different from that under information sharing scenarios for TC and TCS. For the non-information sharing scenarios, the simple traditional forecasting methods, namely, the moving average and double exponential smoothing models perform well although they are not significantly different from several of the other models. The reasonably good performance of the simple forecasting methods may be due to the fact that the demand pattern is relatively stable and that the forecasts from these models work well with the supplier's own forecasts when information is not shared. Despite the fact that information sharing does not appear to bring much benefit to the supplier and the supply chain, it is clear that the retailers benefit directly from information sharing since the GARCH model coupled with information sharing generates the lowest costs for the retailers. When planned order information is shared, the simple forecasting models (moving average and double exponential smoothing) and NN 12 perform significantly worse while the GARCH, Winters', and seasonal ARIMA models outperform the other forecasting models from the perspective of the retailers. Therefore, it can be concluded that advanced forecasting methods such as the GARCH model are the most beneficial for the retailers to use in order to reduce their costs if an information sharing policy is implemented and if capacity tightness is low. However, simple forecasting methods with non-information sharing policy are beneficial to the supplier and the entire supply chain.

Table 4-4

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend with CT= Low

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	14.093	OLN12	A	13.845	OLN12	A	12.575	OLN12
A	14.041	OLM	A	13.803	OLM	B	12.499	OLD
A	14.023	OLD	A, B	13.777	OLD	C, B	12.491	OLM
B	13.885	OLN7	B, C	13.651	OLN7	C, D	12.455	NLN12
B	13.822	OLS	C	13.579	OLS	D, E	12.422	NLG
B	13.815	OLG	C	13.573	OLG	E	12.405	NLW
B	13.814	OLW	C	13.569	OLW	E	12.403	NLN7
C	13.591	NLN12	D	13.200	NLN12	E	12.403	NLS
C, D	13.531	NLW	D, E	13.136	NLW	E	12.400	NLM
C, D	13.523	NLG	D, E	13.114	NLG	E	12.391	NLD
D, E	13.475	NLS	E, F	13.055	NLS	F	12.323	OLN7
D, E	13.469	NLN7	E, F	13.048	NLD	F, G	12.290	OLW
D, E	13.467	NLD	F	13.045	NLN7	F,G	12.289	OLS
E	13.513	NLM	F	12.950	NLM	G	12.277	OLG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

As demonstrated in Table 4-5, when the demand pattern exhibits trend and seasonality with 80% of the error term being common across retailers and with capacity tightness being low, the overall cost of the supply chain (TC) is again significantly lower with non-information sharing than it is with order information sharing. For TC and TCS, the best models are the neural network models with 7 and 12 inputs, Winters' model, and seasonal ARIMA with non-information sharing. This demand pattern is clearly more volatile than the demand data with trend.

Table 4-5

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend and Seasonality with 80% Common Error and with CT = Low

	TC Mean	Scenario		TCS Mean	Scenario		TCR Mean	Scenario
A	14.274	OLD	A	13.990	OLD	A	12.876	OLD
B	14.106	OLN12	A,B	13.852	OLN12	B	12.610	OLN12
B	14.085	OLM	B	13.832	OLM	C, B	12.586	OLM
B	14.051	OLW	B	13.811	OLW	C, D	12.508	OLW
C	13.881	OLN7	C	13.639	OLN7	C, D	12.506	NLM
C	13.834	OLS	C,D	13.591	OLS	D, E	12.497	NLG
C,D	13.804	OLG	C,D	13.554	OLG	D, E	12.495	NLW
C,D	13.762	NLD	D,E	13.462	NLD	D, E	12.460	NLS
D	13.699	NLM	E	13.335	NLM	D, E	12.458	NLN12
D	13.691	NLG	E	13.329	NLG	E , F	12.414	NLN7
E	13.572	NLW	F	13.154	NLW	E , F	12.409	NLD
E	13.524	NLS	F	13.105	NLN7	F , G	12.342	OLN7
E	13.518	NLN12	F	13.097	NLS	G	12.300	OLS
E	13.513	NLN7	F	13.094	NLN12	G	12.293	OLG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

Thus, it is evident that the advanced models consisting of the neural network model with 7 inputs, the seasonal ARIMA model, and the GARCH model significantly outperform other models with information sharing. When planned order information is shared, the double exponential smoothing model performs significantly worse. An interesting observation across the different demand patterns is that the GARCH model is consistently in the top performing models when information is shared. For the low capacity tightness level, the results reveal that advanced forecasting models such as GARCH, neural networks, and seasonal ARIMA play an important role in reducing supply chain costs under certain demand patterns.

