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Containing Risk when Maximizing Supply-Chain Performance

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Abstract

The objective of this dissertation is to develop and test an approach that will quantify the level of risk in the supply chain, evaluate the cost and impact of risk mitigation strategies, validate event management protocols pre-implementation, and optimize across a portfolio of risk mitigation strategies. The research integrates a Mixed Integer Linear Programming (MILP) model and a Discrete Event Simulation model to investigate a production-inventory-transportation problem subject to risk. The MILP model calculates the optimal Net Profit Contribution of the supply chain in the absence of risk. Deviation risks are introduced as volatility in final demand and lead times, with lead time volatility affecting raw material lead times from suppliers to manufacturing plants and finished goods lead times from manufacturing plants to the warehouses. Disruption risks are modelled as temporarily impeding production at the manufacturing plants, in-bound distribution of raw materials from suppliers to the manufacturing plants, and out-bound distribution of finished goods from the manufacturing plants to warehouses. Computational experiments are run to examine the impact of risk on the supply chain. Further experiments explore the consequences of three risk mitigation strategies (inventory placement, expediting, and production flexibility) on supply chain performance in the presence of risk with the aim of discovering whether one strategy dominates or whether a portfolio approach to risk mitigation performs best. In sum, this research seeks to develop a framework that can inform efforts in understanding, planning for and controlling risk in the supply chain.

Chapter 1: Introduction

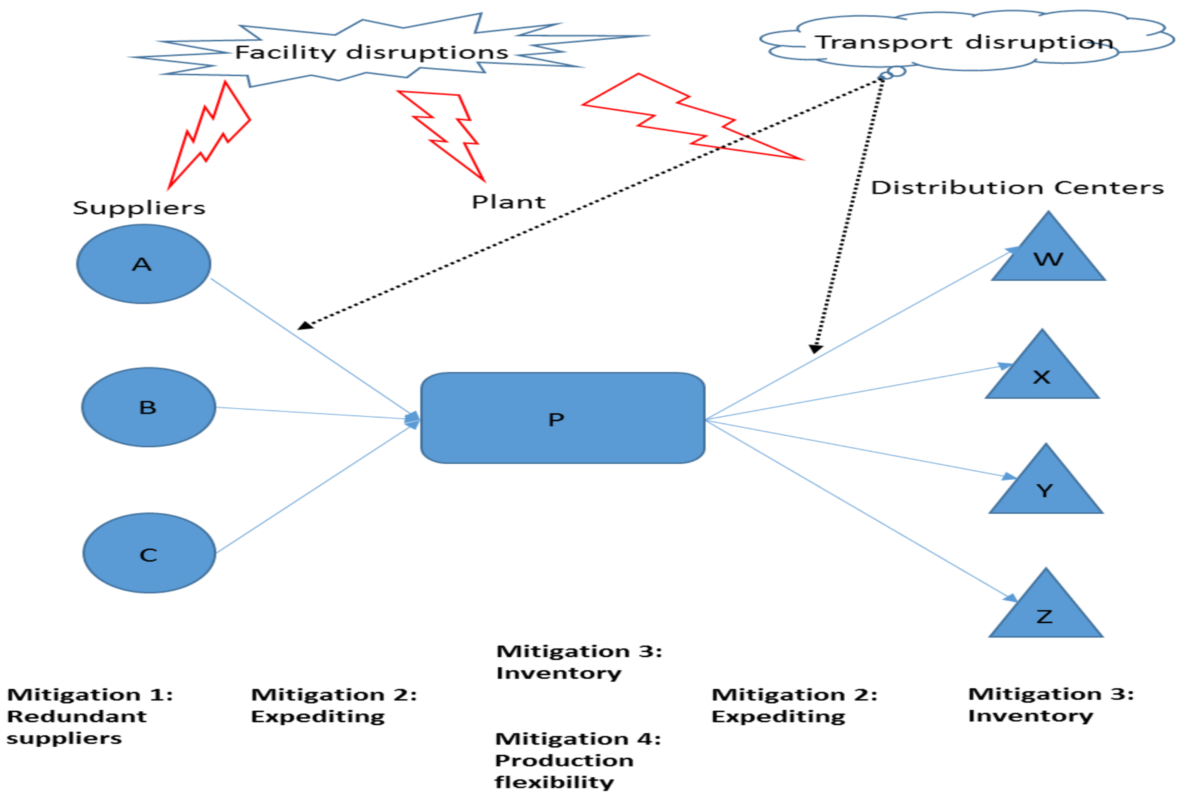
Background

Recent trends in supply chain management such as outsourcing, globalization, and customization are creating significant complexities in supply chains, with global supply chains becoming more susceptible to large-scale natural disasters, terrorist attacks, electrical blackouts, and operational failures (Ghavamifar, Makui, and Taleizadeh, 2018). Moreover, strategies for increasing the efficiency of supply chains can cause them to be less responsive to customer requirements (Puga, Minner, and Tancrez, 2018). As organizations configure their supply chains to improve financial performance and customer service, they are employing various strategies to mitigate risk including inventory positioning, flexibility, diversification, and strategic redundancy. These strategies can be embedded in such mathematical models for optimizing risk as stochastic linear programming, robust optimization, scenario analysis, and simulation (Rajagopal, Venkatesan, and Goh, 2017). Testing the results of such risk mitigation strategies requires consideration of the nature of exposure to adverse events, their interrelationships, and effects on dynamic supply-chain performance. The objective of this dissertation is to develop and test an approach that will quantify the level of risk in the supply chain, evaluate the cost and impact of risk mitigation strategies, validate event management protocols pre-implementation, and optimize across a portfolio of risk mitigation strategies.

Problem Setting

The problem setting is a production-inventory-transportation problem. The impact of risk on the supply network that provides a context for production, inventory placement and transportation decisions and costs are evaluated, with the costs and benefits of various risk mitigation strategies being examined.

Figure 1: Schematic of Disruptions and Risk Mitigation Strategies



Focus of Analysis

The focus of analysis is an individual firm. Specifically, the costs of the various risk mitigation strategies and the potential for optimizing among them are analyzed from the perspective of a single firm seeking to maximize its own performance as a supply-chain participant rather than maximizing the performance of the supply chain as a whole.

Production Strategies

Production strategies are investigated to determine their influence on the characterization of risk in the supply chain and the effectiveness of the various risk mitigation strategies. The three production strategies are:

- Push
- Pull
- Hybrid (push and pull).

Disruption Risks

Events that lead to disruptions in the supply chain are considered and modelled. These risks are modelled along three dimensions:

- Probability of occurrence: how frequently a disruption materializes
- Severity of occurrence: how much of the capacity is disrupted
- Time to recovery: how long the disruption lasts

Stochastic Parameters

Stochastic experiments are undertaken by varying three parameters to assess their impact on supply chain performance:

- Disruption risk characteristics – incidence, severity and time to recovery
- Demand volatility
- Lead time volatility

The demand and lead time volatilities are considered deviation risks.

