Supply Chain Decision Making Under Demand Uncertainty and the Use of Control Systems: A Correlational Study

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Supply Chain Decision Making Under Demand Uncertainty and the Use of Control Systems: A Correlational Study

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Abstract

Decision making under demand uncertainty, a top priority task, has remained as the most challenging problem to many manufacturing leaders due to lack of sufficient information to establish supply chain management (SCM) standard policies. The problem was that business performance could be impeded because optimization models of existing SCM systems lacked appropriate control mechanisms to optimize inventory levels and reduce the bullwhip effect. The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels (OPT) and reduced bullwhip effect (BWE) based on the perceptions of supply chain (SC) senior-level managers of medium-size and large manufacturing firms in the United States. Model predictive control-based inventory optimization (MPC), internal model control-based inventory optimization (IMC), postponement (POS), and collaboration (COL) were used as predictor variables, and SCM performance was the criterion variables as measured by OPT and BWE. A survey was used to collect data from SC senior-level managers. Regression analysis resulted in two significant regression models for OPT and BWE that explained 61% and 49.7 % of the variance respectively for OPT ($p < .05$) and BWE ($p < .05$). As a result, both null hypotheses 1 and 2 were rejected, and support existed for the alternative hypotheses 1 and 2. Practical recommendations included use of MPC to optimize inventory levels, use of POS and COL strategies to reduce the bullwhip effect and optimize inventory levels, and to combine IMC, MPC, POS, and COL to synergistically reduce the bullwhip effect and optimize inventory levels. Recommendations for future research included a replicate quantitative correlation study with expansion to international manufacturing firms, a

quantitative structural equation modeling study to examine relative strength and causal relationships among variables, a quantitative meta-analysis study to critically examine the findings of the study across other studies, a quantitative experimental study to further scrutinize the significant relationships between OPT and BWE, and a quantitative experimental study of archival data to reduce self-selection and self-reporting sampling biases.

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I would like to dedicate this work to my father and my wonderful son Nick. My father taught me the value of education and Nick has been the source of my inspiration to complete this research. Nick's encouragement, understanding, and sacrifices during the final stages of research were invaluable. He has made me so proud over the years with his academic and sports accomplishments.

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Chapter1: Introduction

Good customer service and available inventory increase the profits of a company (Wang, 2011). Manufacturing production managers can provide their product distributors with better customer service by having all products available at all times (Chen, Chen, Parlar, & Xiao, 2011). However, excessive inventory levels lower profits (Kumar & Wilson, 2009). Manufacturing industry leaders have consistently agreed that optimization of inventory levels improves profitability and customer service (Katunzi, 2011; Mizgier, Wagner, & Holyst, 2012). However, optimizing inventory levels to maximize profits is a challenging problem because manufacturing processes are complex and mostly unpredictable. Contextual influences such as changes in customer demands and lead times, lack of collaboration among supply chain (SC) partners, fluctuations in currency exchange rates, and natural disaster disruptions create additional difficulties (Acar, Kadipasaoglu, & Schipperijn, 2010; Zhang, Prajapati, & Peden, 2011). Furthermore, an escalation of customer demands can lead to a discrepancy between supply and demand, which then hinders the efficiency of the product distribution network. This outcome is known as the bullwhip effect (Bray & Mendelson, 2012; Coppini, Rossignoli, Rossi, & Strozzi, 2010). The bullwhip effect occurs when the variance of the manufactured products volume is greater than the variance of the customer orders volume.

To mitigate these difficulties, manufacturing industry leaders have embraced the implementation of responsive supply chain management (SCM) systems. A responsive SCM system can optimize inventory levels and reduce the bullwhip effect within the required timeframes (Williams & Waller, 2011). SCM system responsiveness is characterized as the ability to respond to demand changes expeditiously, in terms of both volume and mix of products (Bottani & Montanari, 2010; Wagner, Grosse-Ruyken, & Erhun, 2012).

The effectiveness and efficiency of a SCM system relies on the accuracy of its mathematical models (Bottani & Montanari, 2010). However, many mathematical models developed for SCM systems are deterministic models created for simplicity and are often tested via linear regression techniques (Badinelli, 2010; Napalkova & Merkuryeva, 2012; Zhang et al., 2011). Stochastic models, also called probabilistic models, are more accurate, as they are developed based on mathematical theories that account for probabilities in real-world manufacturing industry involving events that are uncertain (Badinelli, 2010; Napalkova & Merkuryeva, 2012; Savsar & Aldalhabi, 2012; Zhang et al., 2011). Only stochastic mathematical models can address the randomness of a SCM system statistically via the use of difference or differential equations with deviation parameters (Aharon, Boaz, & Shimrit, 2009; Blavatskyy, 2011; Napalkova & Merkuryeva, 2012; Schwartz & Rivera, 2010). These models can be used to predict optimized inventory levels.

Uncertainty is the lack of access to information sufficient to describe or predict behavior of a system deterministically and numerically (Wang, 2011). Thus, decision making under demand uncertainty remains a difficult problem for manufacturing industry leaders (Acar et al., 2010). However, advanced modern control systems such as model predictive control (MPC) and internal model control (IMC) might handle supply chains uncertainty, thereby allowing manufacturing industry leaders to make faster and more accurate decisions (González & Odloak, 2010; Schwartz & Rivera, 2010).

Background

To acquire a competitive market position, manufacturing industry leaders are challenged to align their SCM systems with respect to operational and financial performances (Datta & Christopher, 2011; Wagner et al., 2012). However, improving internal SC operations does not, by itself, guarantee a competitive market position. Continual increase in demand uncertainty, shorter product life cycles, longer lead times, volatility in supply, and fluctuations in currency exchange rates have all created a challenging environment for manufacturing industry leaders (Acar et al., 2010).

Several production control policies are available to manufacturing industry leaders to improve operational and financial performances of their firms. These policies include push, pull, and a push/pull (hybrid). Manufacturing industry leaders can implement production strategies such as just-in-time (JIT), assemble-to-order (ATO), engineer-to-order, make-to-order (MTO), make-to-stock (MTS), total quality management (TQM), product postponement, safety stock, collaboration, six sigma, and Kanban (Yáñez, Frayret, Leger, & Rousseau, 2009; Kumar & Wilson, 2009). A few advanced control-based inventory optimization models, such as models based on feedback/feedforward, IMC, and MPC, are available to manufacturing industry leaders and may help to improve operational and financial performance by handling demand uncertainty (Schwartz & Rivera, 2010). Determining whether two production control policies have similar effects on the performance of a SCM system is difficult because of complex and unpredictable nature of manufacturing processes (Mascolo & Bollon, 2011).

Motivated by newly developed policies, some SC practitioners have conducted quantitative comparisons among known policies to determine whether a new operation policy will improve the operational and financial performances of a firm (Mascolo & Bollon, 2011). Academic researchers of SCM have also conducted quantitative studies of some of the widely used production control policies based on performance measures of the firms (Agus & Mohd, 2012; Lu, Yang, & Wang, 2011). Although these efforts have led to the identification of several production control policies to reduce demand uncertainty risks, SCM performance is a continuing concern that affects the operational and financial performance of firms (Chin, Li, & Tsai, 2012; Cook, Heiser, & Sengupta, 2011; Golicic & Smith, 2013; Jabbour, Fiho, Viana, & Jabbour, 2011; James & Mbang, 2012; Law & Gunasegaram, 2010). The lack of focus on specific production control policy, inadequate inventory optimization models, and limited examination of SCM sustainability have been identified as potential contributors to impede business performance (Golicic & Smith, 2013). These factors warrant further empirical study in SCM contexts (Golicic & Smith, 2013).

In this study, the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States was investigated. Thus, the study provided a means to identify the special needs of different manufacturing industry firms in coping with demand uncertainty and the bullwhip effect, so that manufacturing industry leaders may select appropriate control mechanisms. Uncertainty and fluctuations in customer demands require more rapid response in inventory levels optimization to ensure high quality customer service and profitability (Lee, 2011). Therefore, a SCM capable of responding to customer demand uncertainty effectively and efficiently, based on any combination of control mechanisms, is highly desirable.

Statement of the Problem

Between 1974 and 2008, two-thirds of 4,689 U.S. companies studied incurred large capital losses because of the bullwhip effect, or the presence of overstocked products (Bray & Mendelson, 2012). Mean orders exceeded customer demands by $20 million quarterly. In May 2001, because of an imbalance between supply and demand for a router product, Cisco faced $2.2 billion in overstocked inventory (Kumar, Chandra, & Seppanen, 2007). The objective of using a responsive SCM system is to reduce the risks of demand uncertainty by optimizing inventory levels and reducing the bullwhip effect, thereby improving profitability and customer service (Mizgier et al., 2012). However, ineffective inventory optimization models or misaligned standard policies have been major sources of failure for many SCM systems (Cook et al., 2011; Chin et al., 2012; Golicic & Smith, 2013; James & Mbang, 2012; Law & Gunasegaram, 2010). As a result, leading manufacturing industry firms have sustained heavy financial losses.

Low levels of SCM performance are a continuing problem, to which SC managers have paid insufficient attention (Fawcett, Fawcett, & Magnan, 2009; James & Mbang, 2012). The problem addressed was that business performance is impeded because inventory optimization models of many existing SCM systems lack appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010). An empirical investigation of the extent to which existing control mechanisms predict optimized inventory levels and reduced the bullwhip effect would assist manufacturing industry leaders in making appropriate decisions under conditions of demand uncertainty (Gligor & Holcomb, 2012; Lo & Power, 2010). Without an empirical comparison among existing control mechanisms, manufacturing industry leaders would not be able to realign their SCM systems and would therefore continue to make decisions without appropriate data, possibly leading to heavy financial losses (Gligor & Holcomb, 2012; Ivanov, 2010).

Purpose of the Study

The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. The predictor variables were four widely used SCM control mechanisms (a) MPC-based inventory optimization, (b) IMC-based inventory optimization, (c) product postponement, and (d) collaboration (Datta & Christopher, 2011; Kumar & Wilson, 2009; Schwartz & Rivera, 2010). SCM performance were the criterion variables, measured in terms of optimized inventory levels, and reduced bullwhip effect. A multiple regression analysis was used to determine the relative contribution of each control mechanism to SCM performance by considering both the individual and collective approach on each of the four control mechanisms (Cook et al., 2011).

Data were gathered using a survey instrument with a 7-point Likert-type scale. The target population comprised 658,871 North America manufacturing industry (see Appendix C). The sampling frame was drawn from a list of SC senior-level managers of medium-size and large (100 or more employees) manufacturing industry firms in the United States with direct involvement in operational and strategic decision-making policies across multiple industries supplied by Infogroup (see Appendix D). Demographic data were also gathered to describe the sample (Gligor & Holcomb, 2012). The minimum sample size was 89 participants, as determined by a power analysis (Faul, Erdfelder, Buchner, & Lang, 2009). A multiple regression analysis was conducted to determine the extent to which the predictor variables predicted the criterion variables of SCM performance.

Theoretical Framework

To gain a competitive market position, manufacturing industry leaders are challenged to align their SCM systems with the operational and financial performances of the firms (Cook et al., 2011; Datta & Christopher, 2011; Katunzi, 2011; Lo & Power 2010). For the strategic management teams within the manufacturing industry firms, there are three theoretical options for achieving the objectives of a competitive market position: (a) structure-based options, (b) strategy-based options, and (c) options based on strategy-structure-performance (SSP; Basu, Mir, Nassiripour, & Wong, 2013). According to the structure-based theory, the manufacturing structure fundamentals of an industry are used to align SCM systems (Basu et al., 2013). In contrast, the strategy-based theory is based on performance optimization. A strategy-based theory is therefore more appealing to strategic management teams (Basu et al., 2013). There have been three research streams within the strategy-based theory of firm performance: (a) the resource-based view (RBV) of the firm; (b) the dynamic capabilities perspective, which buttresses the RBV; and (c) corporate leadership and strategic decision-making (Basu et al., 2013).

Many researchers have expanded the RBV and SSP framework to the SCM context. For example, Gligor and Holcomb (2012) used the SSP and the RBV to examine how the behavioral/relational elements such as coordination, cooperation, and communication affected the operational and relational performances. Chen, Daugherty, and Landry (2009) applied the SSP and the RBV to develop a conceptual model of a SCM. In an exploration of the effects of different SCM practices on SCM performance in the electronics manufacturing industry in Malaysia (Sundram, Ibrahim, & Govindaraju, 2011) the SSP was successfully applied.

In this study, the strategy-based theory was used as the theoretical framework to address the research questions and hypotheses. The dynamic feature of the RBV within the strategy-based theory offered a framework to explain the competitive market position that may be achieved by selecting the appropriate control mechanism to optimize SCM performance. Furthermore, identification of complementary control mechanisms and capabilities can help SC managers combine their resources and more effectively respond to demand changes. SCM performance was measured in terms of both optimized inventory levels and reduced bullwhip effect.

Research Questions

Inventory optimization models of many existing SCM systems lack appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010); as a result, impeding the performance of many business organizations. The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. The four widely used SCM control mechanisms were as the predictor variables in this investigation. These mechanisms are: (a) MPC-based inventory optimization, (b) IMC-based inventory optimization, (c) product postponement, and (d) collaboration (Datta & Christopher, 2011; Kumar & Wilson, 2009; Schwartz & Rivera, 2010). The following research questions guided the study:

Q1. To what extent, if any, is there a relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States?

Q2. To what extent, if any, is there a relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States?

Hypotheses

$H1_0$. There is no statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

H1$_{a}$. There is a statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

H2$_{0}$. There is no statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

H2$_{a}$. There is a significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Nature of the Study

A quantitative method with a correlational design was used in the current study to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing industry firms in the United States (Blome, Schoenherr, & Kaesser, 2013; Cook et al., 2011; Gligor & Holcomb, 2012; Golicic, & Smith, 2013; Law & Gunasekaran, 2010; Tan, Kannan, Hsu, & Leong, 2010). A quantitative method was appropriate since the study was objective-driven, and collected and analyzed numerical data obtained from a survey instrument (Agus & Mohd, 2012; Yanes-Estévez, Oreja-Rodríguez, & García-Pérez, 2010). In contrast, qualitative is a more subjective research methodology where verbal data are gathered through questionnaires and interviews, and therefore, an inappropriate research method since qualitative results are often analyzed and reported in text format (Taneja et al., 2011); while this study was based on extensive empirical calculations and multiple regression analyses. The correlational design was chosen for the study because the study determined whether and to what extent relationships existed between the predictors and criterion variables in a non-experimental setting, and the correlation coefficient served as a comparison reference between the SCM control mechanisms and SCM performance (optimized inventory levels and reduced bullwhip effect). In other words, the strongest correlation coefficient, the most effective control mechanism to optimize SCM performance (optimized inventory levels and reduced bullwhip effect).

The study's predictor variables were: (a) MPC-based inventory optimization; (b) IMC-based inventory optimization; (c) product postponement, and (d) collaboration (Datta & Christopher, 2011; Kumar & Wilson, 2009; Schwartz & Rivera, 2010). SCM performance were the criterion variables, measured in terms of optimized inventory levels, and reduced bullwhip effect. A multiple regression analysis was used to determine each control mechanisms relative contribution to SCM performance by considering both the individual and collective approach of each of the four control mechanisms (Agus & Mohd, 2012; Cook et al., 2011; Gligor & Holcomb, 2012). To answer the research questions and to test the hypotheses, a survey instrument with a 7-point Likert-type scale was used to collect data. Demographic data were also gathered to describe the sample (Gligor & Holcomb, 2012). The target population comprised 658,871 North America manufacturing industry (see Appendix C). The sampling frame was drawn from a list of SC senior-level managers of medium-size and large (100 or more employees) manufacturing industry firms in the United States with direct involvement in operational and strategic decision-making policies across multiple industries supplied by Infogroup (see Appendix D). The minimum sample size was 89 participants, as determined by a power analysis (Faul et al., 2009). A multiple regression analysis was conducted to determine whether the predictor variables predicted the criterion variables of SCM performance (Agus & Mohd, 2012; Cook et al., 2011; Gligor & Holcomb, 2012). Prior testing of the study's hypotheses, using Minitab® statistical software and visual examination of the appropriate plots, along with several tests conducted to check the validity of regression assumptions: (a) linearity, (b) independence of the errors, (c) homoscedasticity, and (d) normality occurred. Finally, to determine the strength associated with each of the predictor and the criterion variables, a multiple regression analysis was conducted using the Minitab® software.

Significance of the Study

Demand uncertainty has negative impact on SCM performance, which is measured by lower productivity and reduced customer satisfaction (Charan, 2012; Datta & Christopher, 2011; Field, Ritzman, Safizadeh, & Downing, 2006; Wang, 2011). The task of identifying sources of demand uncertainty is therefore receiving increasing attention from business leaders in manufacturing firms. Academic researchers of SCM have conducted quantitative studies on production control policies based on operational and financial performance measures (Agus & Mohd, 2012; Furlan, Vinelli, & Giorgia, 2011; Liao, Deng, & Marsillac, 2013; Lu et al., 2011; Wiengarten, Humphreys, Cao, Fynes, & McKittrick, 2010; Yang, Yang, & Williams, 2010). SC practitioners have also assessed whether a new operation policy would improve the operational and financial performances of a firm (Mascolo & Bollon, 2011). However, SCM performance remains an ongoing problem that has affected operational and financial performance, and researchers have recommended further empirical investigation to determine the effectiveness of existing SCM control mechanisms (Cook et al., 2011; Chin et al., 2012; Golicic & Smith, 2013; Jabbour et al., 2011; James & Mbang, 2012; Jüttner & Maklan, 2011; Law & Gunasegaram, 2010). Production control policies can be related, and a combination of lean practices may work synergistically toward improving SCM performance (Furlan et al., 2011). This study may contribute to an understanding of this process.

Academic researchers and practitioners of SCM have identified several production control policies and advanced control-based inventory optimization models to optimize inventory levels and to reduce the bullwhip effect. However, these studies fall short in SCM performance alignment from a holistic perspective (Furlan et al., 2011; Sun, Hsu, & Hwang, 2009). Often, the choices regarding the SCM control mechanism were made based on the paradigm of an industry and its SCM surroundings (Bemporad & Di Cairano, 2011; Garcia, Hernandez, Vilanova & Cuartas, 2012; González & Odloak, 2010; Schwartz & Rivera, 2010). The SC managers believed that using mathematical inventory optimization models based on IMC and MPC were necessary to optimize inventory levels. Product postponement was used to handle manufacturing demand uncertainty by establishing a lean inventory control policy (Huang & Li, 2009; Kumar &

Wilson, 2009; Liao et al., 2013; Yang et al., 2010). Collaboration was the most commonly found SCM control mechanism for the flow of information and synchronization of decisions regarding capacities and material flows (Bayraktar, Demirbag, Koh, Tatoglu, & Zaim, 2009; Datta & Christopher, 2011; Furlan et al., 2011; Weingarten et al., 2010). Collaboration was considered to reduce the bullwhip effect. In addition to the lack of a cohesive and holistic perspective regarding SCM performance alignment, a reason for the need for further research is the lack of measurement reliability (Li, Ragu-Nathan, Ragu-Nathan, & Rao, 2006).

In the present study, the gap in the literature was addressed by identifying the effectiveness level of and by linking each group of control mechanisms to SCM performance. This study contributes to the literature by improving the understanding of commonalities and differences among SCM control mechanisms, the observed effectiveness in inventory optimization levels, and the extent to which the bullwhip effect was reduced. The findings of the current study may provide manufacturing industry leaders with guidance to assess the level of responsiveness of their SCM in reducing demand uncertainty while optimizing inventory levels and reducing the bullwhip effect (Katunzi, 2011; Mizgier et al., 2012). These changes may lead to increased profitability and improved customer service. The estimated total inventory assets of all U.S. retailers in 2007 were $496 billion, representing 36% of total assets (Dedeke & Watson, 2008). Thus, optimization inventory levels and reducing the bullwhip effect would provide a substantial benefit to manufacturing industry firms.

Inefficiency and inaccuracy in the inventory optimization models lead to inaccurate inventory data, a leading cause of financial losses. For example, because of an imbalance between supply and demand for a router product, Cisco faced $2.2 billion in overstocked inventory in May 2001 (Kumar et al., 2007). By means of direct comparisons among the existing inventory control mechanisms utilized by manufacturing industry firms, the findings of this study addressed the gap of knowledge related to the effect of these mechanisms on SCM performance. Finally, the findings may provide manufacturing industry leaders with data-driven decision-making options, rather than speculation to handle demand uncertainty and the bullwhip effect. These increased options to optimize inventory levels and reduce the bullwhip effect may lead to increased profitability and customer satisfaction.

Definition of Key Terms

Assemble to order (ATO). Assemble to order is an operational strategy that involves having the same core assemblies for most products and the ability to vary all other components at the final stage of the production (Simchi-Levi & Zhao, 2005).

Bullwhip effect. The bullwhip effect is a SCM system phenomenon in which an escalation of customer demands can lead to a discrepancy between supply and demand, thereby hindering the efficiency of the product distribution network (Bray & Mendelson, 2012; Coppini et al., 2010).

Bullwhip effect factor. The bullwhip effect factor is a measure of the amount of volatility that occurs when the variance of supply is greater than the variance of customer demands (Cachon, Randall, & Schmit, 2007).

Bullwhip effect reducing response time. The bullwhip effect reducing response time is a period of time that a SCM system takes to reduce the bullwhip effect to the level defined by tactical decision-making policies (Datta & Christopher, 2011).

Closed-loop control. A closed-loop control is a system that can optimize the performance of a process by delivering the desired input value, known as the set point. A sensing mechanism monitors the system output, which is then compared with the set point. If the output exceeds the set point, an error signal is generated. The system will minimize the error and maximize the process performance. A closed-loop control system is also known as a feedback control system (Kilian, 2006).