As shown in Table 4-6, when the demand pattern consists of trend, seasonal, and heterogeneous components with medium capacity tightness, the overall cost of the supply chain increases as compared to the cases with low capacity tightness since more backorder and setup costs occur when capacity becomes relatively tight. Under this demand pattern, the supply chain is better off without information sharing under most of the forecasting methods. For example, the GARCH model and the NN7 model without information sharing lower the costs for the supply chain significantly due to their ability to capture the non-linear activities in the demand process. Surprisingly, these advanced forecasting methods coupled with information sharing might not yield significant cost savings for the retailers, supplier, or the entire supply chain.

Table 4-6

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend, Seasonality, and Heteroscedasticity with CT = Medium

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	14.633	OMD	A	14.233	OMD	A	13.523	OMD
B	14.423	OMN12	B	14.072	OMN12	B	13.257	NMD
B	14.422	OMN7	B, C	14.069	OMN7	B, C	13.211	OMN7
B	14.398	OMM	B, C	14.046	OMM	B, C	13.205	OMN12
B	14.391	OMG	B, C	14.044	OMS	B, C	13.193	NMN12
B	14.389	OMS	B, C	14.042	OMG	B, C, D	13.183	OMM
B	14.385	OMW	B, C	14.038	OMW	B, C, D	13.167	OMG
B	14.353	NMD	C	13.945	NMD	B, C ,D	13.155	OMW
C	14.200	NMN12	D	13.745	NMN12	B, C, D	13.153	OMS
C	14.151	NMS	D, E	13.717	NMM	B, C, D	13.139	NMS

C	14.138	NMW	D, E	13.697	NMS	B, C, D	13.138	NMW
C	14.134	NMM	D, E	13.678	NMW	B, C, D	13.099	NMN7
C	14.082	NMN7	D, E	13.660	NMG	C, D	13.056	NMM
C	14.081	NMG	E	13.612	NMN7	D	13.009	NMG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

This result is not consistent with Zhao et al. (2002), which concluded that forecasting methods with improved accuracy will help the supply chain achieve great cost savings when the planned order information is shared under relatively stable demand. A possible explanation for this inconsistency is that the temporal demand heteroscedasticity makes the retailers' EOQ policies less efficient. Thus, the costs for the supply chain increase.

The total costs for the retailers, supplier, and supply chain still show that non-information is significantly better than planned order information sharing under most scenarios. In other words, the supplier can make better use of his own order forecast than of planned order information sharing to achieve cost saving of his own. Moreover, the retailers and the entire supply chain benefit from advanced models without information sharing when capacity tightness is medium. The double exponential smoothing model coupled with information sharing significantly underperforms under temporal demand heteroscedasticity. However, the moving average method seems to perform well as compared to double exponential smoothing when information is shared.

As shown in Table 4-7, when the demand pattern consists of trend and seasonal components with medium capacity tightness, the cost of the supply chain (TC) is not always significantly lower without information sharing as compared to that with order information sharing. For example, the GARCH model with information sharing performs equally as well as Winters' model without information sharing for the entire supply chain. The supplier still benefits from its own order forecasts, and the total cost for the supplier is significantly lower under Winter's model without information sharing than under the models with information sharing. Among models with information sharing, the GARCH, seasonal ARIMA, and neural network with 7 inputs significantly outperform the other models. However, the retailers benefit directly from information sharing because GARCH, neural network with 7 inputs, and seasonal ARIMA with information sharing significantly outperform the other models in terms of cost, with the exception of the Winters' model with non-information sharing. Thus, it can be concluded that information sharing still plays a role in cost savings for the supply chain.

Table 4-7

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend and Seasonality with CT= Medium

	TC Mean	Scenario		TCS Mean	Scenario		TCR Mean	Scenario
A	14.581	OMD	A	14.215	OMD	A	13.401	OMD
B	14.429	OMN12	B	14.067	OMN12	A, B	13.238	OMN12
B	14.412	OMM	B	14.048	OMM	B	13.224	OMM
B	14.396	OMW	B	14.043	OMW	B	13.197	NMD
B	14.341	NMD	B, C	13.956	NMD	B	13.183	OMW
C	14.167	OMN7	C, D	13.854	OMN7	B, C	13.160	NMG
C	14.165	NMG	D, E	13.826	OMS	B, C	13.141	NMS
C	14.165	NMM	D, E, F	13.755	OMG	B, C	13.140	NMM
C	14.161	OMS	E, F, G	13.719	NMM	B, C	13.130	NMN12
C	14.124	NMN12	E, F, G	13.709	NMG	B, C	13.079	NMN7
C	14.107	NMS	F, G	13.661	NMN12	C, D	12.992	NMW
C	14.084	NMN7	F, G	13.627	NMS	D, E	12.902	OMS
C	14.072	OMG	F, G	13.625	NMN7	D, E	12.849	OMN7
C	14.024	NMW	G	13.583	NMW	E	12.768	OMG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

The commonly used simple forecasting method, the double exponential smoothing method coupled with information sharing, also significantly underperforms other models for TC and TCS. Although the moving average model with information sharing significantly outperforms the double exponential model with information sharing, it still significantly underperforms most other forecasting methods for TC and TCS. In addition, neural network with 12 inputs with information sharing is not significantly different from the double exponential smoothing and moving average models, and it significantly underperforms the neural network model with 7 inputs. This result demonstrates that neural network models require more expertise and skills from managers and practitioners to use them properly. If the neural network models are not configured properly, the forecasting performance of these models deteriorates dramatically.