Methodology

The analytical framework involves a combination of optimization and simulation to evaluate deviation and disruption risks and the impact of risk mitigation.

- Optimization – Mixed Integer Linear Programming (MLIP) Model. MILP is used to determine production, and the flows of raw materials and finished goods in the supply chain network. Model parameters are fixed. Expected values are used for parameter values. The optimization is constructed at a tactical level, with planning assumed to occur with a horizon of 90 days. The output of the optimization consists of a procurement plan, a distribution plan, and a distribution plan.
- Simulation – Discrete Event Simulation. Simulation is used to realistically model the operations and types of variation that occur in the supply chain. The simulation takes as its inputs, among other factors, the procurement plan, the production plan, and the distribution plan that are outputs of the optimization model. This approach allows for the evaluation of the impact of stochastic events and is suitable for introducing various deviations and disruptions into the operations of the supply chain allowing for the testing of the plans under conditions of uncertainty. This approach extends an integrated simulation and optimization model for production-inventory-transportation planning in the face of stochastic demand and lead times (Xu and Smith, 2018). Xu and Smith's work is extended herein by introducing upstream

procurement subject to uncertainty in supply, introducing disruption risk at various stages, and explicitly implementing a variety of risk mitigation strategies.

Theoretical Framework

Two theories inform and underpin this work: (i) Contingency Theory, and (ii) Modern Portfolio Theory.

Contingency Theory

Contingency theory holds that there is no single, best way to organize a firm. Rather, the appropriate structure of a firm depends on its tasks and objectives as well as the environment in which it is operating. In this view, management ought to be focused on achieving alignments between the internal goals of the firm and the external environment (Morgan, 2007). Ginsberg and Venkatraman (1985) point out that the complexity of the strategy concept has led researchers to focus their attention on studying and exploring relationships that hold within a particular context as opposed to investigating and searching for a "grand theory of strategy". Talluri et al. (2013), in developing a framework for assessing risk mitigation strategies in supply chains, base their framework on contingency theory because "the appropriateness and effectiveness of a risk mitigation strategy are contingent on each organization's internal and external environmental characteristics – there is no one-size-fits-all strategy".

In this dissertation we analyze multiple sources of risk that could materialize in supply chains at various times. We implement a combination of risk mitigation strategies against the various risks. If contingency theory holds, we will not expect to discover one optimal risk mitigation strategy that super-dominates. Should that be the case, we will then focus the investigation on the conditions under which the various risk mitigation strategies are most effective.

Modern Portfolio Theory

Modern Portfolio Theory (MPT) was developed by Harry Markowitz (1952) in the context of selecting financial securities when constructing an optimal investment portfolio. Each security has an expected return as well as expected risk, both calculated based on historical data. MPT assumes the investor is risk averse and trades off the mean return and the variance of the return (with variance being the measure of risk). An important insight from MPT is that when analyzing individual securities for inclusion in a portfolio, the appropriate comparison is neither pair-wise nor by looking each security's individual characteristics. Rather, the appropriate analysis is to determine how the security contributes to the total portfolio's overall risk and return (Markowitz, 1952).

Martinez-de-Albeniz and Simchi-Levi (2006) relied on modern portfolio theory to study procurement strategies in a supply chain. Specifically, they applied mean-variance analysis to investigate the trade-offs encountered by a manufacturer who has a portfolio of long-term contracts to reserve capacity with its suppliers and also has access to a spot market. Consistent with MPT, their analysis revealed the existence of an efficient frontier bounded by the maximum expectation portfolio and the minimum variance portfolio.

In this dissertation we implement the various risk mitigation strategies as alternatives for inclusion in a risk mitigation portfolio and investigate the impact of each risk mitigation strategy on the mean supply chain performance measure (net profit contribution) as well as the standard deviation of the net profit contribution across a set of computational experiments.

Research Questions

With a multi-dimensional set of measures to allow for trade-offs between the costs of deviation and disruption risks versus the cost of risk mitigation strategies, we address the following questions:

- Q1: Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?
- Q2: Are the best risk mitigation strategies contingent on the nature of the particular risks (frequency, severity, correlation)? Or, alternatively, are certain risk mitigation strategies globally optimal (dominate all others)?
- Q3: Is there a portfolio effect among risk mitigation strategies? That is, on a risk-adjusted basis, will a combination of mitigation strategies outperform each individual mitigation strategy?
- Q4: Can a blend of risk mitigation strategies be constructed that constitute a Pareto efficient frontier with respect to the performance measure (net profit contribution) versus the risk measure (standard deviation of net profit contribution) thus providing a basis for trading off risk versus performance?

Data

The data for the dissertation is synthetic data inspired by an actual case. The original case was a Mid-western dry goods manufacturing firm with a global supply chain. A sampling of parameters accounted for in the model include:

- Demand: daily product demands aggregated at warehouses
- Lead times: raw material lead times from suppliers to plants and finished goods lead times from plants to warehouses
- Costs: unit production costs, shipping costs, inventory carrying costs, and penalty costs

Contributions

This dissertation will contribute to the literature in the field of supply chain risk management in two primary ways:

- Test whether a counterpart to financial portfolio theory with multidimensional measures of risk and performance may be employed successfully for supply chain risk management.
- Investigate whether supply chain risk mitigation follows contingency theory (different risk mitigation strategies will perform best under different conditions) or whether globally optimal strategies can be constructed.

Limitations

To keep the research tractable, this work is circumscribed by the following limits:

- The portfolio of risk mitigation strategies is limited to inventory placement, expediting, and production flexibility.
- The focus of analysis is a focal firm. Interactions and collaboration across firms in the supply chain are not analyzed.
- A 90-day planning horizon is used. While other planning horizons were studied in the early, exploratory phases, only the results of the 90-day planning horizon are reported herein.

Chapter 2: Literature Review

A brief review of literature in the areas of supply chain planning, risk modeling, risk definition, and risk mitigation strategies was conducted considering foundational papers as well as applications and extensions of methodologies in supply chain risk management.

Supply Chain Planning

Supply chain planning is a research area with a deep and wide literature. While some research streams explore circumscribed component problems in-depth e.g. supply-production problems, production-distribution problems, inventory-distribution problems, and scheduling-allocation problems, other streams investigate the overarching supply-production-distribution problem in an integrated fashion across the entire supply chain. Hong et al. (2018) summarize the research that focuses on the component operational problems as addressing: (i) production-distribution problems investigating production decisions, scheduling decisions, and distribution planning from production facilities to wholesalers or customers, (ii) location-allocation and routing problems identifying convenient location for facilities such as plants or stock points, and allocating and planning transportation routes for customers, and (iii) inventory-transportation problems addressing inventory control at storage facilities and transportation planning from production facilities to wholesalers or retailers and customers.