Customer demand. Customer demand is the volume of finished goods and products requested by the retailers (Skipworth & Harrison, 2006). The customer demand is also known as customer orders.

Customer demand lead-time. The customer demands lead-time is the time between ordering and receiving a product (Wangphanich, Kara, & Kayis, 2010). The customer demands lead-time is also known as the order lead-time.

Demand uncertainty. Demand uncertainty is a SC environmental effect, which often will lead to operational inefficiencies in manufacturing firms such as inability to optimize inventory levels, poor customer demand forecasts, uncertain customer demand lead times, and inability to develop production plan (Chaharsooghi & Heydari, 2010).

Deterministic. Deterministic is an adjective used to quantify nonrandom variables. For example, customer demands and customer lead times are two deterministic values for an online business in which the customers determine the number of ordered products and delivery time (Biswas & Narahari, 2004).

Echelon. The echelon is the number of stages between suppliers and consumers in a SCM system. For example, a SCM system consisting of a supplier and several independent distributors is a two-echelon system. A multiechelon system has more than two stages (Cachon et al., 2007).

Engineer to order (ETO). The ETO is an operational strategy applied to industrial firms in which products are designed and engineered based on customer specifications. Products are made only after receiving the customers' agreement because ETO requires highly specialized equipment and machinery (Zimmermann, 2000).

Factory throughput lead-time. Factory throughput lead-time is the time between the release of an order to production assembly and shipment to the final customer (Wangphanich et al., 2010).

Feedforward. Feedforward is a type of control system for which the set point has been defined as the place the users select for the controlled variable (Kilian, 2006).

Inventory target levels. The inventory target levels are reference levels that maintain optimized inventory levels. The inventory target levels need not be constant and can change (Schwartz & Rivera, 2010).

Lead times. Lead times refer to the amount of time required to finish a task or a process. The operational policies incorporate the production lead times and supply lead times throughout the SCM system (Acar et al., 2010).

Make-to-stock (MTS). The MTS is an operational strategy and part of push-control strategy to reduce the risk of customer demand uncertainty. The MTS policy requires that finished goods and products are stored in several strategic locations before receipt of customer orders (Biswas & Narahari, 2004).

Mixed integer programming (MIP). MIP is a mathematical modeling technique in which large-scale problems are reduced to problems with reasonable computation time (Kreipl & Pinedo, 2004).

Multiagent. Multiagent is a term describing a SCM system that has more than one stage between the suppliers and consumers (Cachon et al., 2007). A multiagent system is also called a multiechelon system.

Open loop. An open loop is a term describing a control system that lacks a feedback mechanism. The controller sends the measured signal to the processing unit, which specifies the desired action. This type of control system is not self-correcting (Kilian, 2006).

Operational decision-making. Operational decision-making is a short-term business process that requires a timeframe between 1 and 7 days for evaluation and modifications. Operational decisions incorporate the uncertainties in customer demands, production lead times, and supply lead times (Acar et al., 2010).

Optimization. Optimization is a procedure or a set of procedures that make a system as effective as possible. Optimization often implies the use of special mathematical and control theories. Optimization tends to result in answers that yield the best outcomes, such as the highest profit, the lowest cost, and lowest inventory levels in a SCM system. Computer-based inventory optimization algorithms can sift the billions of possible combinations of products, sources, warehouses, transport modes, and customer allocations to arrive at a true, global optimum (Almeder, Preusser, & Hartl, 2009).

Optimized inventory levels. Optimized inventory levels, also known as inventory positions, are the total number of products stored at each echelon

(Wangphanich et al., 2010). The inventory optimization model of a SCM system quantifies the optimized inventory level based on the inventory target level.

Optimized inventory levels settle time. The optimized inventory levels settle time is the time needed for optimized inventory levels to reach the steady-state level (Schwartz & Rivera, 2010).

Proportional integral derivative (PID). PID represents three basic feedback control loops: proportional (P), integral (I), and derivative (D). Performance of a control system can improve by applying one or combination of these three feedback loops. The integral feedback loop tends to reduce the steady-state error, and the derivative feedback loop provides faster responses (Kilian, 2006). Although the proportional, integral, proportional-integral, and proportional-derivative feedback loops are widely used in inventory optimization, the derivate feedback loop is rarely used on its own (Kilian, 2006). The PIDs have broad industrial applications because of an acceptable performance despite their relative simplicity. PIDs offer wide range of tuning and autotuning methods that have been devised since 1950 (Veronesi & Visioli, 2011).

Pull-control strategies. The inventory levels in pull-control strategies are set by actual customer demands and after shipping products to the customers, no excessive inventory is left behind (Chan, Yin, & Chan, 2010; Mascolo & Bollon, 2011).

Push-control strategies. The inventory levels in push-control strategies are set by the customer demands forecast (Cochran & Kaylani, 2008; Koulouriotis et al., 2010). These strategies tend to lead to a maximization of the production inventory levels so that the risk of product shortage is minimized (Koulouriotis et al., 2010).

Push-pull (hybrid) strategies. The hybrid strategies are form of production flow control policies that combine elements of both pull and push strategies to minimize inventory levels while meeting customer demands (Cochran & Kaylani, 2008).

Rationing game. The rationing game is a supplier strategy in which customer demands exceed production. During a product shortage, production managers ration the supply of the product to satisfy all customers (Lee, Padmanabhan, & Whang, 2004).

Safety stock inventory (SSI). A SSI is excess inventory maintained by leaders of industrial firms to avoid the cost associated with uncertain supply and demand. The amount of SSI that a firm holds is a measure of the relative uncertainty of the product demand, supply of components, or both. When supply and demand are constant, as in JIT systems, SSI is at a minimum (Holsenback & McGill, 2007).

Simulation. Simulation is an imitation of some real world thing, state of affairs, or process. The act of simulating something generally entails representing certain key characteristics or behaviors of a selected system. Simulating a supply chain provides a valuable validation step that allows the comparison of the model to the real world to ensure that all key costs and relationships have been considered correctly before a new scenario is tested. Simulation models typically allow an assessment of scenarios in which only one input variable has been changed (Zhang & Dilts, 2004).

Strategic decision-making. Strategic decision-making is a business process that requires a timeframe between 5 and 20 years for evaluation and modifications. The number of facilities and their locations such as suppliers, warehouses, and distribution centers are examples of decisions made as part of strategic decision-making processes (Neale & Willems, 2009).

Supply chain (SC). A supply chain is a network of suppliers and product distributers, to deliver finished goods and products from the production sites to customers (Santoso, Ahmed, Goetschalckx, & Shapiro, 2004).

Supply chain management (SCM). A SCM is a set of synchronized decision-making policies and a series of supply and demand processes that enable product distributor managers to deliver products and goods efficiently and expeditiously from the production sites to the customers (Bottani & Montanari, 2010; Janvier-James, 2012; Wangphanich et al., 2010).

Supply chain management (SCM) **system**. A SCM system is an incorporation of an inventory optimization system and a simulation module based on mathematical models representing dynamic and static modes of operations (Acar et al., 2010; Napalkova & Merkuryeva, 2012).

Tactical decision-making. Tactical decision-making is a midrange business process that requires a timeframe between 30 to 90 days for evaluation and modifications. Tactical decisions are related to production, distribution, and earnings (Aberdeen Group, 2004).

Uncertainty. Uncertainty is the lack of access to information sufficient to describe, prescribe, or predict a system, its behavior, or another characteristic deterministically and numerically (Zimmermann, 2000).

Summary

Chapter 1 has included a comprehensive background on supply chain decision making under demand uncertainty, which is the topic of the current study. The chapter continued with the statement of the problem and the purpose of the research, which provided readers with evidence of the continued chronicled problem with SCM performance due to demand uncertainty. The statement of the problem highlighted manufacturing industry firm financial losses due to lack of appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010). The purpose of study declared for a quantitative, correlational study investigating the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. Anchored by the problem statement, an extended theoretical knowledge to the strategy-based theory was used as the theoretical framework to address the research questions and hypotheses (Basu et al., 2013). The research objectives were expressed in term of two research questions to assess potential relationships between IMC-based inventory optimization, MPC-based inventory optimization, product postponement, collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States, and potential relationships between IMC-based inventory optimization, MPC-based inventory optimization, product postponement, collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Given the knowledge gap in the current literature, the significance of the study is to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. One of the contributions of the study may be to convert the inefficient and inaccurate SCMs to more efficient SCMs, enabling manufacturing industry leaders to prevent huge financial losses due demand uncertainty and bullwhip effect. Inefficiency and inaccuracy of the inventory optimization models lead to inaccurate inventory data, the major leading cause of financial losses. Finally, this chapter included reviews of topic-related literature, definitions, and terminologies, which are significant to the study and provide a reference for terms and definitions that may be technical in nature and/or subject to multiple meanings; thus, avoiding possible misinterpretation.

Chapter 2: Literature Review

The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of supply chain (SC) senior-level managers of medium-size and large manufacturing firms in the United States. The four widely used SCM control mechanisms were the predictor variables in this investigation. These mechanisms are: (a) MPC-based inventory optimization, (b) IMC-based inventory optimization, (c) product postponement, and (d) collaboration (Datta & Christopher, 2011; Kumar & Wilson, 2009; Schwartz & Rivera, 2010). The problem was that business performance is impeded because inventory optimization models of many existing manufacturing SCM systems lack appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010). A review of the current literature and an overarching landscape of the problem statement in the current study is provided in this chapter. The following eight themes; (a) SCM control mechanisms, (b) product postponement (c) collaboration, (d) SC performance, (e) optimization inventory levels under demand uncertainty, (f) bullwhip effect, (g) IMC-based and MPC-based controllers, and (h) simulation-based optimization are discussed in detail in that order.

Documentation

The literature was sourced from scholarly, peer-reviewed references, which were searched in ABI Inform, Elsevier, Emerald, EBSCOhost Business Source Complete, ScienceDirect, ProQuest, and Google online databases. The search keywords included (a) *demand uncertainty*, (b) *demand forecasting*, (c) *customer demands*, (d) *model* *predictive control*, (e) *internal model control*, (f) *feedback control*, (g) *feedforward control*, (h) *inventory optimization*, (i) *simulation*, (j) *production control strategies*, (k) *postponement*, (l) *collaboration*, (m) *just-in-time*, (n) *make-to-order*, (o) *assemble-to-order*, (p) *make-to-stock*, (q) *safety stock inventory*, (r) *Kanban*, (s) *bullwhip effect*, and (t) *supply chain management.*

Historical Overview

Alderson (1950) was the first academic researcher of SCM who introduced the product postponement concept to the marketing literature. However, only recently product postponement became an applicable and viable strategy with advancement of information technology (IT). The first scientific study by Forrester (1961) identified the nonlinearity of interactions and lack of information sharing among subdivisions of a SC system as the main cause of bullwhip effect. Tsiakis, Shah, and Pantelides (2001) used a multi-commodity model where the customers demand was considered as a stochastic parameter. Braun, Rivera, Flores, Carlyle, and Kempf (2003) applied a partially decentralized MPC configuration for inventory control of a SCM system where stochastic parameters were used for the customer demands. Svensson (2003) pointed out that the bullwhip effect in a firm's SCM system was based on the gap between the degree of speculation and postponement of business activities. In other words, the bullwhip effect is caused by the value added to business activities. Jung, Blau, Pekny, Reklaitis, and Eversdyk (2004) exploited a simulation-based optimization scheme to incorporate the safety stock strategy into the inventory levels of a SCM system. Santoso et al. (2004) developed a SC product distribution network based on the stochastic parameters. In a JIT study, researchers Wang and Sarker (2004) used Kanban control in conjunction with mixed integer nonlinear programming technique to develop an inventory optimization model for a multi-echelon SCM system. Wal-Mart became the icon of JIT philosophy by developing a technique called *cross-docking*, which transfers the finished products from carrier-to-carrier on the warehouse dock in less than 24 hours (Wal-Mart Annual Report, 2006). Because of such a fast shipping process, the Wal-Mart retail managers have been able to minimize their inventory levels while maintaining a mobile minimum safety inventory (Wal-Mart Annual Report, 2006). Schwartz, Wang, and Rivera (2006) used MPC-based decision-making policies for inventory optimization of a semiconductor-manufacturing industry firm. Shi and You (2007) constructed a dynamic probabilistic network under uncertainty using the stochastic parameters.

SCM Control Mechanisms

Production control is an operational policy that plays an important role in controlling the inventory levels within the SCM system. Koulouriotis, Xanthopoulos, and Tourassis (2010) noted that an efficient flow of materials at manufacturing sites involves an effective production control policy that enables retail managers to meet customer demands with marginal profits in a competitive marketplace. SC managers and academic researchers of SCM have offered many different production control policies. However, Koulouriotis et al. (2010) divided these policies into two major categories: pull-control strategies and push-control strategies. In other studies, Chan, Yin, and Chan (2010), Mascolo and Bollon (2011), and Lu et al. (2011) found evidence of SCM performance improvement associated with the use of pull-type production control strategies; thus, production managers have characterized these strategies as *inventory reduction techniques*. For example**,** having combined two constant work-in-processes

(CONWIP), Lu et al. (2011) developed a lean pull control strategy to lower the risks of demand uncertainty in a multi-product, multi-stage SCM system. Creating a bottleneck (buffer zone) in the path of product development processes that are controlled by two CONWIP allowed production managers to maintain a continuous flow of material toward downstream (Lu et al., 2011). In fact, customer demand uncertainty was treated as a noise factor within an elaborate mathematical model and this unique feature increased the robustness of their proposed SCM system. Having tested the newly developed lean pull control strategy in a real world thin film transistor-liquid crystal display manufacturing company, as a case study under demand uncertainty, the research findings revealed that the average cycle time reduced from 15.4 days to 4.82 days without any loss of throughput, which was a large capital gain for the thin film transistor-liquid crystal display manufacturing company (Lu et al., 2011).

Many pull-type control strategy peer-reviewed articles existed within the body of current literature, which indicates a wide range of pull-type control strategy applications for controlling inventory levels of SCM systems. An example of the pull-type control strategies is the JIT philosophy (also known as JIT lean practices). Harrison and van Hoek (2008) described that JIT is a set of SCM lean practices, which reduces the inventory levels by requiring that parts and components be delivered just as they are needed for production and not before. Danese, Romano, and Bortolotti, (2012) emphasized that JIT lean practices are known as a powerful tool to reduce waste and inefficiency, increase production speed, and delivery performance. However, under a meta-analysis design and qualitative correlation method study, Mackelprang and Nair (2010) investigated the relationship between JIT lean practices and SCM performance within the body of literature spanning from 1992 to 2008. The study was based on two main objectives: identifying correlation between aggregate JIT lean practices and aggregate SCM performance as a group of JIT lean practices and examining the relationships among individual JIT lean practices and SCM performance. The results of Mackelprang and Nair's investigation revealed that there were positive relationships between aggregate JIT and aggregate SCM performance as an individual and a group of lean practices. The findings also suggested; however, about 25% of all individual JIT lean practices' performance resulted in no significant improvement due to weaker moderating factors. In other words, effectiveness of the JIT lean practices were influenced by moderating factors; therefore, expectations should be adjusted accordingly (Mackelprang & Nair 2010).

According to Agus and Mohd (2012), Kanban is a pull control strategy such that raw materials and/or work-in-progress are delivered to downstream echelons only by request with the exact amount of material and at the right time. Some SC practitioners have recommended that the use of Kanban lean practice will enhance the JIT philosophy. For example, in an empirical JIT philosophy study, researchers Koulouriotis et al. (2010) examined the effectiveness of several pull-type production control policies on SCM performance improvement. These pull-type production control policies were: (a) Kanban, (b) Base Stock, (c) CONWIP, (d) hybrid (CONWIP/Kanban), and (e) Extended Kanban. Koulouriotis et al. conducted an empirical analysis using a stochastic-based simulation engine and generated manufacturing data on two separate serial manufacturing lines and two separate assembly systems. Koulouriotis et al. claimed that generalized and extended Kanban mechanisms outperformed less-sophisticated mechanisms such as the

Kanban and the Base Stock. However, the study lacked from a holistic SCM perspective, because it was limited to intra-specific firm capabilities, which was based on conceptual discussion of production operations strategy. The study also lacked practical application significance because of the absence of real-world manufacturing data since generated data were used in the study. Furlan et al. (2011) conducted an empirical analysis study where JIT philosophy and total quality management (TQM) lean practice were used as a complementary control mechanism to improve SCM performance. Predictor variables of the study were JIT, TQM, and human resource management (HRM) and SCM performance was the only criterion variable. A survey instrument with a 7-point Likert scale was used to collect SC quantitative data. The survey included 26 items: (a) seven items for JIT, (b) five items for TQM, (c) eight items for HRM, and (d) six items for performance. The survey instrument was administered to 266 industrial firms with more than 100 employees. Demographic data were also gathered to describe the sample profile. Among the demographic data, age and size of the firm, which respectively were measured by the number years since establishment and number of employees working at the plant, were selected as two control variables. The targeted populations were electronics, machinery, and transportation industries within nine nations; Austria, Finland, Germany, Italy, Japan, Korea, Spain, Sweden, and USA. The sampling frame consisted of plant accounting managers, human resource managers, information systems managers, production control managers, inventory managers, product design engineers, process engineers, plant managers, quality managers, and plant superintendents. Furlan et al. examined the relationship between JIT philosophy and TQM lean practice, and their complementary effects on SCM performance. Furlan et al. demonstrated that JIT and

TQM complemented each other. Furthermore, HRM lean practice was a good catalyst to enhance the complementarity relationship between TQM and JIT. While Furlan et al. gathered a significant amount of global quantitative SCM data over a period of 2 years to test the hypotheses of their study, the study results may not have contributed as significantly to the SCM design body of knowledge as the researchers claimed. For example, it was critical that Furlan et al. include the financial performance of the firm as a criterion variable in their study while examining the relationship between JIT philosophy and TQM practice, and their complementary effects on SCM performance. An addition of a lean practice to a SCM system is often costly; therefore, cost analysis would have been the only method to justify the burden of such an investment for SCM improvements (Pong & Mitchell, 2012).

Mackelprang and Nair (2010) and Furlan et al. (2011) have found a lack of significant relationships between some of the JIT practices and SCM performance. Therefore, they recommended further investigation between JIT practices and SCM performance relationships. In their studies, Mackelprang and Nair argued that 25% of all the associations between JIT practices and SCM performance were contingent to moderating factors (catalysts). Based on Mackelprang and Nair's recommendations, Danese et al. (2012) conducted a hierarchical regression analysis by investigating the interaction between JIT production and JIT supply practices and their impact on the efficiency and delivery of SCM performance. Danese et al. used a survey instrument to collect mechanical, electronics, and transportation equipment firm data from Finland, USA, Japan, Germany, Sweden, Italy, and Austria. The results of the study indicated that JIT production practices positively affected both SCM efficiency and product delivery.

In addition, JIT supply practices positively moderated the relationship between JIT production and product delivery; while, there was an insignificant moderating factor on efficiency. Danese et al.'s study significantly contributed to resolution of an overdue debate on the relationship between JIT practices and SCM performance because they conducted separate analysis on the supply and production parts of a SCM system.

Using an event study methodology, Shafer and Moeller (2012) investigated the impact of Six Sigma on SCM performance improvement over a period of 10 years. The 10-year event consisted of (a) 3 years prior to Six Sigma implementation, (b) the year Six Sigma was adopted, and (c) 6 years post Six Sigma implementation. Having applied rigorously the control variables to ensure the validity of the comparisons and analyzing the collected data and information from 84 Six Sigma industrial firms with a wide range of activities, Shafer and Moeller concluded that Six Sigma implementation positively influenced the firms' organizational performance only through employee efficiency and improvement.

Rahman, Laosirihongthong, and Sohal (2010) investigated the associations between 13 lean practices and SCM performance. Using a survey questionnaire, data were collected for 13 lean practices: (a) reducing production lot size, (b) reducing setup time, (c) focusing on single supplier, (d) implementing preventive maintenance activities, (e) cycle time reduction, (f) reducing inventory to expose manufacturing, distribution and scheduling problems, (g) using new process equipment or technologies, (h) using quick changeover techniques, (i) continuous/one piece flow, (j) using pull-based production system/Kanban, (k) removing bottlenecks, (l) using error proofing techniques/Pokayoke; and (m) eliminate waste. A total of 424 questionnaires were sent to middle and senior managers of Thai manufacturing industry firms and 187 questionnaires (44.1%) were completed. To reduce the complexity of data analysis, Rahman et al. bundled these 13 lean practices in the form of three predictors; (a) JIT, (b) waste minimization, and (c) flow management, and SCM performance was the only criterion of the study. A multiple regression analysis was used to investigate the associations between these three predictors and SCM operational performance. The SCM operational performance was measured in terms of (a) quick delivery compared to competitors, (b) unit cost of products relative to competitors, (c) overall productivity, and (d) customer satisfaction. Rahman et al. concluded that JIT had a higher level of significance in large firms (LEs) compared to small and medium size firms (SMEs); while, waste minimization had reverse results. In other words, waste minimization had higher influence on SCM performance within the SME firms in comparison to the LE firms. Rahman et al.'s study was limited to intra-firm capabilities in conceptual discussion of operations strategy and lacked fundamentals. For example, SMEs were considered to be firms with 200 or fewer employees; while, LE firms had more than 200 employees. Rahman et al.'s study and analysis was based on an extremely narrow breakpoint control variable and requires further studies.