As shown in Table 4-8, when the demand pattern consists of trend with medium capacity tightness, many scenarios are not significantly different. For example, all but three scenarios are not significantly different with respect to TC. The supplier still benefits from its own order forecasts. It is clear that the retailers can achieve cost savings by using a number of models with information sharing, such as the GARCH and Winters' models. In addition, all of the information sharing models, with the exception of the double exponential smoothing model and the neural network with 12 inputs, do not perform significantly differently for the retailers. Thus, it can be concluded that information sharing is beneficial to the retailers. Although the supplier does not seem to benefit from information sharing due to the superior efficiency of its own forecasting and advanced planning, the entire supply chain is able to benefit from information sharing under the GARCH and Winter's models. For the supply chain, the results show that the GARCH and Winters' models with information sharing perform equally as well as the two models without information sharing—the neural network model with 7 inputs and the moving average model. It can be imagined that the value of information sharing will greatly increase if the supplier does not do any forecasting and production planning before it receives any orders from the retailers. For the trend pattern, many of the traditional forecasting models perform as well as the advanced models. The moving average model is not significantly different from the model with the lowest costs for TC, TCS, and TCR. For the supply chain, all models under non-information sharing are not significantly different from each other with the exception of the neural network model with 7 inputs.

Table 4-8

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend with CT= Medium

	TC Mean	Scenario		TCS Mean	Scenario		TCR Mean	Scenario
A	14.405	OMN12	A	14.050	OMN12	A	13.195	OMN12
A	14.365	OMD	A	14.018	OMD	A	13.180	NMG
B	14.192	OMN7	B	13.872	OMN7	A	13.144	NMS
B	14.168	NMG	B	13.828	OMM	A	13.142	NMN12
B	14.147	OMM	B, C	13.800	OMS	A	13.138	OMD
B	14.140	NMS	B, C, D	13.771	OMW	A	13.108	NMM
B	14.130	OMS	B, C, D	13.769	OMG	A	13.099	NMD
B	14.127	NMN12	C, D, E	13.702	NMG	A, B	13.081	NMW
B	14.116	NMD	D, E	13.677	NMS	B, C	12.948	NMN7
B	14.111	NMW	D, E	13.669	NMW	C, D	12.895	OMN7
B, C	14.099	NMM	D, E	13.667	NMD	C, D	12.860	OMS
B, C	14.095	OMW	D, E, F	13.659	NMN12	C, D	12.850	OMM
B, C	14.083	OMG	E, F	13.632	NMM	C,D	12.812	OMW
C	13.992	NMN7	F	13.556	NMN7	D	12.773	OMG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—-forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

As shown in Table 4-9, when the demand pattern exhibits trend and seasonality with 80% of the error terms being common and when capacity tightness is medium, TC and TCS are significantly lower without information sharing as compared to those with order information sharing except for the double exponential smoothing model without information sharing. The simulation results from this study do not support a common expectation that sharing order information will improve supply chain performance especially in a turbulent market. As discussed above, this demand pattern is more volatile compared to other demand patterns such as trend. The result shows the opposite. Specifically, the supply chain performance seems to deteriorate in a volatile market under information sharing and medium capacity tightness. Moreover, the results demonstrate that both advanced forecasting and traditional forecasting methods, except for double exponential smoothing, perform equally well for TC and TCS under both information sharing schemes. That is, advanced forecasting methods do not show any advantages over traditional forecasting methods except for double exponential smoothing. For TCR, it is clear that retailers do not benefit from information sharing as demonstrated in other cases, and the moving average model seems to be good enough to help the retailers achieve cost savings. Once again, double exponential smoothing with information sharing proves to be the worst forecasting model for the retailers in forecasting customer demand.