Hong et al. (2018) addressed a distribution-allocation problem in a two-stage supply chain. They formulated an integer-programming model with variable and fixed transportation costs. The objective was to minimize total supply chain costs with the allocation of retailers to a distribution center and distribution centers to a manufacturing plant as the decision variables. Given the presence of fixed costs, the model was solved using an ant colony optimization-based heuristic.

Devapriya, Ferrell, and Geismar (2017) addressed an extension of the integrated production-distribution scheduling problem. They extended the standard problem that seeks to determine the optimal production batching and distribution scheduling by introducing a planning horizon constraint. This constraint was necessary in their model as the product being produced and distributed was perishable. Their solution methodology relied on a mixed integer program and a genetic algorithm heuristic. Very small problems could be solved to optimality with the linear program, but larger problems required the metaheuristic.

Gao, Qi, and Lei (2015) studied the integrated production-distribution problem with a complicating factor that imposed a no-wait condition between the production and distribution of each batch. Their work was motivated by a real-world problem of producing a chemical ingredient that was so time-sensitive that it could not be inventoried, but had to be produced and shipped daily. Their objective was to minimize the total operating hours required for the production and delivery of a set of customer orders to be delivered by a single vehicle. Cheng, Leung, and Li (2015) also studied the integrated production-distribution problem where the delivery was handled by a third-party logistics provider. Their objective was to minimize the total production and delivery costs for the manufacturer. They proposed an ant-colony optimization to solve the production component and a first-fit-decreasing heuristic (commonly used in the bin-packing problem) to solve the distribution component.

Motivated by real-world supply chain disruption cases, Pariazar and Sir (2018) studied a supply-distribution problem in the context of supply chain design and planning. They developed a multi-objective stochastic model that explored the trade-offs between costs and risks. Their problem setting was a supplier sourcing problem in a two-tiered supply chain with disruptions in supply availability and quality. Their work demonstrated the impact of various disruption mitigation strategies on supply chain cost and risk.

Gao et al. (2018) investigated a product delivery-store network layout problem. They attempted to capture the firm's distribution cost, the consumer's cost, and the total emission of greenhouse gasses. They formulated several mixed integer nonlinear programming models. Solving the optimization problem led them to conclude that there was sufficient "slack" in the distribution system such that total costs and emissions from both firms and consumers could be reduced without unduly burdening consumers.

With respect to investigating problems at the supply chain level, Sawik (2016) studied an integrated supply-production-distribution-scheduling problem. In this problem, he used a stochastic mixed integer program to jointly select suppliers, schedule production, and schedule distribution in a multi-echelon supply chain. The model's two objective functions were the minimization of costs and the maximization of service level subject to disruption risk. The findings highlighted the trade-off between cost and service level as three shipping methods were modelled with different cost and service level profiles – batch shipping with single shipments of different orders, batch shipping with multiple shipments of different customer orders, and individual shipping of each customer order.

Xu (2016) developed an integrated optimization and simulation model to investigate supply chain planning with consideration of risk. The model used a rolling horizon to re-plan production and distribution. Xu investigated the effects of changing the length of the planning horizon when re-planning from 90 days every day as new information became available. While the sum of the longest upstream and downstream lead times plus the production cycle time would seem like a sound starting point for the length of the planning horizon, Xu argued that such a horizon may be either too long for supply chains with international elements or may require too much overhead for analytic models to solve to optimality. Thus, many organizations may choose horizons that are otherwise too short. Further, Xu and Smith (2018) highlighted a value-added approach whereby the expected revenues were recognized as goods were shipped from manufacturing facilities to warehouses rather than when they were shipped from warehouses to customers. They demonstrated that such a value-added approach improved simulated supply chain performance.

Risk Definitions

Risk is a difficult concept to define, with experience across various disciplines demonstrating the failure to arrive at agreement on one unified set of definitions (Aven, 2016). Summarizing the work of the expert Committee of the Society of Risk Analysis, Aven emphasized that risk is generally characterized in relation to the consequences of a future activity with respect to something that is valued. He stated that said consequences are often seen in relation to some reference values (planned value, objectives, etc.), and the focus is normally on negative, undesirable consequences.

Deviations, disruptions and disasters

Gaonkar and Viswanadham (2007) classified supply chain risk problems as manifesting in three broad categories: deviations, disruptions, and disasters. They defined deviations as occurring when one or more parameters stray from their expected value without any changes to the underlying supply chain structure. Among the examples of "deviations" that they identified were variations in demand, costs and lead times. They defined disruptions as occurring when production and logistics elements are unavailable due to more serious unexpected events caused by human or natural factors. Among the examples of "disruptions" they discussed were earthquakes, contagious disease, and industrial actions leading to strikes. Lastly, the defined disasters as irrecoverable shutdowns of the supply chain network due to unforeseen system-wide disruptions, and gave the example of terrorist action. They concluded that it is generally possible to design a supply chain that can profitably operate through deviations and disruptions, but posited the impossibility of designing a network that is robust to disasters.

Delays, distortions and disruptions

Following Gaonkar and Viswanadham (2004), Talluri et al. (2013) proposed a supply chain risk classification of delays, distortions and disruptions. They described delays as recurrent risks related to time that can occur for reasons such as variations in transportation or production lead times. Distortions, by contrast, were described as related to quantities and occur when one or more parameters (e.g. order quantities) vary from their forecasted or expected values. Disruptions, in this classification, occur when the supply chain is "unexpectedly transformed through non-availability of certain production, warehousing, distribution, or transportation options, such as equipment failure".

Mean variance

Harry Markowitz's (1952) introduction of Modern Portfolio Theory ushered in the use of mean-variance as a way to conceptualize and model risk in the selection of individual securities when creating a portfolio of investments. The mean return of individual securities, the volatility of individual security returns and the correlation of the various volatilities all matter in constructing the optimal portfolio. In his formulation, risk was captured as the variance of the returns. An efficient frontier can be estimated by plotting the return versus the variance. The efficient frontier consists of all portfolios that provide the highest level of expected return for a given level of risk and the lowest level of risk for a given expected return. The frontier shows the trade-off between risk (standard deviation of return) and return.

A common criticism of the mean-variance approach is that it penalizes positive, upside variances as much as negative, downside variances which is inconsistent with the way many financial professionals (as well as supply chain managers) think of risk. An alternative is to define a risk measure that only captures and penalizes downside risk. Markowitz (1959) discussed the semivariance which measures the variability of returns below the mean. A number of researchers (e.g. Grootveld and Hallerbach, 1999) have questioned the efficacy of downside risk approaches and have highlighted a number of challenges that these approaches introduce, such as computational intensity since there are no time-saving heuristics in computing aggregate, portfolio level risk.