Product Postponement

As stated by Kumar and Wilson (2009) and Huang and Li (2009), product postponement is a SCM lean strategy that refers to the delay of finished goods and products movement until customer orders are received, and reduces the risk of storing finished products in wrong locations. Over time, the product postponement lean strategy has become an effective global marketing tool overarching product design, production, logistics, and marketing of a SCM system. In practice, the product postponement strategy is applied to mass customization (MC) where the push and pull control product policies interface in an area called push-pull boundary (PPB; Rossin 2012; see Figure 1). Brun and Zorzini (2009) noted that product postponement could be extended from product design in manufacturing to beyond the point at which the end-user receives the product. In a full factor research design, Rossin (2012) studied the impact of the combination information quality and PPB on SCM performance, and the findings of the study demonstrated that both PPB and information quality had significant positive impact on SCM performance. Rossin concluded that location of PPB, driven by demand uncertainty and availability of economies of scale in production, played an important role in SCM performance. In a separate study, findings of Yang et al. (2010) confirmed that identifying accurate location of PPB in a product postponement strategy development plan could increase the amount of process steps to complete a product in advance, thus reducing operational costs and shortening service delivery time. Applying a set of real-world qualitative SCM data from an electronics industry in the US on a highly-volatile daily demand uncertainty product, Kumar and Wilson (2009) investigated the link between off-shoring postponement and inventory levels as well as the benefits and costs associated with each postponement. The outcomes of the study identified an appropriate strategy, which benefitted less than 1% of the total cost. Although, the cost savings under given conditions might not be significant enough to consider the off-shoring postponement as the best strategy, other factors, such as corporate culture and external influences, and other factors that do not necessarily manifest themselves in the costs needed to be considered(Kumar & Wilson, 2009). Overall, the study lacked generalizability, in particular with product volatility demand and off-shoring postponement applications within the industrial world of manufacturing. Wage rates are often much lower in off-shoring service provider nations such as China and India, so the savings cost of off-shoring postponement should have been much higher than 1%.

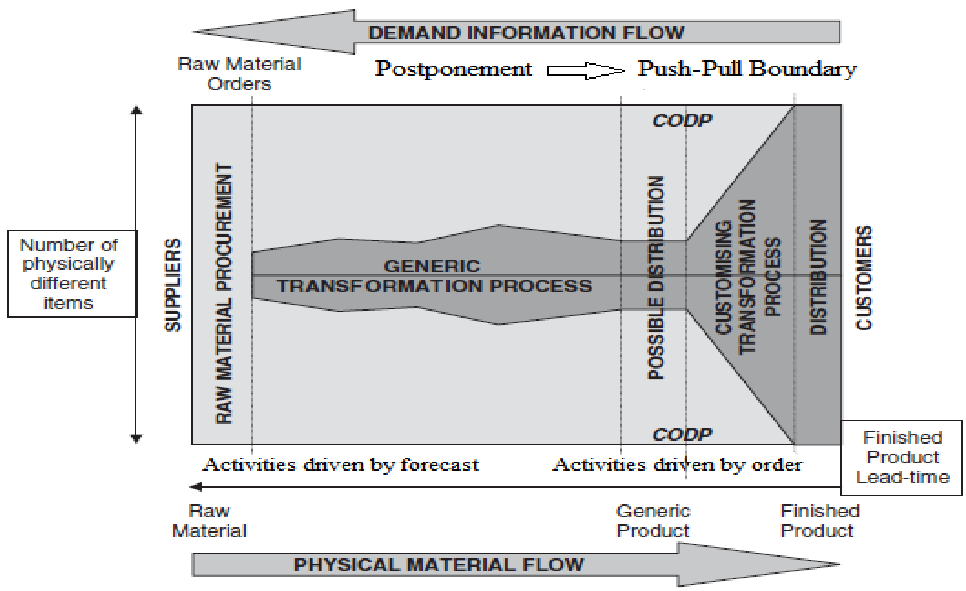

Figure 1. Push-Pull boundary location and product postponement diagram.

Adapted from "Implications of form postponement to manufacturing a customized product," by H. Skipworth and A. Harrison, 2006, *International Journal of Production Research, 44*(8), 1627-1652.

The impact of product related to contextual factors on choices made by 20 Italian companies was the focus of Brun and Zorzini's (2009) case study as they investigated the relationships between product postponement and modularization practices. The research was based on a multi-case study strategy and benefited from factor analysis. The two major factors identified from customer profiles and supplier perspectives were the customization degree of product and the complexity level of product (Brun & Zorzini, 2009). Four different customization strategies in terms of SC structure were included in the framework of the study: (a) rigid, (b) flexible, (c) postponed, and (d) modularized structures. The research findings declared that postponement strategy was only implemented for simple, yet highly customized products; while, modularization was preferred for more complicated products with low customization. The targeted populations were 20 wide-range industrial firms; therefore, the findings of the study can be relatively considered as generalized results and applicable to the rest of manufacturing industries. However, no cost analysis was conducted on the customization strategies, which is an important factor in business marginal profits. Cost control and product differentiation are two major elements of mass customization, which require substantial SCM managerial skills supported by real-word data (Brun & Zorzini, 2009).

Liao et al. (2013) investigated the factors that influence Chinese automotive mass customization supplier capabilities. Developing a collaboration theoretical model and establishing relationships between the exogenous constructs: (a) tactical alignment, (b) product modularity design, (c) process modularity design, (d) postponement practices, (e) supplier segmentation, and (f) mass customization capabilities (endogenous construct), researchers conducted an empirical quantitative study using SEM to test the hypotheses and the model validity. A survey instrument with a 5-point Likert scale was used to collect data. The survey contained 20 items: (a) four items for tactical alignment, (b) three items for product modularity design, (c) three items for process modularity design, (d) four items for postponement practices, (e) three items for supplier segmentation, and (f) three items for mass customization capabilities. Demographic data were also gathered to describe the sample. The survey instrument was pretested in an elaborate scheme. First, the survey instrument was developed in both English and Chinese languages and pretested by two different bilingual SCM practitioners and academic researchers of SCM.

Second, the English and Chinese language surveys were compared for translation accuracy by SCM practitioner and academic researchers of SCM. Third, after minor revisions to the Chinese version, the survey instrument was sent to a senior SC manager of an automotive manufacturing firm and a vice president of an automotive supplier in China and no changes were recommended. The targeted populations were Chinese and Japanese automotive industry and survey instrument was emailed in two separate waves to 421 production plants and supplier firms in an elaborate operation scheme. The sampling frame consisted of purchasing managers, supply chain managers, vice presidents of manufacturing or purchasing. The survey response rate was 41.1% as 173 usable responses were received. While, the minimum sample size was unspecified by the power analysis, the measured items were reliability tested using Cronbach alpha. The Cronbach's alpha values of the constructs were close to or above the commonly acceptable level of .70, which indicated that potential threats to internal validity were minimized. Furthermore, a series of internal validity tests: (a) content, (b) convergent, and (c) discriminant validities were conducted prior to CFA analysis and SEM assessment. The researchers gathered significant amounts of valid data to test the hypotheses and they made significant contribution to Chinese automotive suppliers understanding of mass customization capabilities. However, the study lacked generalizability, in particular with the SEM model design concept and its industrial applications. For example, while the sampling pattern did not follow the Gaussian (normal) distribution, the selected sampling frame by the researchers covered almost a uniform pattern of the respondents. While the study investigated the Chinese automotive suppliers mass customization capabilities, the data were collected only from specific regions in China, which consisted of a small population. An unexpected, but significant finding of the study was the lack of support for the product postponement lean policy, which was manifested by lack of IT infrastructure and support within the Chinese automotive industry. Similar findings and observations have been experienced in other studies where lack of IT infrastructure and support have negatively influenced production control strategies such as postponement and collaboration as noted by Bayraktar et al. (2009) and Yang et al. (2010). Finally, most of the SEM modeling data were gathered in the USA and some European countries using survey instruments (Huang & Li, 2009). Although, product postponement has been widely practiced in many nations including China, very few surveys related to product postponement have been conducted in China. Therefore, status of product postponement in the large and important Chinese market merits further study (Huang & Li, 2009).

Collaboration

SC lean practices in general and collaboration in particular have become active research areas among the SC practitioners and academic researchers of SCM as manufacturing business performance are negatively impacted by inconsistent information shared among SCM partners (Danese, 2011; Datta & Christopher, 2011; Prajogo & Olhager, 2012). Ramanathan, Gunasekaran, and Subramanian (2011) acknowledged that a growing body of literature suggested that the number of manufacturing firms discovering the features and benefits of the collaborative initiatives are significantly high. Several studies, which projected the relationship between supply chain collaboration (SCC) and SCM performance metrics, are listed in Table 1. The SCC initiatives play an important role on SCM performance outcomes. However, SCM performance measurement metrics are reported differently based on the type of the collaborative activities considered by researchers.

Table 1

SCM Performance Metric and SC Collaboration

Role of SCC Essential	Essential elements for SCC	Performance metrics	Authors
Collaborative planning and production, decision making	Cross functional activities	Business strategies (functional capabilities), processes (operational efficiencies), stake holders view (risk/return ratio	Akkermans et al. (1999) and SCC (2001) – SCOR model
	SCC leadership and power Sharing	Order of dominance and decision sharing	Kim and Oh (2005), Simatupang and Sridharan (2004a,b), and Aviv (2007)
	Process alignment	Cost, profit, excess inventory, stock-out, resource measure	Beamon (1999), Lambert and Pohlen (2001), Dong and Chen (2005), and Emmet and Crocker (2006)
Information sharing, forecasting decision making	Joint decision making Information sharing and forecasting	Impact of information quality on forecasting	McCarthy and Golicic (2002), Forslund and Jonsson (2007), Raghunathan (2001), and Chang et al. (2007
	Managing changes (external and Internal)	Reliability, reactivity/flexibility	Forme et al. (2007), Angerhofer and Angelides (2006), and Barratt and Oliveira (2001)
Replenishment, decision making	Internal and logistics performance	Inventory and stock position, stock out, lead time, internal service rate, cross-functional capability, logistics efficiency	Cachon (2001); Ettl et al. (2000), Aviv (2007), Simchi-Levi and Zhao (2005), and Chen and Paulraj (2004)

Note. Adapted from “Supply chain collaboration performance metrics: A conceptual framework” by U. Ramanathan, A. Gunasekaran, and N. Subramanian, 2011, *Benchmarking*, *18*, 856-872.

Collaborative initiatives such as shared information and business process practices among the SCM partners have reduced the risks of demand uncertainty, which have been resulted in resource allocation efficiency, faster response time to a volatile market, and improved SCM performance as noted by (Huang & Li, 2009; Wiengarten et al., 2010). Despite significant features and benefits of collaborative initiatives documented in the findings of several studies conducted by (Gligor & Holcomb 2012; Lee, Klassen, Furlan, & Vinelli, 2014; Singh & Power, 2009; Wiengarten et al., 2010), not many manufacturing industry leaders have embraced a holistic collaborative perspective due to multidimensionality of the collaborative concept, which is perceived as a meta-concept. For example, Wiengarten et al. (2010) conducted an empirical quantitative correlational study to determine the relationship between information quality of collaborative practices and SCM performance. Information sharing, incentive alignment, information quality, and joint decision-making were the independent variables and SCM operational performance was the only dependent variable of the study. A survey instrument with a 7-point Likert-type scale was used to collect data. The survey included 19 items: (a) four items for information sharing, (b) three items for incentive alignment, (c) four items for joint decision-making, (d) four items for information quality, and (e) four items for SCM operational performance. An invitation was emailed to 867 potential survey participating companies ranging from a few to more than 1,000 employees. Demographic data were also gathered to describe the sample. Among the demographic data, company size, measured by number of employees was used as a control variable. The targeted population was the German automotive industry. According to the International Organization of Motor Vehicle, European automotive industry is one of the largest industries in the world with 31% of global production. Germany accounts to 28% of European automotive production (Wiengarten et al., 2010). The sampling frame was the head of the purchasing department of the potential participating companies, which were identified as the most knowledgeable individuals to provide the required information. The survey instrument was pretested in several stages by: (a) academic researchers of SCM, (b) senior automotive consultants and six German purchasing directors, and (c) 18 German purchasing directors. The survey response rate was 17.5% or 152 acceptable responses. While, the minimum sample size was unspecified by the power analysis, the measured items were tested using Cronbach alpha. The study constructs' Cronbach's alpha values were close to or above the commonly acceptable level of .70, which indicated that potential threats to internal validity were minimized. Multiple regression analysis relies on test results of four principal assumptions: (a) linearity, (b) independence of the errors, (c) homoscedasticity, and (d) normality (Osborne & Waters, 2002). Wiengarten et al. applied ordinary least square prior to regression analyses, but only tested linearity and multicollinearity of the four assumptions. In other words, independence of the errors and normality assumptions remain concerned issues within the study. Wiengarten et al. concluded (a) information sharing in a collaborative practice improved the SCM operational performance if the exchanged information was high quality; (b) incentive alignment in a collaborative practice improved the SCM operational performance if the exchanged information was high quality; (c) joint decision-making in a collaborative practice improved the SCM operational performance if the exchanged information was high quality; and (d) the company size, measured by number of employees was irrelevant. Despite significant contribution to the body of SCM literature, external validity remained a major concern. The researchers should have considered the potential threats to external validity or the extent findings could be generalized beyond the study population (Jackson, 2012). Specifically, external validity consisted of population validity because data were collected from one industry (automotive), one nation (Germany), and one sampling frame (purchasing directors). Therefore, the findings may not be applied to settings beyond those that were studied.

Singh and Power (2009) investigated the impact of the SCM partner collaboration on the SCM performance. Developing a collaboration theoretical model and establishing relationships between exogenous constructs: (a) customer relationship, (b) supplier involvement, and (c) firm performance (endogenous construct), researchers conducted an empirical quantitative study using SEM to test the hypotheses validity. A survey instrument with a 5-point Likert-type scale was used to collect data. The survey included 21 items: (a) eight items for customer relationship, (b) six items for supplier involvement, and (c) seven items for firm performance. Demographic data were also gathered to describe the sample. The survey was pretested with eight SC practitioners and academic researchers of SCM as well as pilot-tested with 21 organizations. The target population was Australian manufacturing firms and the survey instrument was mailed in two separate waves to 1,053 production plants. One month after the initial wave, the second wave of survey instrument was mailed as a follow-up to non-respondents. The sampling frame consisted of senior managers (general, operations, quality, production, etc.) who were registered members of Joint Accreditation System of Australia and New Zealand. A series of internal validity tests: (a) multicollinearity, (b) reliability, (c) convergent and discriminant validity, and (d) common methods bias were conducted prior to CFA analysis and SEM assessment. While the researchers gathered significant amounts of data to test hypotheses, the study made no significant contribution to the SCM design body of knowledge. First, the potential threats to external validity existed because the theoretical model was untested in any other SCM firms, except Australian manufacturing firms. Second, the potential threats to internal validity existed because the study used 418 samples without considering an appropriate sampling frame; as a result, 50% of the collected data represented small manufacturing firms with less than 100 employees or less than $10 million in annual revenue. Finally, the goodness-of-fit indices for the model indicated poor fit with data as a result of the unknown sample size. All of these shortcomings limited the design applications.

The impact of IT and information sharing on SCM performance were the most popular research topics. These two topics were studied from different perspectives within the body of literature. As highlighted by several researchers, the technological aspects of collaboration efforts were based on IT infrastructure; while, information-sharing concepts were based on social behavior of the SC partners (Prajogo & Olhager, 2012; Wu, Chuang, & Hsu, 2014). Applying empirical quantitative SCM data to a newly developed SEM model, Wu et al. (2014) investigated a few key social exchange issues of SCM partners in terms of their relationships with SCM performance. The exogenous constructs of the study were: (a) trust, (b) commitment, (c) reciprocity, and (d) power. SCM performance was the only endogenous construct, measured by collaboration and information sharing. Wu et al. used industry types and firm size as two control variables. The industry type was measured by: (a) high-tech industry, (b) traditional industry, and

(c) service and firm size, which was based on the total number of employees in the firm measured by (a) large, (b) medium, and(c) small. A survey instrument with a 7-point Likert-type scale was used to collect data. The target population was 1,000 manufacturing and service provider firms listed on the 2009 Taiwan Stock Exchange Corporation. The sampling frame was top managers of the firms including: (a) general managers, (b) vice general managers, and (c) logistics executives of the industrial and service provider firms. With success rate of 17.7% in survey response, 177 useable surveys served as the source of study's data. The findings of the study indicated that information sharing had a positive, but weaker relationship to SCM performance; however, a stronger relationship to collaboration. On the other hand, collaboration had a significantly strong relationship with SCM performance. The researchers argued that one possible reason for such a weak relationship between the information sharing and SCM performance was that information sharing might be treated as a behavioral intention for SC partners and could have resulted in an actual behavior of collaboration (Wu et al., 2014). Overall, the researchers gathered a high volume of data and information to test the hypotheses of the study and they made significant contribution to understating SCM collaborative efforts.

Kumar and Banerjee (2012) reiterated that the main reason for using collaboration is to develop strategies through achieving excellence in core business processes and to stay competitive in a marketplace. Developing a hierarchical reflective model based on partial least squares, Kumar and Banerjee defined several second-order multidimensional constructs to represent SCM collaboration activities. These constructs were: (a) collaborative culture, (b) joint planning, (c) resource sharing, (d) individuals/groups attributes, (e) strength of relationships, (f) joint planning for executing schedule, (g) joint planning for increasing market share, (h) joint problem-solving and performance measurement, (i) market based information sharing, and (j) internal resource sharing. Using an Internet survey service, Kumar and Banerjee emailed 812 copies of survey to medium and large size firms operating in India. With success response rate of 9.5%, only77 completed surveys were registered. Conducting a SEM, findings of the study revealed that collaboration is a third order, reflective construct. Kumar and Banerjee's study contributed significantly to the body of literature as they offered a new paradigm of SCM modeling.

SCM Performance

SCM performance improvement is a continuous process, which requires analytical performance measurement and realizing key performance indicators (Cai, Liu, Xiao, & Liu, 2009). An early SCM improvement assessment tool was Balanced Scorecard, which was introduced in the 1990s organizing strategic performance management metrics where measures were used to gauge the strategy plan implementation of a firm in terms of: (a) financial, (b) internal process, (c) customers, and (d) innovation as noted by Elrod, Murray, and Bande (2013). However, the majority of studies in the current literature have concentrated only on the financial aspects of SCM, ignoring operations outcomes. The latter perspective key performance indicators (KPI) are uncorrelated to nonfinancial SCM performance factors such as customer satisfaction, collaboration among SCM partners, product quality, and research and development initiatives (Agus & Mohd, 2012; Cook et al., 2011; Gligor & Holcomb, 2012). SCM performance metrics will enable industrial leaders to monitor different aspects of their business operations. Whether it is ISO 9000, TQM, Business Process Reengineering, Six Sigma, Collaboration, Product postponement, JIT, Kanban, or any other best practices, it is important that industrial leaders emphasize on realignment and continuous improvement of their SCM as emphasized by Huehn-Brown and Murray (2010). SCM performance metrics are direct indicators for a continued SCM improvement with the potential business improvement creating opportunities such as cost cutting, lean practices, and new business processes. Accurate SCM performance metrics not only allow firm leaders to improve the quality of their products, but also consider implementation of new lean practices such as JIT, that can reduce costs by cutting cycle times and reducing inventory levels (Doolen, Traxler, and McBride, 2006). For example, Wagner et al. (2012) investigated the relationship between SC fit and the SCM financial performance. The study findings indicated that the higher return on assets was an immediate result of the SC fit, and that the firms with a negative fit resulted in lower performance than firms with a positive fit. SC fitness was described as strategic consistencies between supply and demand uncertainty and the underlying SC design (Wagner et al., 2012).

Applying quantitative SCM data on a newly developed SEM model, Prajogo, Huo, and Han, (2012), investigated a few aspects of ISO 9000 philosophy implementation in terms of their relationships with three key SCM practices: (a) internal processes, (b) supplier relationships, and (c) customer relationships. The purpose of their study was to examine the relationship between the three key SC activities and operational performance measured by (a) cost effectiveness, (b) product innovation, (c) on time delivery, and (d) product performance. The study was based on the RBV as theoretical lens. Using a five-point Likert-type scale survey instrument, qualitative data were collected from 321 middle and senior level managers of ISO 9001 certified firms who were registered members of Joint Accreditation System of Australia and New Zealand and were responsible for managing the quality systems in their organizations. The results of the study indicated that advanced implementation of ISO 9000 was positively related to all three aspects of SC activities; while, supportive implementation was positively related to internal and customer process management. However, basic implementation had no direct influence on any of the SC management practices. The results also indicated that supplier and internal process management both had a positive effect on operational performance, while customer process management had insignificant impact on operational performance. The study also investigated supplier relationship management, which had a positive impact on performance. However, the relationship between customer relationship management and operational performance was insignificant. The later result was interesting because it contradicted the SCM principle since customer relationship management has shown a positive effect on operational performance in prior studies, such as Zhao et al. (2008). The sampling frame was undefined and the minimum sample size was undetermined in Prajogo et al.'s study. Furthermore, the researchers should have considered the potential threats to external validity or the extent findings from the study could be generalized beyond the study population (Jackson, 2012). Specifically, external validity consisted of population validity because of sample pattern and its limitation, one nation (Australia) and one sampling frame (quality system managers). Therefore, the findings may not be applicable to settings beyond those that were studied.

Optimizing Inventory Levels under Demand Uncertainty

SCM systems are continually subject to the local and global sources of uncertainty that can adversely affect productivity, customer satisfaction, and eventually the profitability of manufacturing firms (Babai, Syntetos, Dallery, & Nikolopoulos, 2009; Datta & Christopher, 2011; Lu et al., 2011). Findings from a study of 9,000 SCM professionals who participated in an operations management survey resulted in the sources of uncertainty within the SCM (APICS, 2011). Nine sources of uncertainty were identified based on the participant perceptions (a) natural disaster disruptions, 63%; (b) lack of information sharing between organization and suppliers or customers, 54%; (c) inadequate management relationship with customers and suppliers, 50%; (d) insufficient monitoring of SCM, 42%; (e) partner underperformance, 40%; (f) suppliers going out of business, 40%; (g) liability due to lapses in materials safety, 14%; (h) losses due to theft or other criminal acts, 12%; and (i) other forms of risks were identified, 7% (APICS, 2011).