Table 4-9

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend and Seasonality with 80% Common Error and with CT= Medium

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	14.640	OMD	A	14.246	OMD	A	13.515	OMD
B	14.474	OMN12	B	14.096	OMN12	B	13.343	NMD
B	14.469	OMN7	B	14.091	OMW	B, C	13.318	OMN12
B	14.461	OMS	B	14.091	OMN7	B, C	13.312	OMN7
B	14.455	OMW	B	14.088	OMS	B, C, D	13.295	OMS
B	14.454	OMG	B	14.085	OMG	B, C, D	13.278	OMG
B	14.438	OMM	B	14.072	OMM	B, C, D	13.268	OMW
B	14.403	NMD	B	13.978	NMD	B, C, D	13.255	OMM
C	14.241	NMN12	C	13.780	NMN12	B, C, D	13.246	NMN12
C	14.205	NMW	C	13.766	NMW	B, C, D	13.231	NMN7
C	14.203	NMN7	C	13.728	NMN7	B, C, D	13.195	NMG
C	14.185	NMG	C	13.725	NMM	C, D	13.167	NMW

C	14.165	NMM	C	13.719	NMG	C, D	13.157	NMS
C	14.148	NMS	C	13.682	NMS	D	13.133	NMM

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

As shown in Table 4-10, when the demand pattern consists of trend, seasonal, and heterogeneous components with high capacity tightness, the overall cost of the supply chain increases as compared to the cases under low and medium capacity tightness since more backorder and setup costs occur when capacity tightness becomes higher. In the case of non-information sharing, the neural network model with 7 inputs consistently outperforms other forecasting methods and generates the lowest cost for the supply chain due to its ability to capture the non-linear activities in the demand process. The GARCH model does not perform as well as the NN7 when the supplier's capacity becomes very tight. However, in the case of information sharing, although the supply chain is still better off without information sharing, the GARCH model performs well relative to many of the scenarios without information sharing.

Table 4-10

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend, Seasonality, and Heteroscedasticity with CT= High

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	15.362	OHD	A	14.772	OHD	A	14.555	OHD
B	15.236	NHD	B	14.646	OHM	B	14.445	NHD
B	15.235	OHM	B	14.632	OHN7	B, C	14.426	OHM
B, C	15.210	OHN7	B	14.632	NHD	B, C	14.390	NHG
B, C, D	15.201	OHN12	B	14.623	OHN12	B, C	14.386	OHN7
B, C,D,E	15.193	OHS	B	14.612	OHS	B, C	14.378	OHN12
B, C, D,E	15.185	OHW	B	14.609	OHW	B, C	14.373	OHS
B, C, D,E	15.178	OHG	B	14.601	OHG	B, C	14.360	NHS
B, C, D,E	15.150	NHG	C	14.519	NHG	B, C	14.359	OHW
C, D, E,F	15.124	NHS	C, D	14.505	NHM	B, C	14.355	OHG
C, D, E,F	15.121	NHN12	C, D	14.501	NHN12	C	14.349	NHN12

D, E, F	15.119	NHM	C, D	14.498	NHS	C, D	14.340	NHW
E, F	15.107	NHW	C, D	14.483	NHW	C, D	14.339	NHM
F	15.041	NHN7	D	14.427	NHN7	D	14.260	NHN7

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

Under information sharing, the simple traditional forecasting models are not competitive with the better performing models. In particular, double exponential smoothing with information sharing performs worst for TC, TCS, and TCR and is not recommended.

Table 4-11 presents the results for the demand pattern consisting of trend and seasonality with high capacity tightness. In the case of non-information sharing, many of the traditional models are not significantly different from the advanced models. Seasonal ARIMA under both information sharing schemes helps the supplier, the retailers, and the supply chain reduce their costs significantly. GARCH and NN7 perform equally as well as seasonal ARIMA when information is shared.

Table 4-11

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend and Seasonality with CT= High

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	15.313	OHD	A	14.740	OHD	A	14.483	OHD
B	15.231	OHN12	B	14.646	OHN12	A, B	14.422	NHD
C,B	15.218	NHD	B	14.617	NHD	A, B	14.416	OHN12
C,B,D	15.193	OHM	B	14.616	OHM	B, C	14.384	NHN12
C,B,D	15.187	OHW	B	14.613	OHW	B, C	14.374	NHW
C,D	15.152	NHW	C	14.536	NHW	B, C	14.373	NHN7
D,E	15.143	NHN7	C	14.521	NHN7	B, C	14.368	OHM
D,E	15.138	NHN12	C	14.513	NHM	B, C	14.363	NHG
D,E, F	15.131	NHG	C	14.507	NHG	B, C	14.359	OHW
D,E,F	15.121	NHM	C, D	14.501	NHN12	B, C	14.334	NHM
E,F,G	15.073	OHN7	C, D, E	14.497	OHN7	C, D	14.304	NHS
F,G	15.061	NHS	D, E, F	14.440	OHG	D, E	14.248	OHN7

G	15.131	OHG	E, F	14.436	OHS	E	14.183	OHG
G	15.007	OHS	F	14.427	NHS	E	14.175	OHS

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing . Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

These three models outperform other models when planned order information is shared. More importantly, these advanced models coupled with information sharing lower the costs for the supply chain. Consistent with previous results in the low and medium capacity tightness levels, the double exponential smoothing model underperforms other models consistently under this demand pattern with capacity tightness being high.