The mean-variance approach for capturing risk has been used in operations research to address numerous problems in the presence of risk. Choi, Li and Yan (2008) carried out a mean-variance analysis of the newsvendor problem allowing them to account for decision maker risk preference as they investigated optimal stocking given stochastic demand. Risk averse, risk neutral and risk seeking attitudes resulted in significantly different optimal stocking policies when the risk attitude was modelled using a mean-variance approach.

Martinez-de-Albeniz and Simchi-Levi (2006) observed that the common approach of dealing with overstocking and shortages in supply chain planning is by introducing a newsvendor model whereby a shortage is assumed to lead to lost sales while overstocking leads to penalty holding costs or having to dispose of the inventory at a loss. They noted that a drawback of this approach is that it assumes that decision-makers are risk-neutral and thus only optimizes the expected profit. To address this and allow for a variety of risk tolerances they described a mean-variance approach. They investigated the impact of using a portfolio of suppliers with each supply contract characterized by price and production capacity reserved by the supplier. Their results demonstrated that there exists an efficient frontier bounded by the maximum expectation portfolio and the minimum variance portfolio which fit a risk-neutral buyer and an infinitely risk-averse buyer, respectively.

Risk Modeling

Stochastic linear programming has been the primary method for designing supply chain networks subject to uncertain parameters. Such models tend to be formulated as multi-stage models, with some variables set immediately and others set after uncertainty has been resolved. An important limitation of stochastic linear programming is the assumed risk neutrality which leads to an inability to deal with risk aversion or decision-maker risk tolerance. Pariazar and Sir (2018) developed a multi-objective stochastic linear programming model to address supplier selection and raw material inspection strategies subject to quantity and quality disruptions. They implemented a genetic algorithm metaheuristic to reduce the computational burden of solving the problem given the uncertainty in the parameters. Sawik (2018) described a stochastic mixed integer program for supplier selection. Primary suppliers were selected in the first stage of the model before the occurrence of disruptions. Recovery suppliers and recovery assembly plants were selected in the second stage during and after the disruptions. Chen, Li and Ouyang (2011) proposed a nonlinear mixed-integer model that decomposed into a set of easier sub-problems and could solve to optimality the number and location of facilities across a set of disruption scenarios. Snyder, Daskin and Teo (2007) described a two-stage stochastic linear programming model that accounted for parameter uncertainty by allowing the parameters to be represented by discrete scenarios. In their model, facility location was determined in the first stage while inventory levels were determined in the second stage.

Robust optimization is a technique developed by Mulvey, Vanderbei and Zenios (1995) as an improvement to stochastic linear programming. It combines goal programming with scenario analysis to arrive at a series of solutions that are increasingly less sensitive to realizations of the model data from a scenario set. The optimization model has two components. The structural component is deterministic, while the control component is subject to stochastic inputs. The optimal solutions can be robust in two ways. First, if the solution remains close to optimal for any realization in the solution set then it is referred to as solution robust. Second, if the solution remains almost feasible for any realization in the solution set then it is referred to as model robust. The technique has demonstrated the ability to provide good and stable solutions when accounting for risk in complex systems. There are a number of key differences in the solutions obtained via robust optimization versus those obtained via stochastic linear programming. First, robust optimization optimal solutions tend to be more stable across different scenarios than those obtained via stochastic linear programming. Second, because the approach plans for worst case outcomes, optimal solution costs tend to be higher with robust optimization techniques than those arrived at by stochastic linear programming. Third, in stochastic linear programming there exists a control variable that makes it possible to satisfy the constraints in each realized scenario, while in robust optimization infeasibility is allowed and handled via penalty. Robust optimization has been tested as an improvement over stochastic linear programming in supply chain applications. For example, Mulvey, Vanderbei and Zenios (1995) demonstrated the use of robust optimization to solve diet problems, power capacity expansion problems, scheduling problems, among other logistics problem types. A drawback of robust optimization is its computational expense. Yu and Li (2000) refined a technique to improve the efficiency of robust optimization by devising a more efficient linear transformation. Their transformation required half as many deviation variables as the Mulvey, Vanderbei and Zenios approach. Consequently, their transformation resulted in faster run times while achieving similar results for a production-inventory-transportation problem and an aircraft scheduling problem. Jabbarzadeh, Haughton, and Khosrojerdi (2018) used robust optimization to design a resilient multi-echelon, multi-product, and multi-period supply chain in the presence of uncertainty. The number and location of facilities was determined in the first stage of their model. Quantities and shipments decisions were determined in the second stage. Their robust formulation minimized the sum of the expected value of the base problem and the maximum regret for the problem. The regret was calculated as the difference between the value of the solution under a given scenario and the value of the optimal solution under that scenario had the occurrence been anticipated in advance.

Chance-constrained programming is a modeling technique that is increasingly being used in the literature to account for uncertainty in supply chain applications. Bilsel and Ravindran (2011) implemented chance-constrained optimization to address a supplier allocation problem under uncertainty, where product demand, supplier capacity, and transportation costs were all stochastic, as was the exogenous probability of disruption. In their model, uncertainty was introduced into both right-hand-side and left-hand-side constraints. Demand uncertainty affected the right-hand-side while capacity uncertainty affected the left-hand-side and thus the technology matrix. The key insight into their model was the derivation of deterministic equivalents for demand and capacity chance constraints. These equivalents were derived assuming normal probability distributions for model parameters. The deterministic demand chance constraints were linear, but the capacity constraints were non-linear. The non-linear constraints were linearized by the introduction of additional binary variables. The models were then solved at a 0.95 level of reliability. Li and Zabinsky (2011) implemented a multi-objective stochastic supplier selection problem with business volume discounts. Their model sought to determine the minimum set of suppliers and optimal order quantities. Their approach captured the trade-off between cost and system reliability by selecting suppliers from a set that varied along size (large versus small), location (local versus distant), cost (high versus low), and reliability (high versus low). The model accounted for demand and supplier capacity uncertainty and assumed the two uncertainties were independent. The model arrived at its solution by assuming a probability distribution of the stochastic variables and constraining the probability of not meeting demand. Five objectives were defined in the problem: (i) minimize total purchasing and shipping costs, (ii) maximize probability of satisfying demand and staying within supplier capacity, (iii) minimize total number of selected suppliers, (iv) maximize quality of received components, and (v) minimize late deliveries.