The common catalysts of uncertainty in a SCM system include (a) a lack of qualitative and quantitative information, (b) the complexity of information, (c) conflicting evidence, (d) ambiguity, and (e) measurement errors (Datta & Christopher, 2011). Information complexity means that the process of information exceeds the intelligence of the system, such as when uncertainty is modeled with deterministic parameters. Evidence may conflict when the results of an experiment are different despite similar information. Ambiguity may occur when there is insufficient information for making a proper decision. For example, volatility in the marketplace creates uncertainty, which can bring ambiguity to SCM systems. Measurement errors may result in inaccurate fact-findings. For example, miscalculation in customer demand may lead to measurement errors. Many different mathematical models have been proposed to reduce the risks of customer demand uncertainty. For example, collaborating efforts among the units of a SCM system can reduce the effects of the uncertainty (Datta & Christopher, 2011; Ramanathan et al., 2011). Sharing information or even selecting the right production control policy such as ISO 9000, TQM, Business Process Reengineering, Six Sigma, SCM Collaboration, Product postponement, JIT, Kanban, or any other best practices may improve the performance of a SCM system by reducing the risks of uncertainty (de Sousa Jabbour et al., 2011; Gligor & Holcomb, 2012). The postponement strategy reduces the uncertainty of customer demands (Liao et al., 2013; Manuj & Mentzer, 2008; Yang et al., 2010). The basic principle of a postponement strategy is to delay the movement of finished goods and products throughout a SCM network by positioning these goods and products at one or a few strategic locations until actual customer demands are received (Kumar & Wilson, 2009). Prajogo and Olhager (2012) claimed that the push-control (make-to-stock) strategy to reduce the uncertainty of lead times when a plant manager produces products to finished stock implies that demand volumes are high and that demand variability is low. Lu et al. (2011) offered the pull-control strategy, or lean manufacturing philosophy, to reduce the risks of customer demand uncertainty. In the mathematical modeling and control mechanism arenas, Acar et al. (2010) demonstrated that combination of optimization and simulation methodologies can provide manufacturing industry leaders with a strong decision-making tool to assess the relative impact of demand uncertainty and lead-time on SCM performance. Accurate demand forecasts have always helped SC managers with better demand predictions, thus reducing the risks of demand uncertainty; especially, when it comes to seasonal products. Zhang, Prajapati, and Peden (2011) developed a novel stochastic production-planning mathematical model to control the seasonal demand and growth uncertainties within the global industrial world, where accurate demand forecasting is the key to success to international business competition. Appling real-world manufacturing quantitative data, Zhang, Prajapati, and Peden, demonstrated the effectiveness of their model by annual saving of more than $400,000 in inventory costs in the firm where the study took place.

Many SC practitioners and academic researchers of SCM have contributed to the development of theory and identification of relevant conditions and terms by using analytical modeling. However, the majority of these models are limited in terms of their applicability to the real-world manufacturing environment. A major limitation of analytical modeling is that the developed models are based on the researchers' theoretical framework, environmental assumptions, and selected initial condition for the variables (Huang & Li, 2009). Additional challenges include verification of the models under static and dynamic mode of operations with the real-world manufacturing environment. For example, considering a single-echelon supply chain with a single-product, researchers Babai et al. (2009) developed a forecast-based inventory optimization model to deal with unknown customer demands and replenishment lead times. The authors used probability distribution function as the theoretical framework for their study. Using international pharmaceutical empirical data as their secondary data source, the researchers' data analysis and findings required no special computational need to compare existing inventory optimization models. While reduced computational processes is an advantage for an inventory optimization model, it may reduce the capabilities of the model and limit its applications. If the number of products increases and SC changes to a multiechelon, a commonly used SCM system, then the model will require extensive computational processes.

Assumptions such as a single-product industry, unlimited production capacities, a single-echelon SC, known lead times, and perfectly predictable customer demands, have limited the applications of the described models (Datta & Christopher, 2011). Despite significant improvement in a particular area of a SCM system, the proposed mathematical models were unable to handle the uncertainty of the real-world manufacturing environment (Acar et al., 2010; Lu et al., 2011; Zhang et al., 2011). In developing the inventory optimization models for a SCM system, some researchers have used deterministic parameters for simplicity, whereas others have used stochastic parameters for more accuracy. The majority of existing optimization models have been static and based on the deterministic nature of the selected parameters. These models therefore could not handle the uncertainty of real-world business problems (Sarimveis, Patrinos, Tarantilis, & Kiranoudis, 2008). However, Napalkova and Merkuryeva (2012) noted that higher computational costs and slower convergence of multi-objective algorithms, such as continuous and discrete decision-making policies, were shortcomings of the stochastic simulation-based inventory optimization models. Effective programing has helped some SCM system developers to deal with higher computation cost. Recent advancements in technology and computational processes have enabled SCM researchers to develop large-scale dynamic optimization models based on stochastic parameters, which reduce the risks of uncertainty. For example, Hai, Weiling, and Yanping (2010) used MPC to develop a model of flexible control strategy for dynamic supply chain in a semiconductor-manufacturing industry firm where customer demand forecasts and anticipated periodic demand were unpredictable. In a separate study, Schwartz, Arahal, Rivera, and Smith (2009) reiterated that forecasting highly uncertain demand is the key to success in managing SCM inventory of semiconductor manufacturing industry firms. Schwartz et al. developed an MPC-based forecasting model driven by customers, which provided forecasting signals to the tactical policy of inventory optimization module. Schwartz et al. claimed that their multi-objective formulated model allowed SC managers to generate demand forecasts that minimized inventory deviation and starts' change variance.

Bullwhip Effect

The bullwhip effect occurs in the SCM system of a manufacturing firm when the variance of supply is greater than the variance of customer demands (Coppini et al., 2010; Dooley, Yan, Mohan, & Gopalakrishnan, 2010). For example, Procter & Gamble representatives found that a product order placed by the distributors had a degree of variability unexplainable by consumer demand fluctuations alone. Similarly, at Hewlett-Packard, the orders placed to the printer division by resellers had much bigger swings and variations than existed in customer demands (Farasyn et al., 2011). Researchers Jaipuria and Mahapatra (2014) and Wangphanich et al. (2010) agreed that the bullwhip effect could adversely influence the cost, inventory levels, reliability, customer service, and other important aspects of the operations of a SCM system. In the first scientific study of the bullwhip effect, Forrester (1961) identified the main causes of bullwhip effect as the nonlinearity of interactions and the lack of information sharing among subdivisions of a SCM system. Since 1961, members of the industrial and scientific communities have conducted numerous studies to identify both the causes of a bullwhip and solutions to lower its effects. Among the reviewed literature, closely related to the present study were the studies of Cachon et al. (2007) and Dooley et al. (2010).

Cachon et al. (2007) launched an empirical investigation of the bullwhip effect on some US manufacturers, wholesalers, and retailers as a three-echelon SCM system. The sampling frame consisted of 50 manufacturers, 18 wholesalers, and 6 retailers. Using US Census Bureau monthly data, the researchers measured the volatility of demand imposed on each SCM system echelons by their downstream customers. Cachon et al. postulated that an echelon exhibited bullwhip whenever the variability of the inflow (production) in that particular echelon of the SCM system was greater than outflow (demand) from the same echelon. The authors measured the bullwhip effect at both the echelon level and the overall three-echelon SCM system level. Cachon et al.'s first finding was that the bullwhip occurred at wholesale level, but not at the manufacturing or retail levels. Second, they confirmed that seasonality of a product had a strong impact on the amplification bullwhip effect. In other words, industries with seasonal products tended to smooth production relative to demand whereas industries without seasonality tended to amplify. Third, they demonstrated that price variability was a major contributor to amplification bullwhip effect.

Dooley et al. (2010) conducted an empirical study to examine of the sales volumes and inventory levels on some US manufacturers, wholesalers, and retailers during the 2007-2009 US economic recession. The recession of 2007-2009 created a severe case of demand uncertainty, which resulted in bullwhip across manufacturing sectors where consumers drastically reduced the level of their consumption in many domestic and international products. Using the US Bureau Economic Affairs monthly sales volumes and inventory levels data, Dooley et al. compared the mean and variance of sales volumes and inventory levels across the firms before and after the recession. The researchers concluded that manufacturers, wholesalers, and retailers had different operational strategies to cope with such a strong case of demand uncertainty during the 2007-2009 recession: The wholesalers responded late and drastically, indicative of a bullwhip effect, while retailers responded quickly and more conservatively, indicative of environmental smoothing (Dooley et al., 2010). Thus, smoothing of demand and inventory levels can be used as an alternative solution to a significant change in demand or bullwhip. Other possible solutions to diminish the bullwhip effect include information sharing, single control of replenishment, lead-time reduction, appropriate forecasting methods, and elimination of demand forecast strategies (Pereira, Takahashi, Ahumada, & Paredes, 2009). For example, Xie and Zhou (2012) used the well-established automatic pipeline feedback compensated inventory and order-based production control system for a single echelon SCM system, in which demand uncertainty was modeled by the fuzzy logic and numbers the same as the stochastic. In a separate study, Jaipuria and Mahapatra (2014) applied discrete wavelet transforms analysis and artificial neural networking for demand forecasting. Despite many strategies for reducing the bullwhip effect, however, collaboration within the SCM partners and smoothing replenishment rules are considered the two main classifications (Cannella & Ciancimino, 2010; Dooley et al., 2010).

IMC-Based and MPC-Based Controllers

Advanced modern control systems theories provide sufficient scientific means to analyze, design, and simulate SCM systems, especially in handling demand uncertainty and the bullwhip effect (Bemporad & Di Cairano, 2011; Sarimveis et al., 2008). Zhang and Dilts (2004) insisted that there is strong consensus among SCM system designers and SC practitioners that advanced modern control systems can provide manufacturing leaders with a sense of control over market behavior, thereby helping to reduce the risks of demand uncertainty. Among the advanced modern control systems, the IMC-based and MPC-based controllers are popular for establishing the tactical decision-making policies for inventory management (Schwartz & Rivera, 2010). Design simplicity, faster response, and fewer adjustable parameters make the IMC-based controller more appealing to some SC managers (Chen, Zhang & Gu, 2007; Schwartz & Rivera, 2010).

The IMC-based controller can provide an array of control schemes ranging from PID for a single-input-single-output (SISO) strategy to multi-input-multi-output (MIMO) strategy (Schwartz & Rivera, 2010). For example, Garcia, Ibeas, Herrera, & Vilanova (2012) developed an IMC-based controller to mitigate the bullwhip effect. Schwartz and Rivera (2010) used a controller based on tactical decision-making policies for inventory optimization based on IMC strategy.

A MPC-based inventory optimization model is based on the use of present and past measurements of the optimized inventory levels, customer demands, and inventory target levels to predict future optimized inventory levels during each step of the manufacturing processes (Doganis, Aggelogiannaki, & Sarimveis, 2008; Herzog, Dondi, & Geering, 2007;2007; Schwartz & Rivera, 2010; Skaf & Boyd, 2010). Like the IMC-based controller, the MPC-based controller can govern the optimization of supply and demand processes as either a SISO or a MIMO strategy. However, the MIMO MPC-based controller is known for its robustness and high performance in handling demand uncertainty, to an extent superior to that of SISO or any other control strategies (Giovanini, 2011; Sarimveis et al., 2008).

The MPC has a broad range of applications in industrial control, where disturbances, or uncertainties, are common. Such applications include; in particular, SCM systems, automation, chemical processing, transportation, and finance (Rivera, Mittelmann, Sarjoughian, & Kempf, 2005; Schwartz & Rivera, 2010). Tzafestas, Kapsiotis, and Kyriannakis (1997) developed the first manufacturing application. In this application, a model-based predictive control was used as a decision-making policy to handle complex integrated production planning problems within a stochastic environment.

Ford, Ledwich, and Dong (2008) used MPC to study the stability of a power plant distribution grid, in utility companies. In a study conducted by Aggelogiannaki, Doganis, and Sarimveis (2008), it was found that an MPC-based controller mitigated the bullwhip effect. Schwartz and Rivera (2010) used MPC to optimize a semiconductor manufacturing production inventory system. The focus of this study was to develop a simulation-based inventory optimization for a SCM system, which dealt with demand uncertainty in a semiconductor-manufacturing firm. For establishing the decision-making policies, the study deployed IMC and MPC-based controllers, which had full advantage in dealing with demand uncertainty in particular demand variance and forecast errors. The use of fluid analogy representing of the semiconductor manufacturing process was a brilliant idea that helped readers to a better and deeper understanding of supply and demand within the SCM system. The optimization model benefited from a simultaneous perturbation stochastic approximation (SPSA) algorithm. The authors concluded that IMC and MPC controllers were capable of managing inventory levels in uncertain production inventory and multi-echelon supply/demand networks, respectively. The use of SPSA allowed the researchers to determine controller tunings and operating targets that led to optimal results from either an operational or financial perspective of the SCM performance. The results of the optimization on a single node example showed that it was advantageous to act cautiously with forecasted information and gradually become more aggressive (with respect to feedforward action) as more accurate demand forecasts became available. For the three-echelon problem, the use of the simulation-based optimization method led to insights concerning the proper parameterization and tuning of the tactical MPC decision policy. The amount of SSI necessary for optimal profitability was a function of the accuracy and magnitude of the demand forecast. SPSA provided a way of systematically determining the financially optimal inventory targets and the move suppression values present in the MPC objective function simultaneously. For the semiconductor manufacturing problem case study, it was found that the optimization problem was more sensitive to changes in inventory targets, and less sensitive to changes in move suppression. This allowed for flexibility when tuning the decision policy, as robustness considerations did not have to be cast aside in favor of increased.

For developing an inventory optimization model, the MPC-based controller can be used either as a centralized or decentralized (distributed) configuration. The centralized governing scheme is desirable for a simple inventory optimization of a SCM system. Gabasov, Dmitruk, and Kirillova (2011) argued that impracticality and economical reason, makes the centralized control scheme an unattractive choice for complex structure and large-scale systems. Gabasov et al. reiterated that delays in information exchange and high volume of computational processes disables the central process unit of any computer; therefore, centralized control is impractical for large and complex SCM systems. Giovanini, (2011) also indicated that centralized control scheme is difficult for a multiechelon SCM system because it increases the complexity of computational processes. Camponogara and de Lima (2012) applied a decentralized (distributed) MPC strategy for studying traffic networks and petrochemical plants with dynamic uncertainty.

Simulation-Based Optimization

Simulation is widely adapted as an interactive learning tool to improve the efficiency and productivity of many educational and industrial firms (Weaver et al., 2010). Using a discrete-event simulation, Shi, Liu, Shang, and Cui (2013) developed a model to address a multi-response optimization problem within a SCM system. Shi et al. claimed that their model helped auto parts SC managers identify the operating setting that minimizes the impact of supply uncertainty on the performance of the cross-docking facility. In the healthcare industry, simulation-based training systems have been instrumental in providing training programs through active-learner engagement, repetitive practices, the ability to vary the degree of difficulty of the task, and clinical complexity (Weaver et al., 2010). According to McCullough (2011), in the United States, each nuclear power plant has a control room simulator, which mimics the actual nuclear power plant under static and dynamic mode of operations. McCullough emphasized that simulation-training programs included from routine plant monitoring procedures to the most challenging accident mitigation scenarios. McCullough highlighted that the effective use of simulation will enhance the knowledge transfer to the next generation of workers, keeping the focus on nuclear safety.

In general, simulation is a central part of many scientific and industrial studies, including SCM systems, where the effects of different scenarios are investigated over time (Datta & Christopher, 2011). The leaders of manufacturing firms are continually faced with many decision-making challenges because of the uncertainty nature of the manufacturing processes (Abo-Hamad & Arisha, 2011; Acar et al., 2010; Zhang et al., 2011). Simulation-based optimization techniques empower manufacturing leaders by providing them with the decision-making evaluation tools for strategic, tactical, and operational policies (Mahdavi, Mohebbi, Zandakbari, Cho, & Mahdavi-Amiri, 2009; Napalkova & Merkuryeva, 2012). MIP discrete-event simulation engines are widely used for SCM inventory optimization. In developing a decision-making system to assist manufacturing leaders with SCM product distribution network, Almeder et al. (2009) combined an optimization model with a discrete-event simulation engine. The simulation engine included nonlinear and stochastic parameters, whereas the optimization model represented a simplified version. The stochastic environments provided the researchers with an opportunity to solve real-world uncertainty problems at real-time speed and dynamic mode of operation. Based on initial simulation runs cost parameters, production, inventory levels, and transportation schedules were estimated for the optimization model. Then solution of the optimization model was interpreted into decision-making standard policies for the discrete-event driven simulation engine. The method was applied successfully on a 3-echelon simple SCM system consisting of a supplier, a production distributor, and a customer. Each echelon had its own dedicated inventory optimization and simulation modules and they interacted asynchronously over a data communication network. Every two echelons were tied together via a transportation link, which had its own simulation and optimization modules as well. For instance, there was a link between the supplier and the production facility where the raw materials were delivered by different means of transportation. The use of simulation and optimization in the form of complimentary in a SCM system was a novel idea that established a decentralized simulation-based inventory optimization. This technique allowed running multi-echelon SCM systems on a personal computer with reasonable accuracy results. In fact, the study used a personal computer (Intel P4 2.4GHz, 1GB RAM) with Windows 2000 testing 20 SC actors, 8 products, 5 periods, and 2 transportation modes, considering 3,360 binary variables before optimization and 250 binary variables after optimization within an hour. However, when the number of products were increased from 8 to 10 the computational time was much higher than an hour.

Using a simulation-based optimization, Yáñez et al. (2009) evaluated push and pull control strategies on the Canadian timber industry to determine which strategy better served the ailing timber market. Having developed a three-echelon SCM system (suppliers, sawmill, clients), the researchers applied push or pull control strategies as the theoretical framework on each of three processes (sawing, drying, and planning) within the sawmill facility. Based on theoretical framework, the researchers ran 54 scenarios on a simulator and collected data on four dependent variables: (a) Order-fill rate, (b) Work-in process, (c) Throughput, and (d) Recovery factor. The study's only independent variable was the location where change of control strategy was applied (decoupling point). Using an ANOVA-based statistical analysis, the researchers provided several operational policies from their findings to improve the ailing timber market. The findings indicated that moving decoupling points in the clients' direction (downstream) made the entire supply chain a push-control strategy system and moving the decoupling points toward suppliers (upstream) created a pull-control strategy system. While running 54 different supply chain configurations on a simulator provided a viable option to optimize inventory levels, the study made no significant contributions to the SCM system design body of knowledge. The potential threats to external validity existed because the experimental design has not been tested in any other SCM system (Jackson, 2012). The study used 600 randomly generated samples; however, sampling frame was not large enough to represent other similar industries. Finally, the minimum required sample size was unknown. All of these shortcomings limit the design applications.

Bottani and Montanari (2010) developed a discrete-event simulation to study the effects of different supply configurations on costs and the bullwhip effect. Koulouriotis et al. (2010) deployed a discrete-event simulation to evaluate the major performance measures of the SCM system such as average throughput, average WIP, and average level of backorder demand. Schwartz and Rivera (2010) used MPC-based decision-making policies for the inventory optimization.

A simulation-based optimization is designed based on (a) the number of echelons (single or multiple), (b) the number of commodities (single or multiple), (c) number of periods (single or multiple), and (d) the economic environment (deterministic or stochastic; Melo, Nickel, & Saldanha-da Gama, 2009). Simulation-based optimization techniques can be categorized in several ways. Multiechelon inventory optimization models, based on deterministic programming, are used for strategic or tactical policies. Analytical performance models, based on dynamic and stochastic programing, are used to investigate design or principal management decisions. Finally, simulation and information models are used to analyze complex dynamic and stochastic situations and to understand issues of SCM system decision-making (Napalkova & Merkuryeva, 2012).

Summary

The negative impact of demand uncertainty on SCM performance has forced manufacturing industry leaders to reexamine and realign their SCM systems to remain competitive in market place (Cook et al., 2011; Datta & Christopher, 2011). To mitigate the negative impact of demand uncertainty on SCM performance problems, academic researchers of SCM and SC practitioners have recommend production control and lean practices such as JIT, ATO, ETO, MTO), MTS), product postponement, collaboration, and Kanban to lower the risks of demand uncertainty. JIT lean practices have become important tools to lower the risks of demand uncertainty and improve SCM performance (Mackelprang & Nair, 2010). Kanban was recognized as an effective production control strategy to reduce demand uncertainty, which is mostly applied to assembly production system (Koulouriotis et al., 2010). Product postponement strategy proved to increase the amount of process steps to complete a product, reduced operational costs, and shortening service delivery time (Yang et al., 2010). Collaboration between SC partners has become an important tool to achieve the goal of dealing with demand uncertainty when the shared information is of high quality (Wiengarten et al., 2010). In the mathematical modeling and advanced control systems, the stochastic demand forecast model was considered a strong tool to reduce the risk factors of demand uncertainty and seasonal products, which contributes to the bullwhip effect (Zhang et al., 2011). MPC-based and IMC-based inventory optimization models have proven robust control mechanisms because the models were capable of predicting demand uncertainty (Schwartz & Rivera, 2010). Simulation engines work as a crystal ball enabling industrial leaders to test their possible solution scenarios in coping with demand uncertainty before developing the standard policies (Bottani & Montanari, 2010; Napalkova & Merkuryeva, 2012).