As shown in Table 4-12, when the demand pattern consists of trend with high capacity tightness, GARCH, Winters', seasonal ARIMA, and neural network with 7 inputs either with or without information sharing significantly improve TC, TCS, and TCR over most other models. For the supplier, the double exponential smoothing, NN12, and moving average models with information sharing result in significantly higher costs than other models. As discussed before, the poor performance of neural network with 12 inputs may be due to its suboptimal configuration. The value of information sharing increases because advanced forecasting methods with information sharing lower the costs for the supply chain under relatively stable demand.

Table 4-12

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend with CT= High

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	15.195	OHN12	A	14.615	OHN12	A	14.376	OHN12
A,B	15.182	OHD	A	14.606	OHD	A	14.456	OHD
A,B,C	15.174	OHM	A	14.600	OHM	A	14.349	NHW
A,B,C,D	15.121	NHD	B	14.503	NHD	A	14.347	NHD
B,C,D,E	15.112	NHW	B, C	14.496	OHN7	A	14.345	OHM
B,C,D,E	15.107	NHM	B, C	14.488	NHM	A	14.345	NHG

B,C,D,E	15.099	NHG	B, C	14.485	N HW	A, B	14.334	NHM
C,D,E	15.096	NHN12	B, C	14.475	NHN12	A ,B	14.325	NHN12
D,E,F	15.076	NHS	B, C,D	14.464	NHG	A, B	14.308	NHS
D,E,F,G	15.071	OHN7	B, C,D	14.452	NHS	A, B	14.274	NHN7
E, F,G,H	15.028	NHN7	B, C,D	14.433	OHS	B, C	14.243	OHN7
F,G, H	15.006	OHS	C,D	14.422	OHW	C	14.176	OHS
G, H	14.991	OHW	D	14.402	OHG	C	14.156	OHW
H	14.976	OHG	D	14.392	NHN7	C	14.147	OHG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

As shown in Table 4-13, when the demand pattern exhibits trend and seasonality with 80% of the error terms being common and when capacity tightness is high, a large number of models are not significantly different, making it difficult to separate the information sharing and non-information sharing scenarios.

Table 4-13

Performance of Forecasting Models and Information Sharing for Demand Pattern Consisting of Trend and Seasonality with 80% Common Error and with CT= High

	TC			TCS			TCR	
	Mean	Scenario		Mean	Scenario		Mean	Scenario
A	15.357	OHD	A	14.767	OHD	A	14.547	OHD
B	15.233	OHN12	B	14.646	OHN12	B	14.440	NHD
B	15.228	OHW	B	14.645	OHW	B	14.422	OHN12
B	15.225	NHD	B	14.630	OHM	B	14.411	OHW
B, C	15.214	OHM	B	14.616	NHD	B, C	14.397	OHM
C, D	15.132	NHN12	C	14.519	NHN12	B, C, D	14.358	NHS
D	15.117	NHS	C	14.507	OHN7	B, C, D	14.351	NHN12
D, E	15.099	NHW	C	14.486	NHS	B, C, D,E	14.326	NHW
D, E	15.085	OHN7	C	14.481	OHS	C, D, E,F	14.290	NHN7
D, E	15.066	NHM	C	14.479	NHW	C, D, E,F	14.285	NHM
D, E	15.061	NHG	C	14.453	NHM	C, D, E,F	14.283	NHG
D, E	15.059	OHS	C	14.445	NHG	D, E, F	14.260	OHN7
D, E	15.057	NHN7	C	14.436	OHG	E, F	14.236	OHS
E	15.016	OHG	C	14.433	NHN7	F	14.194	OHG

Note. Means with the same letter are not significantly different. Scenario labels: First Letter—information sharing: O for sharing planned orders and N for non-information sharing. Second Letter—capacity tightness: L for Low, M for Medium and H for High. Third Letter—forecast method: G for GARCH model, N for neural network, W for Winters, S for seasonal ARIMA, M for moving average.

Among the models with information sharing, the GARCH, NN7, and seasonal ARIMA models yield significantly lower costs for TC, TCS, and TCR. The supplier and the retailers both benefit from information sharing when advanced forecasting methods are used by the retailers. When information is not shared, advanced forecasting methods such as GARCH and NN7 yield the lowest costs for the supply chain but are not significantly different from other models. However, the results under the same demand pattern, but with capacity tightness at the medium level, are quite different from the results in this table. Under medium capacity tightness, the value of information sharing is not as obvious as the value of information sharing demonstrated here. Thus, capacity tightness plays an important role in affecting a supply chain's performance. Once again, the double exponential smoothing model results in significantly higher costs for the supply chain.