Scenario analysis was used by Klibi and Martel (2012) to model risk in a supply chain network. The authors used the term uncertainty interchangeably with risk and distinguished among three types of uncertainties: randomness, hazards, and deep uncertainty. They conceptualized randomness as affecting single periods (due to random variables in business-as-usual operations), hazards as affecting multiple periods (low probability, high impact unusual situations), and deep uncertainty as having impacts over multiple periods (no known probability estimates exist). They focused on modeling hazards to determine the impact of the hazards on the supply chain. Hazards were the equivalent of disruption risks. Methodologically, given the stochastic nature of risk, the authors relied on discrete event simulation, augmenting the general approach with recent advances in catastrophe modeling, scenarios planning, and risk analysis to develop an integrated risk modeling approach. In their approach, the information available on the future was presented in the form of a set of scenarios about how the future may unfold. In order to make the modeling and analysis of hazards parsimonious and comprehensible, the authors combined hazards into a limited number of composite multi-hazards. The generic impacts of the multi-hazards on the supply chain were then evaluated by addressing three questions: (i) What could go wrong? (ii) What were the consequences? (iii) What is the likelihood of that happening? A three-phase hazard modeling process was proposed to address each question.

Simulation has also been a commonly used method to model supply chain risk due to its ability to handle stochastic inputs. Rajagopal, Venkatesan, and Goh (2017) described a variety of simulation models including Monte Carlo simulation, system dynamics, discrete event simulation, agent based modeling, and cellular automata. Ge et al. (2016) integrated a simulation model into their optimization model in order to realistically model the nationwide Canadian wheat supply. The output of their simulation model allowed them to examine testing strategies that efficiently balanced the trade-off between testing costs and contamination risk. Schmitt and Singh (2009, 2012) used simulation to model disruption risk in a supply chain. Discrete event simulation was used to realistically model the impact of disruption events on facilities and transportation routes, while Monte Carlo simulation was used to generate the risk profiles that introduced the disruptions into the system. The authors tested the impact of two mitigation strategies - inventory positioning and back-up facilities - to determine relative supply chain performance in the presence of disruption risk, with and without risk mitigation.

Adverse Event Management

An important consideration in managing risk in the supply chain is planning on how to manage the occurrence of disruptive events. In this sense, event management provides the link between strategic planning relating to risk and the operational activities that need to be implemented in order to ensure that the supply chain continues to function in the face of disruption events. Otto (2003) described the goal of supply chain event management (SCEM) as "to identify deviations and minimize their negative impacts before they are detrimental to customer satisfaction and operational efficiency". He discussed two actions that are critical to managing events in the supply chain: (i) eliminating the delay between event occurrence and decision-maker awareness of occurrence, and (ii) eliminating the delay between decision-maker awareness and the generation of a satisfying response. To meet these two critical actions, SCEM generates rules-based resolutions.

Bearzotti, Salomone, and Chiotti (2012) introduced an autonomous approach for SCEM. They focused on the activities that can be undertaken by supply chain partners once a disruption has occurred in the network. Focusing on the software architecture needed by supply chain partners to manage disruptions, and recognizing that collaboration and coordination can be especially difficult in the face of disruptive events, they proposed a multi-agent approach that allows for corrective actions to be made autonomously in reaction to disruptive events. Their approach assumed that a plan is already in place among the supply chain partners that determines, among other things, the way the partners will collaborate to fulfill customer needs. It is then recognized that a disruptive event in the supply chain will cause a deviation to the plan. In a normal supply chain, the challenge resides in getting supply chain partners to optimize their decision-making in order to mitigate the deviations that have already occurred and minimize further deviations. The objective of their approach was to determine the optimal allocation of the slack already in the supply chain to the disrupted resources so as to minimize the negative effects of the disruption. The innovative feaatures of their approach include designing the system as a distributed, collaborative, inter-organizational one, and building in functionality for the system to perform autonomous corrective actions in response to supply chain disruptions. Their approach used a mediated Contract Net Protocol technique to coordinate the allocation of resources and materials among supply chain partners. The system began by taking the supply chain plan as a given, where the plan was that set of allocations of materials, resources, time periods and capacity necessary for the supply chain to execute on its objectives. The plan included the slacks that were necessary to ensure a flexible and robust supply chain. In the face of disruptions, the system generated a solution which was a set of control actions utilizing plan slacks to mitigate the effects of the disruption. An important consideration was that the solution used the plan's slack collaboratively among the supply chain partners. The autonomous event management approach described by the authors was formulated to apply to frequent, low impact risks. The solutions derived from the model were evaluated as being satisfactory 64% of the time thus leaving room for future improvement.

Risk Mitigation Strategies

Mohammaddust et al. (2017) identified a number of risk mitigation strategies that are commonly described in the literature including emergency stock, excess capacity, substitute suppliers and facilities, and supplier development. They implemented four specific strategies in their model: (i) holding back-up stocks at the distribution center, (ii) holding back-up stocks at a centralized distribution center for risk pooling, (iii) reserving excess capacity in the facilities, and (iv) using other facilities in the network to back-up the primary facilities.

Huang, Song, and Tong (2016) concluded that there are two fundamental strategies for mitigating random demand variability. The two are (i) building reactive capacity, which they define as the ability to ramp up production above normal levels in response to demand surges, and (ii) holding safety stocks, either by holding extra inventory at the firm's warehouse or contracting with another vendor to hold inventory on behalf of the firm.

Talluri et al. (2013) classified Chopra and Sodhi's risk mitigation strategies into two categories: (i) redundancy, and (ii) flexibility. In their classification, increasing capacity, redundant suppliers, and increasing inventory are considered redundancy strategies, while increasing responsiveness, increasing flexibility, aggregating demand, and increasing capability are considered flexibility strategies.

According to Chopra and Sodhi (2004) the most generic supply chain risk mitigation strategy is the holding of reserves. The authors identified three reserves as foundational: excess inventory, excess capacity and redundant suppliers. In addition to these core reserves, they identified five augmented strategies to help managers mitigate risk: increased responsiveness, increased flexibility, aggregated or pooled demand, increased capability, and increased customer accounts. These mitigation strategies are often expensive and can significantly reduce profits if deployed sub-optimally.

Four risk mitigation strategies will be reviewed in more detail:

- Inventory Positioning
- Flexibility
- Diversification
- Strategic redundancy

Inventory Positioning

Puga, Minner, and Tancrez (2018) studied safety stock placement in a location-inventory problem with demand uncertainty. They analyzed the trade-offs that influence the performance of various safety stock placement strategies, demonstrating that demand variability pooling and lead time pooling led to different conclusions as to which inventory placement strategy should be selected.

Tomlin (2006) investigated the implementation of inventory control as a disruption management strategy by studying a reliable and an unreliable supplier in a single product setting, where both suppliers were capacity constrained. The results showed that while inventory control can be an effective disruption management strategy, it tended to work poorly in cases of rare but long disruptions.