SCM performance is a continuing concern affecting the operational and financial performances of firms (Cook et al., 2011; Jabbour et al., 2011) despite many studies and efforts, some of which were reviewed in this chapter. Golicic and Smith (2013) insisted that the lack of focus on specific production control policy, inadequate inventory optimization models, and limited examination of SCM sustainability have been identified as potential contributors to impeded business performance. These factors warrant further empirical study in SCM contexts (Golicic & Smith, 2013). From the literature review, it is apparent that most studies concentrated on lean initiatives, which were believed to be viable and effective tools for lowering the risks of demand uncertainty. Many empirical studies were conducted on the relationship between individual control mechanisms and SCM performance, rather than considering SCM performance improvement based on a set of control mechanisms. A noticeable gap in the literature was the lack of attention to combine control-based optimization models and lean practices to lower risks of uncertainty and improve SCM performance. This study will combines two lean practices (collaboration and postponement) and two control-based optimization models (IMC and

MPC) as a complementary control mechanism bundle to optimize inventory levels and reduced bullwhip effect under demand uncertainty. The current study is motivated by the work of Furlan et al. (2011), where JIT and TQM lean practices were used as complementary control mechanisms to maximized overall SCM operational performance (Furlan et al.,2011).

Chapter 3: Research Method

Ineffective control-based inventory optimization models or misaligned standard policies have been the main reasons for failure for many SCM systems in handling demand uncertainty (Acar et al., 2010), leading manufacturing firms to heavy financial losses. The effectiveness and efficiency of a SCM system relies on the accuracy of its inventory optimization model and standard policy declaring the product control strategy (Bottani & Montanari, 2010). Many inventory optimization models developed for current SCM systems are deterministic models created for simplicity and are often tested via linear regression techniques (Badinelli, 2010; Napalkova & Merkuryeva, 2012; Zhang et al., 2011). Stochastic models, also called probabilistic models, are more accurate, as they are developed based on mathematical theories that account for probabilities in real-world manufacturing involving events that are uncertain (Badinelli, 2010; Napalkova & Merkuryeva, 2012; Savsar & Aldalhabi, 2012; Zhang et al., 2011). Only stochastic mathematical models can statistically address a SCM system's randomness via the use of difference or differential equations with deviation parameters to optimize inventory levels and reduce the bullwhip effect (Aharon et al., 2009; Blavatskyy, 2011; Napalkova & Merkuryeva, 2012; Schwartz & Rivera, 2010).

The problem addressed was that business performance is impeded because inventory optimization models of many existing SCM systems lack appropriate control mechanisms to optimize inventory levels and reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010). The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. The predictor variables were four widely used SCM control mechanisms: (a) MPC-based inventory optimization; (b) IMC-based inventory optimization; (c) product postponement, and (d) collaboration (Datta & Christopher, 2011; Kumar & Wilson, 2009; Schwartz & Rivera, 2010).

The adopted research method and design for the current study is provided in this chapter. The research questions with their corresponding hypotheses are stated for the reference followed by a description of research methods, population, sample, and instrument. Then the chapter expands to operational definition of variables, and an explanation of the data collection, processing, and analysis. The methodological of assumptions, limitations, and delimitations related to the study are discussed at the end of the chapter, followed by ethical assurances and a summary.

The following research questions and hypotheses guided the study:

Q1. To what extent, if any, is there a relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States?

H1$_0$. There is no statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

$H1_a$. There is a statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Q2. To what extent, if any, is there a relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States?

$H2_0$. There is no statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

$H2_a$. There is a significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Research Method and Design

A non-experimental and quantitative correlational design was used to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. A non-experimental design was selected because there was no attempt made to control or manipulate independent variables (Vogt, 2007), while, predictor variables were preexisting and non-manipulated values of variables gathered through survey. A quantitative correlation approach was the most appropriate method and design because this was an objective-driven study, and because of the need for statistical analysis among variables for testing the hypotheses (Agus & Mohd, 2012; Yanes-Estévez at el., 2010). In contrast, qualitative is a subjective research methodology, where data are gathered through questionnaires and interviews on specific groups. The qualitative approach was inappropriate because qualitative results are often reported in text format (Taneja et al., 2011); while this study was based on extensive empirical calculations and statistical analyses. The other advantage of using a quantitative methodology was that the survey data were analyzed separately from the researcher's involvement and bias, so that objectivity was preserved (Borrego, Douglas, & Amelink, 2009). The correlational design was chosen for the study because the study determined whether and to what degree relationships exist between the predictors and criterion variables in a non-experimental setting and the correlation coefficient served as a comparison reference between the four widely used SCM control mechanisms and SCM performance (optimized inventory levels and reduced bullwhip effect). In other words, the strongest correlation coefficient, the most effective control mechanism to optimize SCM performance (optimized inventory levels and reduced bullwhip effect). Based on the focus of the study, the relationships among variables, correlational was the most appropriate design.

Population

Manufacturing firms are the most frequent users of SCM systems (Babai et al., 2009; Datta & Christopher, 2011; Lu et al., 2011), and the study target population comprised 658,871 North America manufacturing industry firms (see Appendix C). The sampling frame was drawn from a list of SC senior-level managers of medium-size and large (100 or more employees) manufacturing industry firms in the United States with direct involvement in operational and strategic decision-making policies across multiple industries supplied by Infogroup (see Appendix D). The geographic restriction to United States firms was necessary to ensure that there were no language barriers for potential respondents in answering the survey questions. Demographic and industry category questions were included in the survey instrument since demographic characteristics and industry firms of potential respondents in the sample were varied.

Sample

A purposive sample of 2,000 potential respondents from the target population of SC senior-level managers, estimated at more than 12,000 SCM practitioners listed by Infogroup (see Appendix D), were selected using Run test®, a statistical random selection processor featured by Minitab®. The purposive sampling method was chosen because of the need for pertinent field data (Maxwell, 1996), and the minimum sample size of 89 participants was determined (alpha = .05; power = .80; effect size = 0.17) by a G*Power analysis (Faul et al., 2009). It was estimated there would be an 8% survey completion rate, so that at least 100 useable surveys could serve as the source of data for the study, which exceeded the minimum sample size.

Materials/Instruments

To investigate the relationship between the four widely used control mechanisms and perceived SCM performance, a survey served as an appropriate instrument for collecting data (Vogt , 2007; see Appendix B). The use of survey instruments has increased among SCM researchers (Rungtusanatham, Choi, Hollingworth, Wu, & Forza, 2003) because survey instruments have received greater peer acceptance among SC practitioners and academic researchers of SCM with greater rigor and adherence to research principles (Rungtusanatham et al., 2003). A 7-point Likert-type, survey instrument (see Appendix B) was used to gather participant perspectives on the multifaceted operational aspects of a SCM in coping with demand uncertainty.

The study survey development followed guidelines recommended by Churchill (1979) and was based on the pre-validated subscales of Kumar and Banerjee (2012), Li, Ragu-Nathan, Ragu-Nathan, and Rao (2006), Liao et al. (2013), Mandal (2012), and Omar, Davis-Sramek, Myers, and Mentzer (2012) studies (see Appendix G). The goal of developing survey was to ensure that the questions were fluent in English and double-barreled questions in subscales were revised into two separate questions that each addressed a single concept. The selected subscales were validated by the mentioned researchers and successfully used in SCM systems with various industries, and data were collected based on the perceptions of a purposive sample of SC senior-level managers. For example, the empirical study of Li et al. was based on the impact of SCM practices on competitive advantage and organizational performance with emphasis on product postponement. Omar et al. conducted global analysis of orientation, coordination, and flexibility based on collaboration. An empirical investigation into supply chain resilience was conducted by Mandal based on optimization. Another advantage of using a quantitative survey instrument was the familiarity of the respondents with survey instruments and preferred means to answer well-formatted and concise questions, than to be interviewed for long hours if a qualitative research methodology were selected. All the variables were estimated to the best of knowledge of respondents. The response categories for each variable ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). A set of demographic-based questions were also gathered to describe the study sample (Kumar & Banerjee, 2012). SurveyMokey™ was used as a data download filter, and participant identities were coded for protection of confidentiality, and stored on a password-protected personal computer and exported into a Microsoft® Excel® file document. The collected data were imported into Minitab® statistical software to calculate and report Cronbach's alpha coefficient for internal consistency of reliability (Dillman, 2007).

Operational Definition of Variables

The study involved four predictor variables: (a) MPC-based inventory optimization, (b) IMC-based inventory optimization, (c) product postponement, and (d) collaboration. Each variable was quantified as a composite score from the survey items related to the variable. Each of the four predictor variable measures had been previously used by researchers to determine responsiveness and effectiveness of control mechanism in handling customer demand uncertainty including bullwhip effects (Datta & Christopher, 2011; Kumar & Wilson, 2009; Schwartz & Rivera, 2010). The predictor variables captured evidence of an organization's perceived SCM performance relative to their direct competitors to prevent confounding results with disparate inter-industry standards of performance (Cook et al., 2011). In other words, due to a lack of a valid cross-industry SCM performance measure, SCM performance of a firm can be operationalized by SC senior-level manager's perceptions of the firm's performance in comparison to that of major competitors (Cook et al., 2011).

Two criterion variables to measure SCM performance were used, which were: optimized inventory levels and reduced bullwhip effect (Wangphanich et al., 2010). Composite scores for the criterion variables were calculated from survey items related to each variable. All predictor and criterion variables were estimated by the survey respondents based on their knowledge and experience with their organization or firm's SCM using a 7-point Likert-type scale that varied between 1 (*strongly disagree*) and 7 (*strongly agree*).

The predictor variables for this study were the measures of control mechanisms in handling demand uncertainty, including the bullwhip effect. Criterion variables were the measures of SCM performance. Following are explanations of the predictor and criterion variables used in the present study:

MPC-based inventory optimization (MPC). MPC-based inventory optimization was the first predictor variable. The interval-level variable was gathered using a 7-point Likert-type scale that ranged between 1 (*strongly disagree*) and 7 (*strongly agree*). To quantify the variable, respondents were asked to answer four questions that accurately reflected their perceptions of their organization or firm's MPC-based inventory optimization model. These questions were: (a) detects changes in customer demands in a timely manner, (b) can reconfigure SCM resources in a flexible manner to respond customer demands changes, (c) detects changes in supply in a timely manner, and (d) can reconfigure resources in a flexible manner to respond supply changes (Li, Goldsby, & Holsapple, 2009; Schwartz & Rivera, 2010). The variable score ranged 4 to 28, with a score of 28 considered as the highest level of responsiveness for the control mechanism to optimize inventory levels and reduce the bullwhip effect.

IMC-based inventory optimization (IMC). IMC-based inventory optimization was the second predictor variable. The interval-level variable was gathered using a 7-point Likert-type scale that ranged between 1 (*strongly disagree*) and 7 (*strongly agree*). To quantify the variable, respondents were asked to answer four questions that accurately reflected their perceptions of their organization or firm's IMC-based inventory optimization model. These questions were: (a) detects changes in customer demands in a timely manner, (b) can reconfigure SCM resources in a flexible manner to respond customer demands changes, (c) detects changes in supply in a timely manner, and (d) can reconfigure SCM resources in a flexible manner to respond to supply changes (Foley et al., 2010; Li et al., 2009; Schwartz & Rivera, 2010). The variable score ranged from 4 to 28, with a score of 28 considered as the highest level of responsiveness for the control mechanism to optimize inventory levels and reduce the bullwhip effect.

Product postponement (POS). Product postponement was the third predictor variable. The interval-level variable was gathered using a 7-point Likert-type scale that ranged between 1 (*strongly disagree*) and 7 (*strongly agree*). The variable was measured by six subpart questions of survey item 12 (12a, 12b, 12c, 12d, 12e, 12f), which were summed to reflect participant perceptions of their organization or firm's product postponement. These questions were: (a) products are designed for modular assembly, (b) modular assembly products reduces demand uncertainty risks in my firm, (c) final product assembly activities are delayed until customer orders have actually received, (d) delaying final product assembly activities until customer orders have actually received reduces demand uncertainty risks in my firm, (e) final product assembly activities are delayed until the last possible position (or nearest to customers) in the supply chain, and (f) delaying final product assembly activities until the last possible position (or nearest to customers) in the supply chain reduces demand uncertainty risks in my firm (Kumar & Wilson, 2009; Li et al., 2009; Skipworth & Harrison, 2006). The potential variable range was 6 to 42, with a score of 42 considered as the highest level of effectiveness for the control mechanism to optimize inventory levels and reduce the bullwhip effect.

Collaboration (COL). Collaboration was the fourth predictor variable. The interval-level variable was gathered using a 7-point Likert-type scale that ranged between 1 (*strongly disagree*) and 7 (*strongly agree*). To quantify the variable, respondents were asked to answer six subpart questions of survey item 13 (13a, 13b, 13c, 13d, 13e, 13f), which were summed to reflect participant perceptions of their organization or firm's collaboration. These questions were: (a) information are shared with suppliers on operational decisions, (b) sharing information related to operational decisions with suppliers reduces demand uncertainty risks in my firm, (c) knowledge and specific know–how are shared with suppliers on operational decisions, (d) shared knowledge and specific know–how on operational decisions reduces demand uncertainty risks in my firm, (e) work closely with suppliers on issues related to operational decisions , and (f) working closely with suppliers on issues related to operational decisions reduces demand uncertainty risks in my firm (Cannella & Ciancimino, 2010; Omar et al., 2012). The potential variable range was 6 to 42, with a score of 42 considered as the highest level of effectiveness for the control mechanism to optimize inventory levels and reduce the bullwhip effect.

Optimized inventory levels (OPT). Optimized inventory levels was the first criterion variable. The interval-level variable was gathered using a 7-point Likert-type scale that ranged between 1 (*strongly disagree*) and 7 (*strongly agree*). To quantify the variable, respondents were asked to answer five subpart questions of survey item 14 (14a, 14b, 14c, 14d, 14e), which were summed to reflect participant perceptions of their organization or firm optimized inventory levels. These questions were: (a) customer demands fluctuates drastically from week to week, (b) MPC-based inventory optimization is capable to optimize inventory levels in a timely manner, (c) IMC-based inventory optimization is capable to optimize inventory levels in a timely manner, (d) product postponement helps to optimize inventory levels in a timely manner, and (e) collaboration helps to optimize inventory levels in a timely manner (Schwartz & Rivera, 2010; Wangphanich et al., 2010). The potential variable range was from 5 to 35, with a score of 35 considered as the highest level of SCM performance in optimizing inventory levels.

Reduced bullwhip effect (BWE). Reduced bullwhip effect was the second criterion variable. The interval-level variable was gathered using a 7-point Likert-type scale that ranged between 1 (*strongly disagree*) and 7 (*strongly agree*). To quantify the variable, respondents were asked to answer six subpart questions of survey item 15 (15a, 15b, 15c, 15d, 15e, 15f), which were summed to reflect participant perceptions of their organization or firm's reduced bullwhip effect. These questions were: (a) SCM experiences the bullwhip effect, (b) seasonal customer demands has high impact on the bullwhip effect problem, (c) MPC-based inventory optimization is capable to reduce the bullwhip effect in a timely manner, (d) IMC-based inventory optimization is capable to reduce the bullwhip effect in a timely manner, (e) product postponement helps to reduce the bullwhip effect in a timely manner, and (f) collaboration helps to reduce the bullwhip effect in a timely manner (Bray & Mendelson, 2012; Cannella & Ciancimino, 2010; Coppini et al., 2010; Costantino, Di Gravio, Shaban, & Tronci, 2014; Datta & Christopher, 2011). The potential variable range was 6 to 42, with a score of 42 considered as the highest level of SC performance in reducing the bullwhip effect.

Data Collection, Processing, and Analysis

A web-based, self-administered survey was hosted by SurveyMonkey™ using a uniquely assigned Uniform Resource Locator (URL). Internet surveys are advantageous because they provide a high level of anonymity and privacy. Contact information of the potential respondents were obtained from Infogroup (see Appendix D). A pre-notification email was sent to 2,000 potential respondents to explain the nature of the study. After the 5-day period of sending the pre-notification email, an invitation e-mail providing a link to the survey (see Appendix E) was sent to the potential respondents, requesting their voluntary participation in the survey. A reminder e-mail to encourage participations and requesting a response was sent to the potential respondents eight days after the initial invitation. In an empirical investigation comparing the effectiveness of different web-based response-enhancement techniques, Keusch (2012) suggested that sending pre-notification e-mails had a positive effect on web-based survey participation. However, increasing the number of contacts of potential respondents may not increase the survey response rate. Therefore, only pre-notification, invitation, and reminder were considered as the recruitment tool to increase the survey response rate. Cook et al. (2011), Lo and Power (2010), and Patel and Jayaram (2014) applied similar response enhancement techniques in their studies. Potential respondents' consent to participate in the survey was communicated as well as the promise of confidentiality of their responses to the survey questions. The consent statement was integrated into the first part of survey, and the survey did not proceed until participants' informed consent was obtained. From 2,000 potential survey respondents, an expected survey completion rate of 8% would have satisfied the minimum sample size of 89. The collected survey data from SC professionals was downloaded and saved as Microsoft® Excel® file documents.

A multiple regression analysis was conducted using Minitab® statistical software to determine whether the predictor variables had a predictive value for the criterion variables of SCM performance. Multiple regression analysis quantitatively contributed to the derivation of SCM theoretical models (Agus & Mohd, 2012; Done, 2011; Gligor & Holcomb, 2012) and was used for hypothesis testing (Cook et al., 2011; Huang & Li, 2009; Rahman et al., 2010). Minitab® statistical software was used for analyses (Danese et al, 2012; Jabbour et al., 2011; Law & Gunasegaram, 2010). However, multiple regression analysis relies on tests of four principal assumptions: (a) linearity, (b) independence of the errors, (c) homoscedasticity, and (d) normality (Osborne & Waters, 2002). Therefore, prior to testing of the study's hypotheses, several tests were conducted to check the validity of the critical regression assumptions using Minitab® statistical software and visual examination of the appropriate plots.

Validity is one of the indicators for a high-quality research and a majority of researchers attempt to minimize the potential threats to their claims (Goldstein &

Renault, 2004). Internal validity refers to factors that compromise researchers' ability to conclude the sole cause of the observed changes in the dependent variable (Cook & Rumrill, 2005). Threats to internal validity may be experienced from an invalid survey instrument design, or violation of multiple regression assumptions. To increase the reliability and validity, the scaled items in the survey (see Appendix B) were be pretested (Dillman, 2007) with a panel of SCM experts that will include five individuals from academia and industry professionals. Cronbach's alpha was conducted after data collection to assess the instrument's reliability with an alpha .70 or higher indicating adequate reliability (Churchill, 1979). The potential threats to external validity may be minimized by testing within similar environments and target populations (Jackson, 2012).

Assumptions

Three assumptions were made, which may threaten the internal validity of the present study; (a) sample of the study accurately represents the SCM population, (b) a survey response rate of 8% or higher, and (c) no violation of multiple regression assumptions. Without these assumptions, such a dynamic and complex SCM system study would be possible. However, to have valid and reliable results, it is important to reduce the level of threats to these assumptions. The sampling frame was based on manufacturing industry firms in the United States, which use SCM systems. Similar studies have used the same sampling frame with useful results; thus, the assumption probably had an insignificant effect on the outcomes of the present study (Cachon et al., 2007; Field et al., 2006; Omar et al., 2012; Patel & Jayaram, 2014). Potential respondents were encouraged via email three times over a period of month to respond. Multiple regression tests can accurately estimate the relationship between predictor and criterion variables of the study if the relationships are linear. The linearity assumption was examined by visual inspection of residuals scatterplots (Pedhazur, 1997). The reliability of independence of the errors assumption was assessed using Minitab® statistical software boxplots of residuals and examining the median, high and low values, and possible outliers (Keith, 2006). Third, the homoscedasticity or constancy of the variance assumption of the study's criterion variables was examined from plots of the residuals against any of the predictor variables using Minitab® statistical software. Fourth, a normality test determining whether the residuals were normally distributed or not (skewness and kurtosis) from the sample and testing their departures from the corresponding normal values was conducted using Minitab® statistical software and visual inspection of histogram plots. However, input data transformation technique was a viable solution if the testing had revealed that a particular multiple regression assumption was unsatisfied. Most frequently applied transformations are: (a) logarithmic, (b) square root, (c) inverse, and (d) square, which are featured by Minitab® statistical software.

Limitations

The main limitation of the current study was that only a small sample of medium-size and large (100 or more employees) manufacturing industry firms in the United States were surveyed. Further research considering a broader range of SCM systems within industrial global economy was needed. Another limitation was in identifying the most qualified individuals who have direct involvement with the operational and strategic decision-making policies of the firms to serve as respondents. Despite directing the survey invitations to medium-size and large manufacturing firms with SC senior-level managers, the accuracy of collected data was contingent on respondents' perceptions of their organization or firm SCM systems, which is solely based on knowledge, skills, and ability of those individuals. Further research considering real-world manufacturing industry data may be an enhancement to the current study.

Delimitations

The imposed challenges, which established delimitations for the current study, were the drawing of samples of United States manufacturing industry firms provided by Infogroup (see Appendix D). This action excluded the manufacturing industry firms whose SC practitioners were unlisted by Infogroup. Another significant delimiter was the number of SCM control mechanisms, which was purposely limited to four widely used SCM control mechanisms; (a) Model predictive control (MPC)-based inventory optimization; (b) Internal model control (IMC)-based inventory optimization; (c) product postponement, and (d) collaboration. Narrowing the scope of investigation within a limited number of SCM control mechanisms, may have excluded other SCM systems, which use other lean practices such as JIT, ATO, ETO, MTO, MTS, TQM, safety stock, Six Sigma, or Kanban.

Ethical Assurances

To obtain formal approval for the study, an application was made to the Institutional Review Board (IRB) of Northcentral University. No data was collected for the research questions and testing the hypotheses without formal approval from the IRB. More than 2,000 SCM practitioners listed by Infogroup (see Appendix D) were invited to participate in the survey. No experimental interventions were involved in this study, and potential participants were not selected from vulnerable layers of society, such as the infirm, elderly, children, or prisoners. Risk of harm to subjects was minimal to none and was limited to personal reactions to answering the survey questions. The first page of the survey contained the informed consent form (see Appendix F), which highlighted the questionnaire's purpose, participation requirements, researchers, potential risk/discomfort, potential benefit, anonymity/confidentiality, and right to withdraw. Those participants who did not accept the informed consent acknowledgement exited the online survey site.