CHAPTER 5

DISCUSSIONS AND CONCLUSIONS

This chapter reports the major findings of this dissertation, discusses implications of those findings, and identifies the limitations and possible future extensions of this research. The primary objective of this study was to investigate the impact of forecasting method selection and information sharing on supply chain performance. Specifically, this study examined the effects of traditional and nontraditional forecasting methods coupled with information sharing on supply chain performance in terms of cost under different demand patterns and levels of capacity tightness.

Support for Hypotheses

Conclusions for the hypotheses are derived from the results of a completely randomized factorial experiment and a multiple comparison procedure following this analysis. Results from Table 4-1 indicate that the forecasting method selection and a number of interactions therewith are statistically significant at the 0.05 level of significance. That is, forecasting method selection by the retailers significantly affects the costs of each firm and of the entire supply chain by interacting with the policy of information sharing and the environmental variables. Examination of Figures 4-5 through 4-11 shows that several advanced models, such as the GARCH model with information sharing, consistently outperform other models under most scenarios, which provides solid support for Hypothesis I.

Compared to the GARCH model, the performance of the neural network models seems to depend more on their configurations. It is noted that NN12 does not perform as well as NN7. The reason for the poor performance of NN12 is not clear, although it may be over-fitting the data.

Zhang & Qi (2005) argued that neural network forecasting models will result in a high variance and poor forecasting accuracy if seasonal or trend patterns are ignored by these models. In addition, they concluded that neural networks built with deseasonalized data and detrended data could produce significantly more accurate forecasts than those with raw data. The poor performance of NN12 may be due to the fact that non-deseasonalized and non-detrended data were used in this study. Moreover, Plummer (2000, p. 49) stated that "neural networks are sometimes unpredictable, and a change in architecture or parameters may result in dramatic changes in performance." Thus, the proper configuration of the neural network model and preprocessing the raw data may improve its performance. In fact, NN7 performs much closer to the GARCH model under most scenarios. Thus, it can be concluded that forecasting model selection significantly affects supply chain performance by interacting with information sharing.

Table 4-1 shows that the demand pattern factor and a number of its interactions are statistically significant at the 0.05 level of significance. That is, demand patterns significantly affect the performance of the forecasting models and the supply chain. In addition, by examining Figure 4-5 through Figure 4-11, one can easily tell that trend and trend with seasonality are relatively stable, while trend with common error and trend with heteroscedasticity are more volatile. In particular, demand patterns with heteroscedasticity are the most volatile. The presence of heteroscedasticity does affect the supply chain performance in some cases. For example, advanced forecasting models such as the GARCH, NN7, and seasonal ARIMA models coupled with information sharing result in higher supply chain costs when capacity tightness is low as compared to other demand patterns. However, in other cases, the presence of heteroscedasticity does not always result in higher supply chain costs as compared to the other demand patterns investigated. However, in general, more volatile demand patterns always result in higher costs for the supply chain. Therefore, we can conclude that Hypothesis II is supported by this simulation study.

This study provides solid evidence to support Hypothesis III, which states that simple forecasting methods significantly influence a supply chain's performance and that the misspecified forecasting models will result in worse system performance. Double exponential smoothing and moving average are considered to be misspecified models in the presence of seasonality and heteroscedasticity. Under most scenarios, the moving average and double exponential models underperform most other forecasting models, especially when information is shared.

Table 4-1 also demonstrates that the factor of capacity tightness and a number of its interactions are statistically significant at the 0.05 level of significance. Examination of Figures 4-5 through 4-11 under different forecasting methods shows that higher capacity tightness will result in higher supply chain costs. When CT is high, the supplier usually has to use most of its capacity to produce in order to meet customer demand. Under this situation, increased setup costs and backorder costs may occur. Thus, higher supply chain cost will be incurred. However, this study also demonstrates that the value of information sharing increases as capacity tightness increases. When CT is medium or low, a supply chain's performance often can improve more from using the supplier's own demand forecasts than from using information sharing. Thus, Hypothesis IV is supported by this study.

Major Findings

From comprehensive simulation experiments and subsequent analysis of the simulation outputs, the important findings are as follows:

- A factorial experimental design was used to determine the significance of forecasting method, information sharing, capacity tightness, and demand patterns and their interactions. Because of the significance of most interactions, the impact of forecasting methods and information sharing were analyzed under different levels of capacity tightness and demand patterns. The value of information sharing depends on demand patterns, capacity tightness, and forecasting method. In some cases, such as when capacity tightness is low, the supplier does not benefit from information sharing since the supplier uses its own forecasting intelligence to forecast future orders and plan its production schedule ahead of time. The effect of forecasting models with information sharing appears to play a more significant role in improving the supply chain as the level of capacity tightness increases. Under most demand patterns, the advanced models tend to group among the models that were the most significant in generating lower costs. Noticeable was the cluster of advanced models consisting of GARCH, neural networks with 7 inputs, and seasonal ARIMA. These advanced models tended to cluster with the better performing models as indicated by Duncan's multiple range tests with a significance level of 5%. It is also observed that the sharing of planned orders is beneficial to the supply chain when demand pattern (such as trend) is relatively stable. However, under temporal demand heteroscedasticity, advanced forecasting methods such as GARCH and NN7 with information sharing usually result in higher supply chain cost. This result is in contrast to Zhao et al. (2002), which states that forecasting methods with increased accuracy coupled with information sharing can yield great cost savings for the supply chain. Our results show the opposite. The difference can be explained by the fact that Zhao et al. (2002) only considers relatively stable demand patterns and also uses a different policy for the case of non-information sharing.