In their numerical analysis, Schmitt and Singh (2009) identified that the level of customer service in a supply chain pursuant to a disruption is dependent on inventory levels. Specifically, it is dependent on the level of inventory immediately prior to the beginning of the disruption.

Under postponement as an inventory positioning and production strategy, the final configuration of a product and its packaging are delayed to allow for modifications in response to uncertainties in final demand. This minimizes inventory holding costs and obsolescence, but comes at the cost of foregoing scale economies. Manuj and Mentzer (2008) discussed form and time postponement. Form postponement includes labeling, packaging, assembly, and manufacturing; while time postponement refers to the transportation of goods only after a customer order has been received. They posited that delaying the commitment of resources in the face of uncertainty can lead to potential benefits.

In addition to being a means of inventory positioning, Tomlin and Tang (2008) identified postponement as a means of increasing flexibility in the supply chain by shifting production quantities across different products. Postponement can be useful in managing some demand risks. Among demand risks, Thun and Hoenig (2011) identify demand forecasts and inefficient capacity utilization. They further identified the holding of safety stocks as a risk management strategy employed in the German automotive industry. In this case, postponement allows for managing safety stock to minimize obsolescence.

Fan, Schwartz, and Voss (2014) used computational experiments from a two-stage stochastic mixed-integer linear programming model to demonstrate that postponement could help mitigate risk and make a supply chain network more flexible when faced with stochastic catastrophic risks. They concluded that postponement is especially advantageous if the probability of a disruption to the supply chain is high.

Flexibility

In their literature review, Manders, Caniels, and Ghijsen (2017) distinguished between "flexibility in the supply chain" and "supply chain flexibility". In their view, the former "covers the many different flexibility dimensions used by the different members of the supply chain to improve their organizational performances and hopefully contribute to the overall supply chain flexibility goals" while the latter is "the ability of the supply chain to change or react to environmental uncertainty, to meet the increasing variety of customer expectations without excessive costs, time, organizational disruptions or performance losses".

Emaeilikia et al. (2016) described a flexible supply chain as one that can quickly adapt in the face of frequent uncertainties such as interruptions in supply, demand, manufacturing, and logistics operations. They identified a number of areas in which flexibility had been categorized including volume, delivery, operational design, storage, process, logistics, manufacturing, vendor, and sourcing. For example, manufacturing flexibility may include manufacturing multiple product types at each plant, tactical production capacity expansion, or backlogging.

Using survey data and structural equations modeling, Sreedevi and Saranga (2017) identified supply flexibility, manufacturing flexibility, and distribution/logistics flexibility as having a moderating influence in mitigating the three major supply chain risks – supply risk, manufacturing process risk, and delivery risk – that arise from environmental uncertainty. Their study found that the benefit of flexibility was "contingent upon several factors, including the dimension of supply chain risk the firm is exposed to and the type of environment in which the firm is functioning".

Diversification

Diversification is a strategy whereby a firm distributes its key supply chain resources across various dimensions. These factors include production facilities, intermediate goods and/or final output, markets, suppliers, and products. For example, a firm may choose to locate its key manufacturing plants in different countries, or may choose to enter different markets for its final goods, or may choose to produce a mix of different goods. This strategy is analogous in the natural world to genetic survival, where organisms are much more likely to survive and propagate in challenging environments if they have genetic diversity.

Diversification can be effective at limiting the negative impacts of disruption risks. By spreading its reach across various countries and regions, a supply chain can limit the disruption that may be caused by localized natural disasters, bilateral trade disputes and expropriations by government entities.

Manuj and Mentzer (2008) highlighted dual sourcing and multiple contracting as ways of hedging risk via diversification. Specifically, dual sourcing can be used to hedge against risks of quality, quantity, disruption and price, while multiple contracting can shield against variability in performance and single supplier opportunism. Thun and Hoenig (2011) confirmed the importance of multiple sourcing in an empirical study of the automotive industry in Germany and found dual and multiple sourcing to positively affect supply chain performance.

Pettit, Fiksel and Croxton (2010) discussed "dispersion" as the strategic decision by a firm to distribute or decentralize its assets. This diversification can be implemented by distributing decision-making, capacity and assets; by decentralizing key resources; and by location-specific empowerment. However, just as supply chain managers face trade-offs among costs so too do they face trade-offs among risks. While dispersion can be effective in mitigating the risk of catastrophic failure in a consolidated enterprise, it nevertheless increases the risk of loss of control, which can itself lead to significant losses. Dispersion may also increase transactions costs.

Strategic Redundancy

Strategic redundancy refers to the integration of back-up resources and processes into the supply chain to prevent system failure. Strategic redundancy comes at a cost and reduces the leanness of the supply chain. Among its benefits are potential contribution to higher service levels and continuing capacity in the event of disruptions.

Sawik (2018) demonstrated the use of primary and recovery suppliers and assembly plants as a risk mitigation strategy. The results showed the value of strategic redundancy in mitigating disruption risks and optimizing the recovery process.

Ivanov et al. (2016) highlighted the use of back-up suppliers as well as back-up depots and transportation modes as disruption recovery strategies. They modelled a supply chain with a number of characteristics, including (i) supply chain performance depended on perturbations, (ii) some supply chain elements became unavailable during disruptions, and (iii) some disrupted elements recovered over time. They studied the trade-off between efficiency and resiliency when, among other risk mitigation measures, back-up suppliers and assembly capacity were built into the supply chain.

Chopra and Sodhi (2004) identified redundant suppliers as a mitigation strategy for managing procurement risk, inventory risk, and disruptions. The idea was that it was improbable that all suppliers would suffer a disruption at the same time. The authors proposed supplier redundancy as a good mitigation strategy for products with high holding costs and/or a high rate of obsolescence. They pointed to Motorola as a company that follows this strategy, mitigating the cost of redundancy by using multiple suppliers for high-volume products and sole sourcing for low-volume products.

Norrman and Jennson (2004) discussed the example of a fire at the Ericsson plant in Albuquerque, NM that led to significant losses. A sole source sub-supplier experienced a fire that interrupted the production of a vital chip for one of Ericsson's key consumer products. Nokia, an Ericsson competitor who also used the same supplier, had hedged against supplier risk by investing in parallel, alternative supply sources. The disruption led to large loses at the un-hedged Ericsson, while the hedged Nokia gained market share largely at Ericsson's expense.

Chapter 3: Optimizing Model

Mathematical Formulation for the Mixed Integer Linear Programming Model

Optimizing Model Formulations

Three versions of the optimizing model were formulated in order to facilitate a comparative study of the levers that drive the shape of the final solution:

(i) Push Formulation: Revenues are recognized when finished goods are shipped to warehouses from the manufacturing plant.