The survey was web-based and no personally identifiable data were collected, and each set of responses was coded. Contact information for the researcher, the dissertation chairperson, and the Northcentral University IRB was available on the first page of the survey. Written permission from Kumar and Banerjee (2012), Li et al. (2006), Liao et al. (2013), Mandal (2012), and Omar et al. (2012) had been attained to use the their respective subscales prior to conducting the study (see Appendix G).

No deception was involved in this study. The potential participants were informed that their participation was voluntary, that they were being permitted to skip any question they did not wish to answer, and that they might withdraw from the study at any time. The confidentiality of the potential participants was maintained by removing all personal information from the collected data. Potential participants were told that they were responsible for releasing any sensitive data and information, which compromised the integrity of their firms. However, other possible ethical concerns were (a) the use of private information and data, (b) conflicts of interest, and (c) researcher bias. First, this study used a personal computer to code all collected data and the raw data were saved in a secure environment. Second, the study included neither private financial resources nor sponsorship; therefore, no financial conflict of interest occurred. Third, every effort was made to lessen the impact of researcher bias by applying appropriate objective statistical analysis.

Summary

Business performance of many firms is impeded because inventory optimization models of many existing SCM systems lack appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010). The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. A quantitative survey instrument is an appropriate and frequently used methodology in SCM studies (Agus & Mohd, 2012; Kumar &Banerjee, 2012, Yanes-Estévez, 2010), and a survey instrument was used to gather data for four widely used SCM control mechanisms and perceived SCM performance measured by optimized inventory levels and reduced bullwhip effect. The sampling frame was drawn from a list of SC senior-level managers of medium-size and large (100 or more employees) manufacturing industry firms in the United States with direct involvement in operational and strategic decision-making policies across multiple industries supplied by Infogroup. A purposive sample of 89 respondents from the target population was sought by approaching an estimated 2,000 SCM practitioners listed by Infogroup and selected using Run test®, a statistical random selection processor featured by Minitab®. The minimum purposive sample size of 89 participants was determined based on alpha = .05 power = .80, effect size = 0.17, by a G*Power analysis (Faul et al., 2009). A multiple regression analysis was conducted to assess whether the predictor variables predicted the criterion variables of SCM performance (Wagner et al., 2012; Iyer, Srivastava, & Rawwas, 2014). Finally, findings of the study may assist manufacturing leaders in design and development of strategies to minimize risk of demand uncertainty and expand opportunities to increase brand image and stay competitive in a marketplace.

Chapter 4: Findings

The purpose of this quantitative correlational study was to investigate the extent to which supply chain management (SCM) control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of supply chain (SC) senior-level managers of medium-size and large manufacturing firms in the United States. The problem addressed in the study was that business performance has been impeded because inventory optimization models of many existing SCM systems lack appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Schwartz & Rivera, 2010). The predictor variables were four widely used SCM control mechanisms (a) MPC-based inventory optimization, (b) IMC-based inventory optimization, (c) product postponement, and (d) collaboration. SCM performance was used as the criterion variables, measured in terms of (a) optimized inventory levels and (b) reduced bullwhip effect. A multiple regression analysis was conducted to determine the relative contribution of each control mechanism to SCM performance by considering both the individual and collective approach on each of the four control mechanisms. Chapter 4 presents the findings from the data collection and analysis of the study variables. The chapter concludes with an evaluation of the findings and summary of the results.

Results

Survey invitations were sent to 740 SC senior-level managers of medium-size and large (100 or more employees) manufacturing firms in the United States, and 124 acceptable responses were received for a 16.75% response rate and final sample size of 124. SurveyMonkey™, an online and secured survey service provider was the website host to collect data for the study. Prior to hypotheses testing, Cronbach's alpha (α) was used to assess scale reliability and internal consistency for the items used in the variables of the study. Cronbach's α values were higher than the acceptable level of .70, which indicated a high level of internal consistency and reliability for all variables: (COL = 0.868; MPC = 0.855; POS = 0.872; IMC = 0.859; OPT = 0.840; BWE= 0.850; Cronbach, 1970).

Demographic characteristics. The majority of the respondents were SC senior-level managers (71%) and worked in manufacturing firms with100 or more employees (65.32%). Additionally, the majority of respondents reported SC work experience of more than 20 years (23.4%), followed by 5 to 10 years (19.4%), 10 to 15 years (16.1%), 15 to 20 years (16.1%), 3 to 5 years (9.7%), and less than 3 years (15.3%), and a majority (76.6%) had earned a college degree (Associate, Bachelor, Master, and Doctor of Philosophy). Frequency tables for demographic characteristics can be reviewed in Appendix H.

Data assumptions. Regression analysis relied on test results of four principal assumptions: (a) linearity, (b) independence of the errors, (c) homoscedasticity, and (d) normality (Osborne & Waters, 2002). Prior to testing the hypotheses of this study, assumptions of parametric tests were examined. The fit test indicated that all predicted variables were linear, and the residuals versus order plots were used to test independence of errors violations, which after visual examination indicated that residuals had neither positive nor negative correlations and displayed no pattern (see Appendix I). Therefore, it was concluded that independence of errors assumption was satisfied. Plots of the residuals versus predicted variables also were used to search for inconsistency and violations of homoscedasticity, which indicated violation of homoscedasticity was minimized for all variables (see Appendix I). Normal probability plot was used to test normally distributed errors of the variables and the plots indicated that the residuals were normally distributed (see Appendix I). Variance inflation factors (VIF) was used to test multicollinearity among predictor variables (Myers, 1986), and VIF values were less than 10 for all study variables, which reported low to moderate correlation among predictor variables and multicollinearity test was met: (COL = 1.82; MPC = 2.68; POS = 1.38; IMC = 2.44). In summary, the data assumptions were met and multiple regression analysis for hypotheses testing was pursued.

Descriptive analysis. Prior to hypotheses testing of this study, descriptive analysis was conducted. Measures of central tendency for each variable were used to assess variability and emergent patterns from the collected data (see Table 2). Mean and standard deviation for the six variables ranged from a lowest (*M* = 19.395; *SD* = 4.112) for IMC-based inventory optimization predictor variable to the highest (*M* = 28.861; *SD* = 6.819) for collaboration predictor variable.

Table 2

Descriptive statistics: Study variables

Variable	*M*	*SD*	Min	Max
Collaboration (COL)	28.861	6.819	6	36
MPC-based inventory optimization (MPC)	19.463	4.098	7	24
Product postponement (POS)	26.708	6.612	6	36
IMC-based inventory optimization (IMC)	19.395	4.112	7	24
Optimized inventory levels (OPT)	23.468	4.605	9	30
Reduced bullwhip effect (BWE)	27.347	5.305	6	36

Note. N=124.

Correlation analysis. Pearson correlation coefficients were generated using Minitab® to assess direction and strength of relationships among the study variables prior to hypotheses testing (see Table 3). The criterion variables optimized inventory levels and reduced bullwhip effect were tested with collaboration, IMC-based inventory optimization, product postponement, and MPC-based inventory optimization predictor variables, and 15 significant correlated variable pairs were found (see Table 3). All four predictor variables showed six moderate positive relationships, which included a moderate positive relationship between MPC and IMC (r = 0.670; $p < .05$); a moderate positive relationship between MPC and POS (r = 0.441; $p < .05$); a moderate positive relationship between MPC and COL (r = 0.652; $p < .05$); a moderate positive relationship between IMC and POS (r = 0.399; $p < .05$); a moderate positive relationship between IMC and COL (r = 0.557; $p < .05$); and a moderate positive relationship between POS and COL (r = 0.473; $p < .05$).

In addition, all four predictor variables had nine moderate to strong positive relationships with optimized inventory levels and the reduced bullwhip effect criterion variables, which included a moderate positive relationship between OPT and MPC (r = 0.655; $p < .05$); a moderate positive relationship between OPT and IMC (r = 0.480; $p < .05$); a moderate positive relationship between OPT and POS (r = 0.629; $p < .05$); a moderate positive relationship between OPT and COL (r = 0.618; $p < .05$); a moderate positive relationship between BWE and MPC (r = 0.529; $p < .05$); a moderate positive relationship between BWE and IMC (r = 0.424; $p < .05$); a moderate positive relationship between BWE and POS (r = 0.590; $p < .05$); a moderate positive relationship between

BWE and COL ($r = 0.549$; $p < .05$), and a strong positive relationship between BWE and OPT ($r = 0.755$; $p < .05$).

Table 3

Pearson correlation matrix: Predictor and criterion variables

Variable	MPC	IMC	POS	COL	OPT	BWE
MPC-based inventory optimization	-					
IMC-based inventory optimization	0.670*	-				
Product postponement	0.441*	0.399*	-			
Collaboration	0.625*	0.557*	0.437*	-		
Optimized inventory levels	0.655*	0.480*	0.629*	0.618*	-	
Reduced bullwhip effect	0.529*	0.424*	0.590*	0.549*	0.755*	-

Note. $N = 124$; $^*p < .05$.

Hypotheses testing.

Hypothesis 1.

$H1_0$. There is no statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

$H1_a$. There is a statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Using Minitab®, a multiple regression analysis was conducted between the four study predictor variables (IMC, MPC, POS, COL) and OPT, the first criterion variable. The results of regression analysis for hypothesis 1 suggested that collectively, IMC, MPC, POS, and COL, explained 61.0% of the variance in the optimized inventory levels ($R^2 = 0.61$, $F(4, 113) = 46.81$, $p < .05$), and collaboration ($p = .029$), MPC-based inventory optimization ($p = .007$), and product postponement ($p < .05$) were found to be significant predictors of optimized inventory levels (see Table 4). Therefore, one significant regression model resulted in the following predictor equation:

OPT = 4.54 + 0.114*COL + 0.284*MPC + 0.257*POS + 0.164*IMC.

Based on the results of regression analysis, null hypothesis 1 was rejected and support existed for the alternate hypothesis 1.

Table 4

Regression analysis: Optimized inventory levels

Predictor Variable	*B*	*SE*	Beta	*t*	*p*
Constant	4.540	1.429		3.18	0.002*
Collaboration (COL)	0.114	0.051	0.164	2.22	0.029*
MPC-based inventory optimization (MPC)	0.284	0.102	0.247	2.76	0.007*
Product postponement (POS)	0.257	0.044	0.211	5.78	0.000*
IMC-based inventory optimization (IMC)	0.164	0.102	0.142	1.60	0.112
$R^2 = .610$*					
$F = 46.81$					

Note. $N = 124$; *$p < .05$.

Hypothesis 2.

$H2_0$. There is no statistically significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

$H2_a$. There is a significant relationship between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

A second multiple regression analysis was conducted between the four study predictor variables (IMC, MPC, POS, COL) and BWE, the second criterion variable. The results of regression analysis for hypothesis 2 suggested that collectively, IMC, MPC, POS, and COL, explained 49.7% of the variance in the reduced bullwhip effect ($R^2 = 0.497$, $F(4, 110) = 29.14$, $p < .05$), and collaboration ($p = .045$), IMC-based inventory optimization ($p = .007$), and product postponement ($p < .05$) were found to be significant predictors of reduced bullwhip effect (see Table 5). Therefore, one significant regression model resulted in the following predictor equation:

BWE = 7.72 + 0.134*COL + 0.013*MPC + 0.309*POS + 0.365*IMC

Based on the results of regression analysis, null hypothesis 2 was rejected and support existed for the alternate hypothesis 2.

Table 5

Regression analysis: Reduced bullwhip effect

Predictor Variable	*B*	*SE*	Beta	*t*	*p*
Constant	7.722	1.898		4.07	0.000*
Collaboration (COL)	0.134	0.065	0.233	2.03	0.045*
MPC-based inventory optimization (MPC)	0.013	0.133	-0.275	0.10	0.924
Product postponement (POS)	0.309	0.060	0.465	5.15	0.000*
IMC-based inventory optimization (IMC)	0.365	0.132	0.125	2.76	0.007*
R^2 = .497*					
F = 29.14					

Note. N = 124 *p < .05.

Evaluation of Findings

In this study, SCM performance was measured in terms of both optimized inventory levels and reduced bullwhip effect. Regression analysis suggested that based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States, there were two significant relationships among the study variables. First, there was a significant relationship between (IMC, MPC, POS, COL) and OPT. Second, there was a significant relationship between (IMC, MPC, POS, COL) and BWE. Regression analysis resulted in two significant regression models for optimized inventory levels and reduced bullwhip effect, and two predictor equations that explained 61% and 49.7 % of the variance respectively for OPT and BWE. As a result, both null hypotheses 1 and 2 were rejected, and support existed for the alternative hypotheses 1 and 2. Following is an evaluation of the hypothesis results as compared and contrasted with current SC literature findings:

Hypothesis 1. Hypothesis 1 results indicated a significant positive relationship between MPC-based inventory optimization and optimized inventory levels, the first criterion variable. MPC-based inventory optimization was a significant predictor of optimized inventory levels (β = .247, p = .007). This hypothesis 1 finding was aligned with the conclusions of Hai et al. (2010), Schwartz and Rivera (2010), and Wang, Rivera and Kempf (2007) studies. Hai et al.'s study used MPC to develop a model of flexible control strategy for dynamic SC in a semiconductor-manufacturing industry firm where customer demand forecasts were unpredictable. Schwartz and Rivera's and Wang et al.'s studies demonstrated the robustness of MPC-based inventory optimization in managing inventory levels of manufacturing firms with demand uncertainty. Second, hypothesis 1 results also noted a significant positive relationship between product postponement and optimized inventory levels, the first criterion variable, and product postponement was a significant predictor of optimized inventory levels (β = .211, p < .05). This finding of hypothesis 1 was comparable to findings of Brun and Zorzini (2009), Liao et al. (2013), Rossin (2012), and Yang et al. (2010) who suggested that postponement had the potential to improve responsiveness of SCM while reducing inventory levels. Rossi's findings demonstrated that postponement had significant positive impact on SCM performance. Similarly, Yang et al.'s study outcomes demonstrated that postponement allowed manufacturing firm leaders to operate without storing finished products inventory and maintained their inventories in form of pre-customized. However, this finding of hypothesis 1 was contrary to Kumar and Wilson (2009) who found a less significant relationship between product postponement and optimized inventory levels in an off-shoring SCM system, and concluded the cost savings might not be significant enough to consider the off-shoring postponement as a good optimizing inventory levels strategy in an off-shoring SCM system.

Third, hypothesis 1 results showed a significant positive relationship between collaboration and optimized inventory levels, the first criterion variable, and collaboration was a significant predictor of optimized inventory levels (β = .146, p = .029). This finding of hypothesis 1 was in agreement with results of Kumar and Banerjee (2012) and Iyer et al. (2014) on the significance of the relationship between collaboration and optimized inventory levels. Kumar and Banerjee concluded that the main reason for using collaboration was to develop strategies through achieving excellence in core business processes and to remain competitive in a marketplace by optimizing inventory levels. However, this hypothesis 1 outcome was in contrast with Kumar and Banerjee (2012) who suggested a nonlinear relationship between collaboration and optimized inventory levels. Iyer et al.'s findings suggested extensive collaborative efforts with partners resulted in superior SCM performance.

Finally, the results of hypothesis 1 noted a significant regression model whereby; collectively, IMC, MPC, POS, and COL explained 61% of the variance of optimized inventory levels (p <.05). This hypothesis 1 finding provided empirical evidence of the value and support for the prior results Furlan et al. (2011) that demonstrated combination of control mechanisms acted synergistically toward improving SCM performance.

Hypothesis 2. Hypothesis 2 results indicated a significant positive relationship between IMC-based inventory optimization and reduced bullwhip effect, the second criterion variable, and IMC-based inventory optimization was a significant predictor of reduced bullwhip effect (β = .125, p = .007). This finding of hypothesis 2 was consistent with findings of Garcia et al. (2013), and Xie and Zhou (2012) studies. Garcia et al. used a two-degree-of-freedom feedback IMC-based design for bullwhip effect avoidance in a SCM system and their study found a significant relationship between IMC-based inventory optimization and reduced bullwhip effect. Xie and Zhou used an automatic pipeline feedback compensated inventory and order-based production control system with fuzzy logic to reduce the bullwhip effect. Second, hypothesis 2 results noted a significant positive relationship between collaboration and reduced bullwhip effect, the second criterion variable, and collaboration was a significant predictor of reduced bullwhip effect (β = .233, p = .045). This finding of hypothesis 2 was comparable to the findings of Agrawal et al. (2009), Banbury, Helman, Spearpoint, and Tremblay (2010), Cannella and Ciancimino (2010), Costantino et al. (2014), Madlberger (2009), and Lee et al. (2014) who found collaboration and information sharing were critical to meet the goals of reduced bullwhip effect. For example, findings of Costantino et al. (2014) confirmed the role of collaboration in reduced bullwhip effect and clearly demonstrated how the coordination of the control policies, in term of demand forecast and safety stock level at each echelon of a SCM system played an important role in reduced bullwhip effect and provided better customer service. Similarly, findings of Banbury et al. (2010) demonstrated the significant role of collaboration in reducing the bullwhip effect, and concluded from a mixed method study that collaborative efforts among SC partners enabled them to adopt optimum strategies in reducing bullwhip effect. This lean practice increased hold on ordering strategy, which led to a smaller bullwhip effect (Banbury et al., 2010). Third, hypothesis 2 results showed a significant positive relationship between product postponement and reduced bullwhip effect, the second criterion variable, and product postponement was a significant predictor of reduced bullwhip effect ($\beta = .465$, $p < .05$). This hypothesis 2 finding supported the findings of Ngniatedema (2012) who concluded a well-designed postponement strategy through mass customization processes in conjunction with proper information had reduced bullwhip effect.

Finally, the results of hypothesis 2 indicated a significant regression model whereby, collectively, IMC, MPC, POS, and COL explained 49.7% of the variance of reduced bullwhip effect ($p <.05$), which provided empirical evidence of the value and support for the prior results of Cannella and Ciancimino (2010), Dominguez, Cannella, and Framinan (2014), and Lee et al. (2014) who demonstrated combination of control mechanisms helped reduced bullwhip effect and eventually SCM performance. For example, Cannella and Ciancimino, and Dominguez et al. concluded that the best result in reducing bullwhip effect was experienced when product postponement (smoothing replenishment) and collaboration were combined. However, the findings of hypothesis 2 were inconsistent with Cachon et al. (2007) who studied the bullwhip effect in a SCM system and found that wholesalers were affected by bullwhip effect, but retailers and manufacturer firms were not affected. Cachon et al. also concluded that manufacturing firms did not have greater demand variability (amplification) than retailers, which contrasted with the hypothesis 2 results in the current study.

Summary

The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. A final sample of 124 SC senior-level managers of medium-size and large manufacturing firms in the United States responded to the survey. Overall, 15 moderate to strong significant positive relationships were found among the variables of the study: six moderate positive relationships were found between the predictor variables, which included a moderate positive relationship between MPC and IMC ($r = 0.670$; $p < .05$); a moderate positive relationship between MPC and POS ($r = 0.441$; $p < .05$); a moderate positive relationship between MPC and COL ($r = 0.652$; $p < .05$); a moderate positive relationship between IMC and POS ($r = 0.399$; $p < .05$); a moderate positive relationship between IMC and COL ($r = 0.557$; $p < .05$); and a moderate positive relationship between POS and COL ($r = 0.473$; $p < .05$). In addition, all four predictor variables had nine moderate to strong positive relationships with optimized inventory levels and the reduced bullwhip effect criterion variables, which included a moderate positive relationship between OPT and MPC ($r = 0.655$; $p < .05$); a moderate positive relationship between OPT and IMC ($r = 0.480$; $p < .05$); a moderate positive relationship between OPT and POS ($r = 0.629$; $p < .05$); a moderate positive relationship between OPT and COL ($r = 0.618$; $p < .05$); a moderate positive relationship between BWE and MPC ($r = 0.529$; $p < .05$); a moderate positive relationship between BWE and IMC ($r = 0.424$; $p < .05$); a moderate positive relationship between BWE and POS ($r = 0.590$; $p < .05$); a moderate positive relationship between BWE and COL ($r = 0.549$; $p < .05$), and a strong positive relationship between BWE and OPT ($r = 0.755$; $p < .05$). Regression analysis resulted in two significant regression models for optimized inventory levels and reduced bullwhip effect and two predictor equations that explained 61% and 49.7 % of the variance respectively for OPT ($p < .05$) and BWE ($p < .05$). As a result, both null hypotheses 1 and 2 were rejected, and support existed for the alternative hypotheses 1 and 2.

The hypothesis 1 findings of this study indicated that MPC-based inventory optimization, product postponement, and collaboration were individually significant predictors of optimized inventory levels, and one significant regression model was found whereby, collectively, IMC, MPC, POS, and COL explained 61% of the variance of optimized inventory levels. The hypothesis 1 findings were aligned with the conclusions of several SCM researchers including Brun and Zorzini (2009), Furlan et al. (2011), Hai et al. (2010), Iyer et al. (2014), Kumar and Banerjee (2012), Liao et al. (2013), Rossin (2012), Schwartz and Rivera (2010), Wang et al. (2007), and Yang et al. (2010). Findings of hypothesis 1 were inconsistent with previous research outcomes reported by Kumar and Wilson (2009) and Kumar and Banerjee (2012). Hypothesis 2 results indicated that individually, IMC-based inventory optimization, product postponement, and collaboration were significant predictors of reduced bullwhip effect. The results of hypothesis 2 also indicated one significant regression model whereby, collectively, IMC, MPC, POS, and COL explained 49.7% of the variance of reduced bullwhip effect. Findings of several SCM practitioners and academicians, such as Agrawal et al. (2009), Banbury et al. (2010), Cannella and Ciancimino (2010), Costantino et al. (2014), Dominguez et al. (2014), Garcia et al. (2013), Lee et al. (2014), Madlberger (2009), Ngniatedema (2012), and Xie and Zhou (2012), reported research outcomes similar to the hypothesis 2 findings that IMC-based inventory optimization, product postponement, and collaboration were effective both the individual and collective approach to reduce the bullwhip effect. However, findings of the hypothesis 2 were inconsistent with research results reported by Cachon et al. (2007) that manufacturing firms did not have greater demand variability (amplification) than retailers. In other words, most of manufacturing firms did not exhibit the bullwhip effect based on Cachon et al.'s findings.