- Results from this study also demonstrate that capacity tightness significantly affects the supply chain performance. Based on the capacitated lot-sizing model, the production plan was optimized during each replanning cycle. Three levels of capacity tightness were investigated in this study. Intuitively, high capacity tightness results in higher supply chain cost since the supplier has to use most of its capacity to produce in order to meet customer demand regardless of the accuracy of the demand forecast. Simply put, the system does not have the flexibility to respond to this useful information, and thus, supply chain performance cannot improve much. Gavirneni et al. (1999) demonstrated that the value of information was lowered by imposing a constraint on the supplier in their model. When capacity tightness is low or medium, the entire supply chain performance improves since the system is able to respond to more accurate demand forecasts. The study shows that as capacity tightness increases, the supply chain performance might not differ significantly under both of the information sharing schemes. Under certain scenarios, the supply chain performance is better off with information sharing when capacity tightness is medium or high rather than low.
- Compared to traditional forecasting methods, advanced forecasting models such as the GARCH and neural network models (configured properly) can capture nonlinear patterns that the traditional forecasting methods cannot and thereby reduce supply chain costs. Thus, it is reasonable for retailers to apply advanced forecasting models to forecast demand so as to improve their own performances. However, the application of advanced forecasting models on the retailers' side does not necessarily help the supplier and the

entire supply chain yield significant cost savings. Thus, it is wise for the supply chain managers to select a forecasting method coupled with other critical factors to reduce the entire supply chain cost. In contrast to the performance of advanced forecasting models, the commonly used simple traditional forecasting methods (moving average and double exponential smoothing) usually result in worse system performance. In particular, double exponential smoothing with information sharing tends to significantly underperform most models under different demand patterns and capacity tightness levels. Of course, patterns with seasonality and heteroscedasticity cannot be captured by a double exponentially smoothed model. Forecasting models misspecified for a demand pattern result in significantly higher supply chain cost. Moreover, this result provides support to prior studies, which demonstrated that suboptimal decision making (regarding forecasting model selection in this case) usually leads to suboptimal supply chain performance.

- The simulation results from this study do not support the expectation that the forecasts from most models will negatively affect supply chain performance under temporal demand heteroscedasticity. However, there are a few cases which show that temporal demand heteroscedasticity results in high supply chain costs. Recent work by Zhang (2007) demonstrates that "ignoring temporal heteroscedasticity can increase firm's inventory costs by as much as 30% when demand autocorrelation is highly positive" (Zhang, 2007, p. 127). Our study is not able to demonstrate the significant effect of temporal demand heteroscedasticity on supply chain performance, perhaps because of the heteroscedastic pattern selected. Further experimentation with other types of heteroscedastic patterns may prove that temporal demand heteroscedasticity can dramatically affect a supply chain's costs.

Implications

The overall conclusion obtained for this study is that the supply chain will benefit from advanced forecasting models, such as the GARCH and neural network models (configured properly), which may allow retailers to better manage their inventories and allow the supplier to better utilize its capacity efficiently under certain scenarios. This study provides guidance for supply chain managers in the following areas:

- When selecting forecasting methods, supply chain managers should have a better understanding of the demand for the product being managed. For example, different forecasting models should be applied for high-tech and low-tech products, respectively, because these two types of products have different demand distributions. Mismatch between forecasting method and demand pattern might result in higher costs for the supply chain. Thus, it is important for the supply chain managers to identify the demand pattern before they make their decisions about which forecasting method should be used to forecast demand.
- Although traditional models such as moving average and double exponential smoothing are widely used in practice due to their simplicity and ease of implementation, supply chain managers should realize the costs impact of the simple forecasting models on supply chain performance and understand when to avoid using these models to keep supply chain cost under control. For instance, double exponential smoothing performs well under the demand pattern with trend only in the case of non-information sharing. However, when information is shared, this model consistently underperforms all other models here investigated.