(ii) Pull Formulation: Revenues are recognized when finished goods are received at the warehouses, or, in the case of expedited deliveries, when shipped directly to customers from the manufacturing plants.

(iii) Hybrid Formulation: Revenues are recognized when deliveries are received at the warehouse. Additionally, goods shipped from the manufacturing plant that are expected to arrive at the warehouse after the end of the horizon have their revenue recognized when shipped to the warehouse from the manufacturing plants.

Optimizing Model for Procurement, Production Scheduling, and Distribution Decisions

Daily shipment of raw materials from suppliers, production at the manufacturing plants, shipment to warehouses and aggregated deliveries to customers are determined with consideration of line capacities, lower and upper inventory limits at the plant and in warehouses, transit times to warehouses, and possible alternative sources of supply in the event of stock-outs at the warehouses. Parameters, decision variables, objectives and constraints are defined as follows:

Parameters (in alphabetical order):

$agrmcostP_pW_w$ = the raw material cost embedded in product p inventory at warehouse w.

$cleanhrsL_lM_m$ = time for cleaning and setup on line L at manufacturing plant M between production batches

csP_pW_w = cost (per kg) of shortage of product p at warehouse w

$DemP_pW_wD_d$ = Customer demand for product p (kg) at warehouse w on day d

dem_pwhse_w = average daily demand for product p at warehouse w

gwloss = goodwill loss on unfilled demand recognized as a percentage of lost revenue. Unfilled demand is placed on backorder

icP_pM_m = inventory carrying cost ($/kg per day) for finished product p at manufacturing plant M

icP_pW_w = inventory carrying cost ($/kg per day) for product p at warehouse w

icR_rM_m = inventory carrying cost ($/kg per day) for raw material r at manufacturing plant M

$itcP_pW_w$ = cost of carrying product p ($/kg per day) in transit to warehouse w

$ItsP_pW_wD_d$= in transit shipments at time 0 (kg) of product p to arrive at warehouse w at end of day d

$idlepenL_lM_m$ = idle penalty per hour for Production Line L at manufacturing plant M considering allowed hours of operation

$kgperhrP_pL_lM_m$ = production rate (kg per hr) for product p on line L at manufacturing plant M

$maxinvP_pM_m$= maximum inventory at manufacturing plant M for product p

$maxinvP_pW_w$ = maximum inventory of product p held at warehouse w (including outstanding orders)

$maxinvR_rM_m$ = maximum inventory at manufacturing plant M for raw material R

$maxshiftsL_lM_m$ = Maximum number of shifts per day to operate Line L at manufacturing plant M

$maxshipP_pM_m$ = maximum shipment lot size of product p from manufacturing plant M

$mininvP_pM_m$ = minimum inventory at manufacturing plant M for product p

$mininvP_pW_w$ = minimum inventory of product p held at warehouse w (including outstanding orders)

$mininvR_rM_m$ = minimum inventory at manufacturing plant M for raw material R

$MXprodL_lM_m$ = Maximum daily throughput (kg) on line L at manufacturing plant M

$OvrPenaltyP_pM_m$ = daily penalty (per kg) for excess of product p inventory at manufacturing plant M

$OvrPenaltyR_rM_m$ = daily penalty (per kg) for excess raw material m inventory at manufacturing plant M

$OvrPenaltyP_p$ = daily penalty (per kg) for excess product p inventory systemwide

$productcostP_pM_m$ = the production cost embedded in product p inventory at manufacturing plant M. This is captured only for inventory p at manufacturing plant m that was in stock on day 1 of the horizon.

$productcostP_pW_w$ = the production cost embedded in product p inventory at warehouse w.

pcP_pW_w = production cost (per kg) of product p delivered from warehouse w

$recipeR_rP_pL_lM_m$ = ratio representing the amount in kg of raw materials R required to produce 1 kg of product P on line l at plant m

$revP_pM_mW_w$ = revenue (per kg) of product p delivered from manufacturing plant m to warehouse w when sold to customers from the warehouse
$revP_pW_w$ = revenue (per kg) of product p when delivered to customers from warehouse w

$rmcostR_rS_s$ = cost per kilogram of raw material r from supplier s

$scP_pM_mW_w$ = Shipping cost (per kg) of shipments of product p from manufacturing plant m to warehouse w

$shiptimeW_wM_m$ = $\delta(w)$ = Shipping delay (days) to warehouse w from manufacturing plant M

$shiptimeM_mS_s$ = δ(s) = Shipping delay (days) to manufacturing plant M from supplier S

$ShtPenaltyP_pM_m$ = daily penalty (per kg) for under-production leading to shortage of product p inventory at manufacturing plant M

$ShtPenaltyP_p$ = daily penalty (per kg) for shortage of product p inventory systemwide

$ShtPenaltyR_rM_m$ = daily penalty (per kg) for shortage of raw material r inventory at plant m

$startinvP_pM_m$ = beginning inventory of product p on day 1 at manufacturing plant M

$startinvP_pW_w$ = beginning inventory of product p on day 1 at warehouse w

$startinvR_rM_m$ = beginning inventory of raw material r on day 1 at manufacturing plant M

Decision Variables (in alphabetical order):

$IdelP_pW_wD_d$ = deliveries (kg) of product p from warehouse w to customers in day d from inventory originally held at the warehouse at the beginning of the horizon

$IdleL_lM_mD_d$= number of hours idle on production line L at manufacturing plant M relative to hours in allowed number of shifts.

$InvP_pM_mD_d$ = inventory of product p at manufacturing plant M at the beginning of day d

$InvP_pW_w D_d$ = inventory of product p held in warehouse w at beginning of day d

$InvR_rM_mD_d$ = inventory of raw material r at manufacturing plant M at the beginning of day d

$LASTP_pL_lM_mD_d$ = 1 if product p is the last product produced on line L at manufacturing
plant M on day d

$OOP_pM_mW_wD_d$ = outstanding orders of product p produced at manufacturing plant m for delivery to warehouse w at beginning of day d

$OOR_rM_mD_d$ = outstanding orders of raw material R for delivery to manufacturing plant M at beginning of day d

$OP_pM_mW_wD_d$ = amt of product p produced at manufacturing plant m ordered on day d for delivery to warehouse w

$OR_rM_mD_d$ = amt of raw material R ordered on day d for delivery to manufacturing plant M

$OSMP_pM_mD_d$ = over-stockage (above max desired inventory) at manufacturing plant M for product p on day d

$OSMR_rM_mD_d$ = over-stockage (above max desired inventory) at manufacturing plant M for raw material R on day d

$OSWP_pW_wD_d$= over-stockage (above max desired inventory) at the warehouse for product p on day d

$ProdP_pL_lM_mD_d$ = production (kg) of product p on line L at manufacturing plant M on day d