Chapter 5: Implications, Recommendations, and Conclusions

The problem addressed in the study was that business performance has been impeded because inventory optimization models of many existing SCM systems lack appropriate control mechanisms to optimize inventory levels and to reduce the bullwhip effect (Bray & Mendelson, 2012; Fawcett et al., 2009; James & Mbang, 2012, Li et al., 2006; Prajogo & Olhager, 2012; Schwartz & Rivera, 2010). The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predicted optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States (U.S.). Greater peer acceptance and adherence to research principles, survey has become a popular instrument among researchers to collect data (Rungtusanatham et al., 2003); however, collecting data using survey instruments have certain limitations as self-report measures may have provided data that exceeded the objective measured values (actual data). Additionally, use of non-experimental correlational research design and regression, potentially limited the results of the study because causal inference cannot be achieved.

Ethical assurances were provided to all participants with clear instructions regarding their rights and no ethical issues were uncovered during the study. Each participant acknowledged receipt of the informed consent form and those who did not accept the informed consent acknowledgement exited the survey website before starting the survey and the research was conducted in accordance with the guidelines of the Institutional Review Board of Northcentral University policies and procedures. All data were coded, de-identified, stored in a secure environment. Chapter 5 continues with a discussion of the implications of each hypothesis followed by recommendations for practice and future research, and conclusions.

Implications

Research question 1. The first research question queried the extent of relationships between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and optimized inventory levels based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Hypothesis 1. Three significant positive relationships between IMC-based inventory optimization (IMC), MPC-based inventory optimization (MPC), product postponement (POS), collaboration (COL), and optimized inventory levels (OPT) resulted from hypothesis 1 testing, and one significant regression model resulted whereby, collectively, IMC, MPC, POS, and COL explained 61% of the variance of optimized inventory levels. First, a significant positive relationship between MPC and OPT implied that manufacturing leaders who dealt with demand uncertainty while optimizing inventory levels considered MPC-based inventory optimization as a superior inventory optimization model (Bray & Mendelson, 2012; Hai et al., 2010; Schwartz & Rivera, 2010), and this hypothesis 1 result also indicated that manufacturing leaders uncovered MPC-based inventory optimization model to be more robust than IMC-based inventory optimization model to optimize inventory levels (Wang et al., 2007). Second, a significant positive relationship between POS and OPT implied that manufacturing SC managers applied product postponement and mass customization lean practices to optimize of inventory levels (Brun & Zorzini, 2009; Liao et al., 2013; Rossin, 2012;

Yang et al., 2010). Third, a significant positive relationship also found between COL and OPT projected that collaboration was a strong strategic objective choice for many manufacturing firms, to the extent collaboration was practiced extensively among SC partners (Iyer et al., 2014; Kumar & Banerjee, 2012). Finally, the hypothesis 1 regression model implied that combination of control mechanisms, IMC, MPC, POS, and COL, explained 61% of the variance of optimized inventory levels for a synergistic improvement of SCM performance (Furlan et al., 2011).

Research question 2. The second research question queried the extent of relationships between (a) IMC-based inventory optimization, (b) MPC-based inventory optimization, (c) product postponement, and (d) collaboration, and reduced bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States.

Hypothesis 2. Three significant positive relationships between IMC, MPC, POS, COL, and reduced bullwhip effect (BWE), and one significant regression model, resulted from hypothesis 2 whereby, collectively, IMC, MPC, POS, and COL explained 49.7% of the variance of reduced bullwhip effect. First, a significant positive relationship between product postponement and reduced bullwhip effect implied that manufacturing leaders who experienced drastic customer demand fluctuations used product postponement to reduce the bullwhip effect (Ngniatedema, 2012). Second, a significant positive relationship between IMC-based inventory optimization and reduced bullwhip effect demonstrated that manufacturing leaders applied IMC-based inventory optimization to detect the changes in customer demand in a timely manner (Garcia et al., 2013; Xie & Zhou, 2012). Third, a positive relationship between collaboration and reduced bullwhip effect implied that sharing information with SC partners on operational decisions in medium-size and large U.S. manufacturing firms reduced the bullwhip effect (Agrawal et al., 2009; Banbury et al., 2010; Cannella & Ciancimino, 2010; Costantino et al., 2014; Madlberger, 2009; Lee et al. (2014). Finally, the significant regression model implied that combination of control mechanisms, IMC, MPC, POS, and COL explained 49.7% of the variance of reduced bullwhip effect to synergistically reduce the bullwhip effect of medium-size and large U.S. manufacturing firms (Cannella & Ciancimino, 2010; Dominguez et al., 2014; Lee et al.,2014).

Recommendations

To gain a competitive market position, manufacturing industry leaders are challenged to align their SCM systems based on the operational and financial performances of the firms (Cook et al., 2011; Datta & Christopher, 2011; Katunzi, 2011; Lo & Power 2010). In search of a holistic alignment to SCM performances, the current study was conducted with a broader spectrum than the earlier studies of Agrawal et al. (2009), Bray and Mendelson (2012), Cannella and Ciancimino (2010), Costantino et al. (2014), Datta and Christopher (2011), Garcia et al. (2013), Iyer et al. (2014), Kumar and Banerjee (2012), Kumar and Wilson (2009), Lee et al. (2014), Liao et al. (2013), Madlberger (2009), and Schwartz and Rivera (2010), as they searched solely on different drivers to improve performance of SCM systems. This study investigated the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large U.S. manufacturing firms, and this section includes recommendations for practical application of the research findings and for future research.

Recommendations for practice. The study findings provided sufficient evidence that suggested appropriate control mechanisms improved SCM systems performances, which was measured in terms of both optimized inventory levels and reduced bullwhip effect and there are four recommendations for practice related to the current study. Therefore, the first recommendation for practice was for use of the MPC-based inventory optimization model to optimize inventory levels as represented in the hypothesis 1 result and in previous studies by Hai et al. (2010), Schwartz and Rivera (2010), and Wang et al. (2007) demonstrated the robustness of MPC-based inventory optimization in optimizing inventory levels of manufacturing firms where demand forecasts were unpredictable. Second recommendation for practice is to use product postponement strategy to reduce the bullwhip effect and optimize inventory levels. The hypotheses 1 and 2 results and previous studies by Brun and Zorzini (2009), Liao et al. (2013), Ngniatedema (2012), Rossin (2012), and Yang et al. (2010) proved that postponement had the potential to reduce the bullwhip effect and optimize inventory levels through mass customization process. Third recommendation for practice is to use collaboration strategy to optimize inventory levels and reduce the bullwhip effect. Studies conducted by Iyer et al. (2014), Kumar & Banerjee (2012), and Wiengarten et al. (2010) along with the results from the hypotheses 1 and 2 of current study confirmed that as a strategic objective choice among U.S. manufacturing firm, collaboration reduced the bullwhip effect and optimized inventory levels. Final recommendation for practice is to combine IMC, MPC, POS, and COL control mechanisms to synergistically reduce the bullwhip effect and optimized inventory levels. The results of the hypotheses 1 and 2 from the current study, as also supported by Cannella and Ciancimino (2010), Dominguez et al. (2014), Furlan et al.

(2011), and Lee et al. (2014) studies, suggested that stronger results in optimizing inventory levels and reducing the bullwhip effect were obtained when combination of the IMC, MPC, POS, and COL control mechanisms was used).

Recommendations for future research. The results of study uncovered five recommendations for future research. First, a quantitative correlation study should be done to replicate the current study with an expanded sample to include international manufacturing firms to increase the generalizability research within global market as suggested in the delimitation section of this study. Second, to enhance the operationalization of study variables, a quantitative structural equation modeling (SEM) study may be conducted to examine relative strength and causal relationships among variables. Third, a quantitative meta-analysis study may be considered to integrate and critically examine the findings of the current study across numerous individual studies via quantitative analysis (Nair, 2006). Fourth, a quantitative experimental study should be done to further scrutinize the significant relationships identified in hypotheses 1and 2 between optimized inventory levels and reduced bullwhip effect. Fifth, a quantitative experimental study should be conducted using archival data such as COMPUSTAT or Wharton Research Data Services (WRDS), which may reduce self-selection and self-reporting sampling biases (Aleda, 2007) also to reduce any bias that may have limited results in the nonexperimental current study through the self-reported variables.

Conclusions

The purpose of this quantitative correlational study was to investigate the extent to which SCM control mechanisms predict optimized inventory levels and reduced the bullwhip effect based on the perceptions of SC senior-level managers of medium-size and large manufacturing firms in the United States. The theoretical framework of strategy-based framework specially the tenets of resource-based view (RBV), which guided the investigation of this study on the effects of different SCM control mechanisms on SCM performance in manufacturing firms was inferentially supported (Basu et al., 2013; Sundram et al., 2011). The implications and recommendations of the study resulted from statistical analysis and analytical evaluation of the findings were offered to both professional practice and future scholarly SCM research earlier in this Chapter. The study findings were significant, supportive of the purpose statement, and contributed to current landscape of SCM literature, which are highlighted below.

Three significant positive relationships between IMC, MPC, POS, COL, and optimized inventory levels, and one significant regression model resulted from hypothesis 1 whereby, collectively, IMC, MPC, POS, and COL explained 61% of the variance of optimized inventory levels. In addition, three significant positive relationships between IMC, MPC, POS, COL, and reduced bullwhip effect, and one significant regression model resulted from hypothesis 2 whereby, collectively, IMC, MPC, POS, and COL explained 49.7% of the variance of reduced bullwhip effect. Practical recommendations for the findings include: (a) use of MPC-based inventory optimization model to optimize inventory levels; (b) use of product postponement strategy to reduce the bullwhip effect and optimize inventory levels; (c) use of collaboration strategy to optimize inventory levels and reduce the bullwhip effect; and (d) to combine IMC, MPC, POS, and COL control mechanisms to synergistically reduce the bullwhip effect and optimized inventory levels.

Recommendations for future studies include: (a) to conduct a replicate quantitative correlation study with expansion to international manufacturing firms to increase the generalizability research within global market; (b) to conduct a quantitative structural equation modeling (SEM) study to examine relative strength and causal relationships among variables, which enhances the operationalization of study variables; (c) to conduct a quantitative meta-analysis study to integrate and critically examine the findings of the current study across numerous individual studies via quantitative analysis; (d) to conduct a quantitative experimental study to further scrutinize the significant relationships identified in hypotheses 1and 2 between optimized inventory levels and reduced bullwhip effect; and (e) to conduct a quantitative experimental using archival data such as COMPUSTAT or Wharton Research Data Services (WRDS), which may reduce self-selection and self-reporting sampling biases also to reduce any bias that may have limited results in the nonexperimental current study through the self-reported.

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Appendixes

Appendix A: U.S. Standard Industry Classification (SIC)

According to the North American Industry Classification System (NAICS Association, 2008), followings constitute the U.S. standard industry classification(SIC): (1) agriculture, forestry, fishing and hunting, (2) mining, quarrying, and oil and gas extraction, (3) utilities, (4) construction, (5) manufacturing, (6) wholesale trade, (7) retail trade, (8) transportation and warehousing, (9) information, (10) finance and insurance, (11) real estate and rental and leasing, (12) professional, scientific, and technical services, (13) management of companies and enterprises, (14) administrative and support and waste management and remediation services, (15) educational services, (16) health care and social assistance, (17) arts, entertainment, and recreation, (18) accommodation and food services, (19) other services (except public administration), and (20)public administration.

Appendix B: Study Survey Instrument

1. As a participant, you will choose between "I agree" and "No, thank you". Invitees who choose "No, thank you" do not accept the Informed Consent Acknowledgement and will exit the survey.

   ****This question is required.*
   Informed Consent Acknowledgement:

   I agree to participate in the research. I have read the description of the study, "Supply Chain Decision Making Under Demand Uncertainty" and understand the conditions of participation. This choice will take me to the electronic survey.

   No, thank you. By clicking this choice, I will exit the survey.

2. In this research study, we are interested in knowing the extent to which specific SCM control mechanisms can be used to optimize inventory levels and reduce the bullwhip effect. The study will provide a means to identify the special needs of different industrial firms in coping with demand uncertainty and the bullwhip effect, so that industrial leaders can devise efficacious operational responses.

   Uncertainty and fluctuations in customer demands require more rapid response in inventory optimization to ensure high-quality customer service and profitability. Therefore, a SCM capable of responding to customer demand uncertainty effectively and efficiently, based on a combination of operational mechanisms is highly desirable.

   ****The following information is required.* The collected data and information will help the research team to understand differences in various business settings.

3. Which term best describes your industry? Please check all that apply:

_Automotive	_Electronics
_Chemicals/plastics	_Computer Software
_Medical/pharmaceutical	_Semiconductors
_Appliances	_Industrial Machinery/Components
_Military/Government/Technic	_Building Materials
_Consumer packaged goods	_Apparel/textiles
_Other:________________	

4. The North American Industry Classification System (NAICS) is the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. business

economy. Please select the code of NAICS, which ties closest to your company. If you are unsure of your company's NAICS code, please choose the best answer:

Select	NAICS number	Description
	31-33	Manufacturing
	42	Wholesale
	44-45	Retail
	48-49	Transportation and Warehousing
	54	Professional, Scientific, and Technical Services
	55	Management of Companies and Enterprises
	62	Health Care and Social Assistance
	72	Accommodation and Food Services
	81	Other Services (except Public Administration)

5. Total number of employees:
   _Less than 100 _Between 500 and 1000
   _Between 100 and 500 _More than 1000

6. What is your designation (job title)?
   _Director _Vice President/President
   _Chief executive officer (CEO) _Chief operating officer (COO)
   _Manager _Consultant/Analyst
   _Other

7. Please indicate your level of work experience with supply chain management(SCM):
   _<1 year _1-3 years
   _3-5 years _5-10 years
   _10-15 years _15-20 years
   _20+ years

8. Please indicate how long you've been with your current firm:
   _< 1 year _1-3 years
   _3-5 years _5-10 years
   _10-15 years _15-20 years
   _20+years

9. Please indicate your level of education:
   _Associate's degree _Some College
   _College Graduate/Bachelor's Degree _Masters/MBA
   _ Doctorate

10. Please indicate how strongly you agree with the following statements. With Model Predictive Control (MPC) in in our SCM system:

		Strongly disagree			Neutral		
a	My firm SCM can detect changes in customers demand in a timely manner.	1	2	3	4	5	
b	My firm can reconfigure SCM resources in a flexible manner to respond customers demand changes.	1	2	3	4	5	
c	My firm can detect changes in supply in a timely manner.	1	2	3	4	5	
d	My firm can reconfigure resources in a flexible manner to respond supply changes.	1	2	3	4	5	

11. Please indicate how strongly you agree with the following statements. With Internal Model Control (IMC) in our SCM system:

		Strongly disagree			Neutral		
a	My firm SCM can detect changes in customers demand in a timely manner.	1	2	3	4	5	
b	My firm can reconfigure SCM resources in a flexible manner to respond customers demand changes.	1	2	3	4	5	
c	My firm can detect changes in supply in a timely manner.	1	2	3	4	5	
d	My firm can reconfigure resources in a flexible manner to respond supply changes.	1	2	3	4	5	

12. Please indicate how strongly you agree with the following statements. With postponement lean practice our SCM system:

		Strongly disagree			Neutral			Strongly agree
a	In my firm, products are designed for modular.	1	2	3	4	5	6	7
b	Modular assembly products reduces demand uncertainty risks in my firm.	1	2	3	4	5	6	
c	In my firm, final product assembly activities are delayed until customer orders have actually received.	1	2	3	4	5	6	7
d	Delaying final product assembly activities until customer orders have actually received reduces demand uncertainty risks in my firm.	1	2	3	4	5	6	
e	In my firm, final product assembly activities are delayed until the last possible position (or nearest to customers) in the supply chain.	1	2	3	4	5	6	7
f	Delaying final product assembly activities until the last possible position (or nearest to customers) in the supply chain reduces demand uncertainty risks in my firm.	1	2	3	4	5	6	

13. Please indicate how strongly you agree with the following statements. With collaboration in our SCM system:

		Strongly disagree			Neutral	
a	In my firm, information is shared with suppliers on operational decisions.	1	2	3	4	5
b	Sharing information related to operational decisions with suppliers reduces demand uncertainty risks in my firm.	1	2	3	4	5
c	In my firm, knowledge and specific know–how are shared with suppliers on operational decisions.	1	2	3	4	5
d	Shared knowledge and specific know–how on operational decisions reduces demand uncertainty risks in my firm.	1	2	3	4	5
e	In my firm, we work closely with suppliers on issues related to operational decisions.	1	2	3	4	5

f	Working closely with suppliers on issues related to operational decisions reduces demand uncertainty risks in my firm.	1	2	3	4	5		

14. Please indicate how strongly you agree with the following statements. The optimized inventory levels in our SCM system:

		Strongly disagree			Neutral	
a	In my firm, customer demand fluctuates drastically from week to week.	1	2	3	4	5
b	In my firm, MPC-based inventory optimization is capable to optimize inventory levels in a timely manner.	1	2	3	4	5
c	In my firm, IMC-based inventory optimization is capable to optimize inventory levels in a timely manner.	1	2	3	4	5
d	In my firm, postponement helps to optimize inventory levels in a timely manner.	1	2	3	4	5
e	In my firm, collaboration helps to optimize inventory levels in a timely manner.	1	2	3	4	5

15. Please indicate how strongly you agree with the following statements. The bullwhip effect in our SCM system:

		Strongly disagree			Neutral	
a	In my firm, SCM experiences the bullwhip effect.	1	2	3	4	5
b	In my firm, seasonal customer demand has high impact on the bullwhip effect problem.	1	2	3	4	5
c	In my firm, MPC-based inventory optimization is capable to reduce the bullwhip effect in a timely manner	1	2	3	4	5
d	In my firm, IMC-based inventory optimization is capable to reduce the bullwhip effect in a timely manner	1	2	3	4	5
e	In my firm, postponement helps to reduce the bullwhip effect in a timely manner.	1	2	3	4	5

f	In my firm, collaboration helps to reduce the bullwhip effect in a timely manner	1	2	3	4	5	6	7

16. Any other comments

Your response is very important to us. All responses will be treated with confidentially and no sources will be disclosed in any outputs from this research. Thank you for taking the time to assist in this research. We would be happy to answer any questions that may arise about the study.

Michael Zohourian, Doctoral Candidate

Appendix C: North American Industry Classification System: Industry Count

Code	Industry Title	Count*
11	Agriculture, Forestry, Fishing, and Hunting	439,154
21	Mining, Quarrying, and Oil and Gas Extraction	32,209
22	Utilities	279,639
23	Construction	1,440,911
31-33	Manufacturing	658,871
42	Wholesale Trade	743,751
44-45	Retail Trade	1,287,896
48-49	Transportation and Warehousing	336,121
51	Information	321,336
52	Finance and Insurance	676,215
53	Real Estate and Rental and Leasing	688,994
54	Professional, Scientific, and Technical Services	1,803,748
55	Management of Companies and Enterprises	21,358
56	Administrative and Support and Waste Management and Remediation Services	1,130,823
61	Educational Services	297,068
62	Health Care and Social Assistance	1,162,133
71	Arts, Entertainment, and Recreation	282,386
72	Accommodation and Food Services	747,482
81	Other Services (except Public Administration)	1,767,215
92	Public Administration	227,581
	Total:	**14,344,891**

* Number of U.S. businesses with that code.

Appendix D: Letter of Collaboration

From: Campbell, Dave <Dave.Campbell@infogroup.com> Sent: Fri 4/25/2014 2:50

To: Zohourian, Michael

Cc:

Subject: Infogroup | data for academic research

Message | Academic Whitepaper 2014.pdf (908 KB)

My name is Dave Campbell and I'm a representative with Infogroup. I'm currently working with Michael Zohourian on a survey project involving supply chain management. The criteria we used to create a list was based on the following:

- Geography = total US
- Industries = NAICS codes 31, 32, 33, 42, 44, 45
- Employee Size = 100 + employees at location
- Executive Contacts = Operations, Chief Operation Officer, Operations Executive
  - There were slightly over 12,000 records fitting Michael's criteria in our database. We will be randomly pulling 2,000 records from that universe.

You'll find a document outlining our compilation process to this email. Please contact me if further information is required.

Thanks,
Dave

Dave Campbell
Account Executive

Infogroup
Office: 402-836-1283
Fax: 866-511-4691
Cell: 402-953-7007
dave.campbell@infogroup.com

Appendix E: Survey Letter of Invitation

Michael Zohourian
Doctoral Candidate
Northcentral University
10000 E University Drive
Prescott Valley, AZ 86314

Date:

As a doctoral candidate at Northcentral University school of Business and Technology, I am conducting a research, the extent to which supply chain management (SCM) control mechanisms can be used to optimize inventory levels and reduce the bullwhip effect will be investigated. Thus, the study will provide a means to identify the special needs of different industries in coping with demand uncertainty and the bullwhip effect, so that supply chain (SC) managers can select appropriate control mechanisms.

You as a SCM official who has direct involvement in operational and strategic decision-making policies within your industry can contribute significant information for developing robust SCM systems.