- In today's SCM, advanced forecasting methods such as the neural network and GARCH models should be promoted in SCM in order to better forecast demand and improve system performance. With the development of new forecasting models, advances in computing power, and availability of large amounts of data, the application of advanced forecasting models in SCM is necessary and important for firms to gain competitive advantages. In addition, supply chain managers should realize that more accurate forecasting models alone might not account for the cost savings achieved for the supply chain. Accurate forecasting models coupled with other operational factors such as information sharing could help improve supply chain performance significantly. Furthermore, great care and skill are needed in order to use these advanced forecasting models properly and make them yield the expected results.
- Environmental factors such as capacity tightness should also be considered when selecting a forecasting method. When capacity tightness is high, the supplier does not have enough capacity to respond to useful information such as accurate demand forecast. Thus, higher costs will occur for the supply chain. For example, when a demand pattern exhibits trend and seasonality with common error and capacity tightness being medium, the results show that advanced forecasting models perform only equally as well as those of simple forecasting models. Thus, it will not make much difference if a simple forecasting model is used under this situation.
- Although the effect of information sharing is not obvious for the supplier in a few cases in this study, the value of information increases as advanced forecasting methods are used by the retailers under stable demand patterns. In practice, it is still reasonable for supply chain managers to consider the effect of information sharing on other aspects of the

supply chain operations because information sharing and coordination are important efforts in improving channel efficiency (Sahin & Robinson, 2005). This study also shows that advanced forecasting methods coupled with information sharing result in higher costs for the supply chain under temporal demand heteroscedasticity, which is consistent with Hung et al. (2008). That is, information sharing is not beneficial to the supply chain in a turbulent market as manifested in the seasonal demand pattern. Therefore, information sharing policy should be carefully selected.

Limitations and Future Research Extensions

Although the findings from this simulation study provide important insights about forecasting method selection and information sharing in a capacitated supply chain, there are also limitations. The limitations of the study and possible issues for future research are listed below.

- This study considered only a simple supply chain consisting of one capacitated supplier and four retailers. However, real supply chains may involve many tiers, each having a large number of chain members. Many possible supply chain structures (such as multiple suppliers and multiple retailers, and multiple-echelon supply chain structures) are available. In order to generalize the results to a more realistic supply chain setting, future research could extend the supply chain structure from two echelons to three echelons consisting of three types of firms: retailer, distributor, and supplier.
- In this study, the supplier uses the single item capacitated lot size rule to make his production decision while the retailers employ EOQ policy to calculate their order quantities in order to replenish their inventories. Other capacitated lot sizing rules in the literature should be investigated in future research. It would be useful to check whether

the conclusions drawn from this study are still valid when using other lot-sizing rules. With regard to retailers, inventory policies other than EOQ should be investigated in future research. EOQ was selected because Zhao et al. (2002) used this method in their simulation study similar to this one. It is noted that EOQ policy is not the optimal policy in this study since some of the demand patterns violate the EOQ assumption, which needs demand to be continuous and relatively stable. The more discontinuous and non-uniform the demand, the less effective EOQs will be. EOQ also assumes that the ordering and inventory holding costs are the only significant ones to consider (Plossl & Orlicky, 1994). In fact, several other approaches are available in determining optimal order quantity when the demand is stochastic, such as lot-for-lot ordering, Silver-Meal heuristic, periodic order quantity, and part-period algorithms (Tersine, 1994). Future research focusing on the impact of alternative production and inventory policies on the supply chain performance may also be a fruitful area.

- In this study, we simulated the capacity constraints by using only three different values of capacity tightness. In the real world, many firms face not only capacity constraints but also production yield uncertainty or even supply chain disruptions. It would be useful to investigate how these factors affect supply chain performance in future research.
- This research focused only on the sharing of planned orders among firms along the supply chain. It would be interesting to evaluate the effect of different information sharing strategies, such as real-time inventory level information sharing, POS data sharing, and production yield information sharing on the performance of a supply chain and determine how the choice of forecasting methods affects the costs and service level for the entire supply chain. Furthermore, information sharing for the supply chain can be

further complicated by privacy and security issues. For example, the members of a supply chain may not want to share sensitive information such as unit cost or capacity related information with the supplier. Thus, future research should investigate how to efficiently manage the supply chain with limited information sharing as well.

- This study investigated the impact of only a few demand patterns. It would be interesting to look at how other demand processes, such as demand with decreasing trend or real data, influence the value of information sharing and supply chain performance. Furthermore, using a GARCH (1,2) rather than GARCH(1,1) or other GARCH error structures to investigate the impact of temporal demand heteroscedasticity on the supply chain performance would be a good research area.
- This study did not investigate the case in which the demand pattern is stationary. Simple traditional forecasting models such as the double exponential smoothing model and the moving average model may be viable competitors to the more advanced models under these conditions.

In conclusion, this dissertation made contributions towards an understanding of the impact of the forecasting method selection on system performance in a realistic supply chain setting. The findings can help supply chain managers select the proper forecasting method coupled with other critical factors such as capacity tightness and information sharing so as to improve the entire supply chain performance. Furthermore, this dissertation pointed out several fruitful areas for future research.

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