Please kindly complete a short survey to assess the significant relationship among the variables used in this study. The information that you provide will be held in strict confidence including your identity and your company information. Complete anonymity will be assured. All data will be coded so that your identity will not be associated with your answers.

Please feel free to email me at mzohruian@devry.edu should you have any questions. If you would like a copy of the study results, please email me at the above email address with *study results* as the subject line.

Thank you for your invaluable assistance for completing this survey.

To complete the survey, please open the following link:
https://www.surveymonkey.com/s/SupplyChainsOptimization

Appendix F: Informed Consent Form

A Correlational Study of Supply Chain Decision Making Under Demand Uncertainty

What is the study about? You are invited to participate in a research study being conducted for a dissertation at Northcentral University in Prescott, Arizona. The study is interested in your knowledge and perception of your organization's supply chain Management (SCM) system effectiveness in optimizing inventory levels and reducing the bullwhip effect under demand uncertainty. You were selected based on your direct involvement in operational and strategic decision-making policies in SCM.

What will be asked of me*?* You will be asked to answer some questions where you indicate your perceptions from rating scales about the effectiveness of your organization's SCM system in optimizing inventory levels and reducing the bullwhip effect while coping with demand uncertainty. It is estimated, it will take less than 30 minutes to complete the survey.

Who is involved? The following people are involved in this research project and may be contacted at any time: Michael Zohourian, MSEE (Northcentral University Doctoral Candidate) and Robin Thorne, PhD (Northcentral University Dissertation Committee Chair).

Are there any risks*?* There are no known risks in this study. However, you may stop the study at any time. You can also choose not to answer any question that you feel uncomfortable in answering.

What are some benefits*?* There are no direct benefits to you by participating in this research. No incentives are offered. The results will have scientific interest that may eventually have benefits for SCM community.

Is the study anonymity/ confidential*?* The collected data in this study are confidential. Your name or personal information is not linked to data. Only the researchers in this study will see the data.

Can I stop participating the study? You have the right to withdraw from the study at any time without penalty. You can skip any questions on survey if you do not want to answer them.

What if I have questions about my rights as a research participant or complaints?
If you have questions about your rights as a research participant, any complaints about your participation in the research study, or any problems that occurred in the study, please contact the researchers identified in the consent form. Or if you prefer to talk to someone outside the study team, you can contact Northcentral University's Institutional Review Board at irb@ncu.edu or 1-888-327-2877 ex 8014.

We would be happy to answer any question that may arise about the study. Please direct your questions or comments to:
Michael Zohourian, MSEE
mzohourian@devry.edu
925-997-7565

Robin Throne, PhD
rthrone@ncu.edu
888.327.2877, Ext. 6029

Signatures
I have read the above description for the A Correlational Study of Supply Chain Decision Making Under Demand Uncertainty. I understand what the study is about and what is being asked of me. My signature indicates that I agree to participate in the study.
Participant's Name: _________________Researcher's Name: ______________
Participant's Signature: _______________Researcher's Signature: ___________
Date: _____________

Appendix G: Permission to Use Instruments

Re: [SPAM]Regarding your article "Factors that influence Chinese automotive suppliers' mass

Kun Liao <liaok@cwu.EDU>

You replied to this message on 4/7/2014 3:08 PM.

Sent: Mon 4/7/2014 2:19 PM

To: Zohourian, Michael

Michael,

Thanks for your interest in my research. Yes, you can use the measurements from my studies as long as you follow the way of professional citation. Please feel free to contact me when you have questions on that. Good luck with your dissertation!

Best,
Kun

Kun Liao, PhD, CQE

Associate Professor of Operations and Supply Chain Management
Department of Finance & Supply Chain Management, College of Business
Central Washington University
CWU-Lynnwood
20000 68th Avenue West
Lynnwood WA 98036
Phone: (425)-640-1574 x 3891
Fax: (425)-640-1488

You replied to this message on 4/8/2014 6:03 PM.
Click here to download pictures. To help protect your privacy, Outlook prevented automatic download of some pictures in this message.

From: Gopal Kumar <gopshal.kr@gmail.com> Sent: Tue 4/8/2014 4:37
To: Zohourian, Michael
Cc:
Subject: Re: Your article "Collaboration in supply chain"

Hi Michael,

I am happy to know your interest in collaboration. As far as permission for using/editing questionnaire is concerned, you can go ahead.

Thanks.

Kind Regards,

--
Dr. Gopal Kumar
Postdoctoral Researcher
Room No. S364
Dublin City University (DCU)
Glasnevin | Dublin 9 | Ireland

Tel: +353-01-7005712 +353-01-7005712 (O)

You replied to this message on 4/7/2014 5:30 PM.

From: Suhong Li <sli@bryant.edu> Sent: Mon 4/7/2014 5:09
To: Zohourian, Michael
Cc:
Subject: Re: Regarding your article "The impact of supply chain management practices on competitive advantage

Hi Michael,

Thank you for your interest in my research. Yes, please feel free to use the instruments in my paper.

Suhong

Sent from my iPad

Re: Your Article "A Global Analysis of Orientation, Coordination, and Flexibility in Supply Chains"

Davis-Sramek,Elizabeth <elizabeth.davissramek@louisville.edu>

You replied to this message on 4/14/2014 8:11 AM.

Sent: Mon 4/14/2014 4:31 AM
To: Zohourian, Michael

Of course. You can utilize any published scale for your research as long as it is cited.

Best of luck with your dissertation.

Dr. Beth Davis-Sramek
Associate Professor
Department of Marketing
College of Business
University of Louisville
Louisville, KY 40292
ph: 502-852-3472
fax: 502-852-7672

Re: Your Article: An Empirical Investigation into Supply Chain Resilience

Santanu Mandal <shaan.nitw@gmail.com>

Sent: Fri 4/18/2014 10:32 PM
To: Zohourian, Michael

Dear Sir,

Yes, You can adapt the scale!!!!

Best-

Santanu Mandal
B.Tech(Chemical Engg,NITW),
MBA(Marketing & Finance,Kalyani University),
Visiting Scholar,Oklahoma State University(2012-2013)
Doctoral Research Scholar
Faculty of Operations Management
IBS, Hyderabad, India.
+91-7731081495

Appendix H: Demographic Characteristics Frequency Tables

Table H1

Principal Industry

Characteristics	Frequency	Percent
Accommodation	0	0.00
Agriculture, Forestry, Fishing, and Hunting	3	2.42
Arts, Entertainment, and Recreation	0	0.00
Airlines & Aerospace (including Defense)	1	0.81
Apparel / Textiles	4	3.23
Appliances	1	0.81
Automotive	7	5.65
Banking, Investment, and Insurance	3	2.42
Chemical / Petrochemical	2	1.61
Construction	2	1.61
Computer (Hardware & Software)	4	3.23
Educational Services	4	3.23
Electrical / Electronics	4	3.23
Food & Beverages	7	5.65
Government	1	0.81
Healthcare, Pharmaceuticals, and Social Assistance	0	0.00
Information Technology, and Internet Services	10	8.06
Nonprofit	1	0.81
Retail & Consumer Durables	7	5.65
Real Estate	3	2.42
Semiconductors	4	3.23
Utilities, Energy, and Extraction	0	0.00
Other	56	45.16

Note N=124.

Table H2

Business Classification (NAICS)

Characteristics	M	SD	Range
Agriculture, Forestry, Fishing and Hunting	11	1	0.81
Mining, Quarrying, and Oil and Gas Extraction	21	0	0.00
Utilities	22	0	0.00
Construction	23	2	1.61
Manufacturing	31-33	81	65.32
Wholesale Trade	42	2	1.61
Retail Trade	44-45	4	3.23
Transportation and Warehousing	48-49	3	2.42
Information	51	4	3.23
Finance and Insurance	52	2	1.61
Real Estate and Rental and Leasing	53	2	1.61
Professional, Scientific, and Technical Services	54	7	5.65
Management of Companies and Enterprises	55	3	2.42
Administrative and Support and Waste Management	56	0	0.00
Educational Services	61	2	1.61
Healthcare, Pharmaceuticals, and Social Assistance	62	0	0.00
Arts, Entertainment, and Recreation	71	1	0.81
Accommodation and Food Services	72	0	0.00
Other Services (except Public Administration)	81	0	0.00
Public Administration	92	0	0.00
Other		10	8.06

Note N=124.

Table H3

Firm Size (number of employees)

Characteristics	Frequency	Percent
Less than 100	37	29.84
Between 100 and 500	27	21.77
Between 500 and 1000	18	14.52
More than 1000	42	33.87

Note N=124.

Table H4

Designation (job title)

Characteristics	Frequency	Percent
Vice President/President	5	4.03
Chief executive officer (CEO)	8	6.45
Chief operating officer (COO)	8	6.45
Director	24	19.35
Manager	43	34.68
Consultant/Analyst	7	5.65
Other	29	23.39

Note N=124.

Table H5

Education

Characteristics	Frequency	Percent
Some college	29	23.39
Associate's degree	10	8.06
Bachelor's degree	42	33.87
Some graduate school	13	10.48
Master's degree or equivalent	25	20.16
Doctorate	5	4.03

Note N=124.

Table H6

Work Experience

Characteristics	Frequency	Percent
<1 year	9	7.26
1-3 years	10	8.06
3-5 years	12	9.68
5-10 years	24	19.35
10-15 years	20	16.13
15-20 years	20	16.13
20+ years	29	23.39

Note. N=124.

Table H7

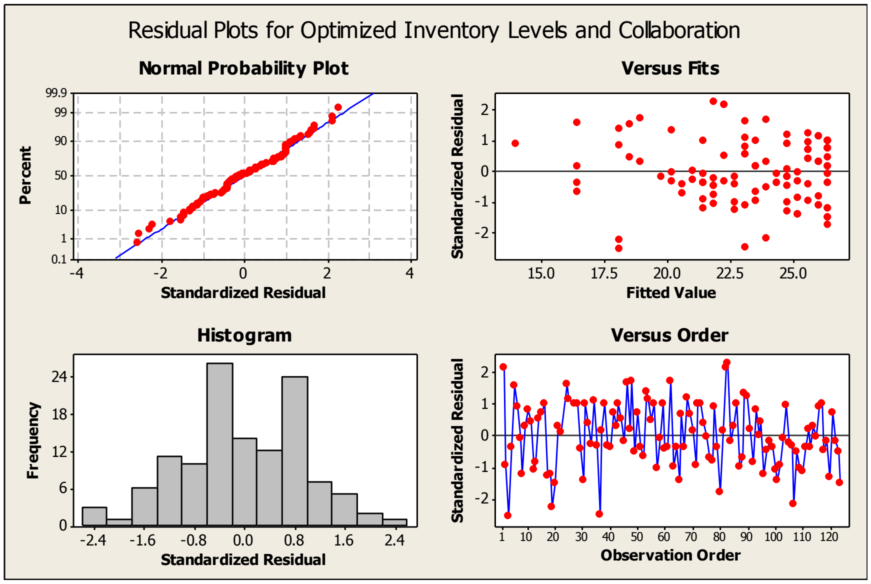
Number of Years Working at Current Firm

Characteristics	Frequency	Percent
<1 year	6	4.84
1-3 years	20	16.13
3-5 years	20	16.13
5-10 years	18	14.52
10-15 years	21	16.94
15-20 years	16	12.90
20+ years	23	18.55

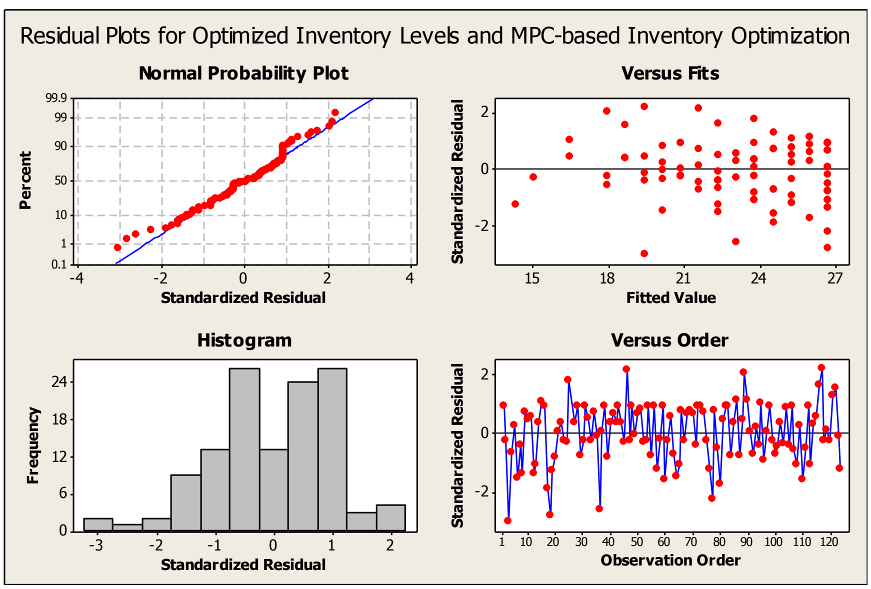
Note. N=124.

Appendix I: Data Assumptions

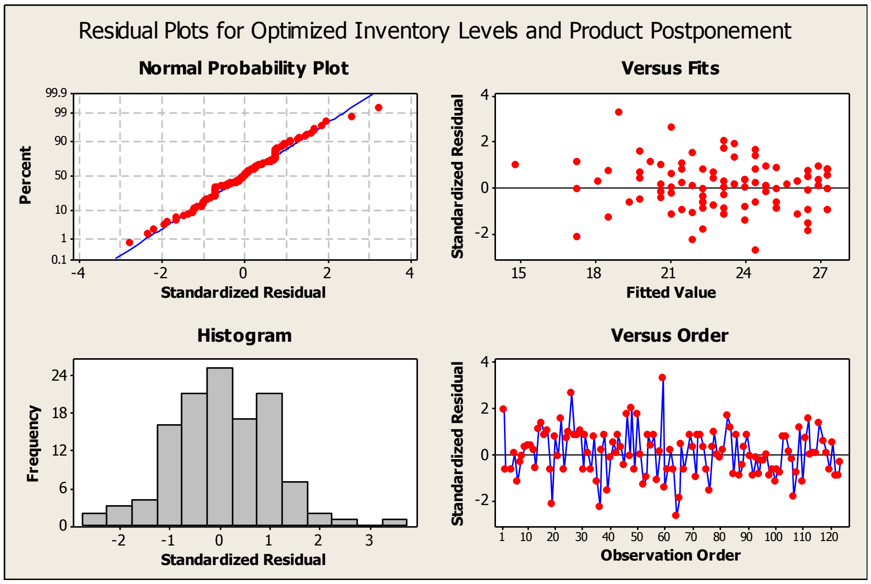
Residual Plots for Optimized Inventory Levels and Collaboration



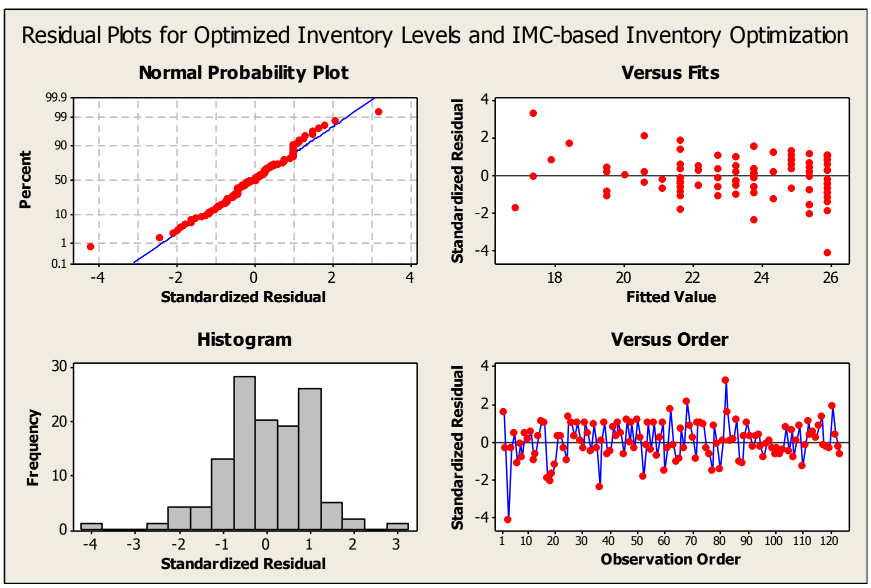
Residual Plots for Optimized Inventory Levels and MPC-based Inventory Optimization



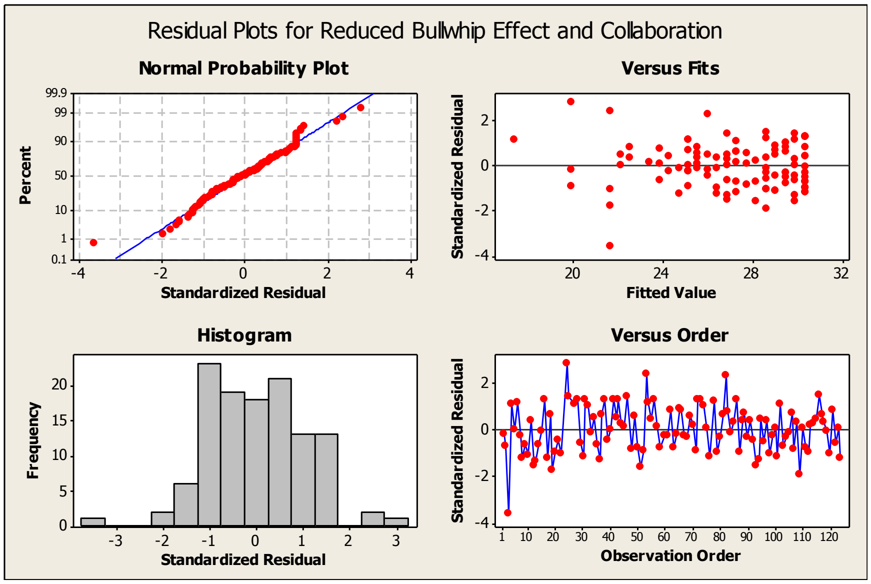
Residual Plots for Optimized Inventory Levels and Product Postponement



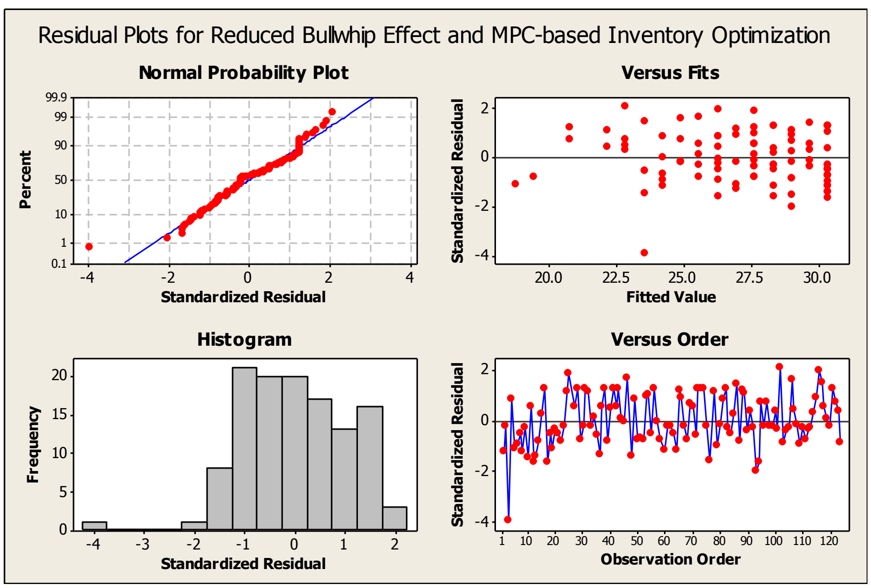
Residual Plots for Optimized Inventory Levels and IMC-based Inventory Optimization



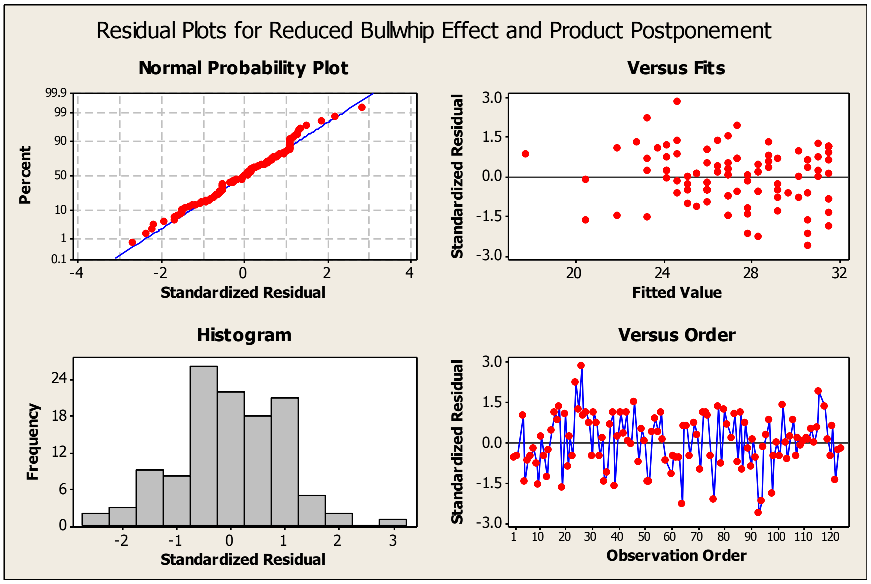
Residual Plots for Reduced Bullwhip Effect and Collaboration



Residual Plots for Reduced Bullwhip Effect and MPC-based Inventory Optimization



Residual Plots for Reduced Bullwhip Effect and Product Postponement



Residual Plots for Reduced Bullwhip Effect and IMC-based Inventory Optimization