$ShpP_pM_mW_wD_d$ = shipment (kg) of product p from manufacturing plant M to warehouse w at end of day d

$ShpR_rS_sM_mD_d$ = shipment (kg) of raw material R from supplier S to manufacturing plant M at end of day d

$SUL_lM_mD_d$= 1 if line 1 at manufacturing plant M is activated for production on day d; 0 otherwise

$SUP_pL_lM_mD_d$=1 if setup completed for product p on line L at manufacturing plant M in Day d; 0 otherwise

$TrP_pW_wD_d$ = Product p (kg.) in transit to warehouse w at beginning of day d

$TrR_rM_mD_d$ = Raw material R (kg.) in transit to manufacturing plant M at beginning of day d

$UFP_pW_wD_d$ = amount of product p in kilograms at warehouse w on day d that is unfilled i.e. amount by which demand exceeds deliveries

$UseR_rM_mD_d$ = amount (kg) of raw material R used at manufacturing plant M in day d

$USMP_pM_mD_d$ = under-stockage (shortage from reorder point) at manufacturing plant M for product p on day d

$USMR_rM_mD_d$ = under-stockage (shortage from reorder point) at manufacturing plant M for raw material R on day d

$USWP_pW_wD_d$ = under-stockage (shortage from reorder point) at the warehouse for product p on day d

Additional levers:

The model contains a number of levers that shape the solution process including:

- Inventory lower bounds
- Inventory upper bounds
- Penalties on lost sales and excess inventory

Notation

Set	Description
R{r}	Set of raw materials
S{s}	Set of suppliers
M{m}	Set of manufacturing plants
P{p}	Set of products
W{w}	Set of warehouses
D{d}	Set of days in planning horizon
SR{r}	Set of suppliers for raw material r
RP{p}	Set of raw materials used in producing product p
PM{m}	Set of products produced in manufacturing plant m
PR{r}	Set of products require raw material r for production
RM{m}	Set of raw materials used in producing products at manufacturing plant m
PW{w}	Set of products distributed through warehouse w
WP{p}	Set of warehouses to which product p is delivered
DRMS {r, s, m}	Set of days on which raw material r from supplier s is scheduled to arrive at manufacturing plant m
DFGS {p, m, w}	Set of days on which product p from manufacturing plant m is scheduled to arrive at warehouse w

Objective (NETCONTR) for Push Formulation:

Push Formulation Net Profit Contribution = (Revenue from finished goods when shipped from plants to warehouses – Product shipping costs – Cost of lost sales – Product in transit costs – Product inventory holding costs at plants and warehouses – Production cost – Raw material inventory holding costs at plants – Raw material inventory shortage costs at plants – Raw material inventory overstocking costs at plants – Product inventory shortage costs at plants and warehouses – Product inventory overstocking costs at plants and warehouses –Raw material shipping costs – Raw material in transit costs – Plant setup costs – Plant idle costs)

$$\text{"Push" } Objective: \qquad Max\left[\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{d=1}^{D}\big((revP_pM_mW_w - scP_pM_mW_w\big) \right.$$

$$* ShpP_pM_mW_wD_d - gwloss * revP_pW_w \ * UFP_pW_wD_d$$

$$- icP_pW_w \ * InvP_pW_wD_d - itcP_pW_w \ * TrP_pW_wD_d - ShtPenaltyP_p * USWP_pW_wD_d$$

$$- OvrPenaltyP_p * OSWP_pW_wD_d)$$

$$-\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{d=1}^{D} pcP_pM_m * ProdP_pL_lM_mD_d$$

$$-\sum_{r=1}^{R}\sum_{s=1}^{S}\sum_{m=1}^{M}\sum_{d=1}^{D} rmcostR_rS_s * ShpR_rS_sM_mD_d$$

$$-\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}(icP_pM_m * InvP_pM_mD_d$$

$$+ ShtPenaltyP_pM_m * USMP_pM_mD_d \tag{1}$$

$$+ OvrPenaltyP_pM_m * OSMP_pM_mD_d)$$

$$-\sum_{r=1}^{R}\sum_{m=1}^{M}\sum_{d=1}^{D}(icR_rM_m * InvR_rM_mD_d + ShtPenaltyR_rM_m * USMR_rM_mD_d$$

$$+ OvrPenaltyR_rM_m * OSMR_rM_mD_d + icR_rM_m * TrR_rM_mD_d)$$

$$-\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{d=1}^{D}(idlepenL_lM_m * IdleL_lM_mD_d$$

$$\left. + idlepenL_lM_m * cleanhrsL_lM_m * SUL_lM_mD_d \ )\right]$$

Constraints:

Cannot produce product p on line l at manufacturing plant m on day d unless the line has been set up for it (constraints $ULP_pL_lM_mD_d$)

$$ProdP_pL_lM_mD_d \leq MXprodL_lM_m * SUP_pL_lM_mD_d \qquad (2)$$

for each line at each manufacturing plant on each day and each p ϵ PL{L}

Sum of activity times for day d on line l at manufacturing plant m cannot exceed the operating time for the line (constraints $TPRODL_lM_mD_d$).

$$\sum_{p \in PL\{L\}} \left((1/\ kgperhrP_pL_lM_m) * ProdP_pL_lM_mD_d + cleanhrsL_lM_m * SUP_pL_lM_mD_d \right) \qquad (3)$$
$$+ IdleL_lM_mD_d = 8 * maxshiftsL_lM_m$$

for each line and day

Place order for product p to be produced at manufacturing plant m to ensure desired safety stock at warehouse w on day d (constraints $MNOP_pW_wD_d$).

$$\sum_{m \in M\{m\}} OP_pM_mW_wD_d + \sum_{m \in M} OOP_pM_mW_wD_d + InvP_pW_wD_d \geq mininvP_pW_w - USWP_pW_wD_d$$

each day for each plant and warehouse and day (4)

Restrict order of product p to be produced at manufacturing plant m to prevent overstock at warehouse w on day d (constraints $MXOP_pW_wD_d$).

$$\sum_{m \in M\{m\}} OP_pM_mW_wD_d + \sum_{m \in M} OOP_pM_mW_wD_d + InvP_pW_wD_d \leq maxinvP_pW_w + OSWP_pW_wD_d$$

each day for each plant and warehouse and day (5)

Note that the minimum inventory is set to cover demand in the current day with safety stock to allow for variation in delivery times for goods on order.

Produce sufficient goods at manufacturing plant m to provide safety stock at the plant (constraints $MNPRP_pM_mD_d$).

$$\sum_{l \in L\{l\}} ProdP_pL_lM_mD_d + USMP_pM_mD_d + InvP_pM_mD_d \geq mininvP_pM_m \qquad (6)$$

each day for each product (on its designated line) at each plant.

Restrict production of product p (on designated line l at manufacturing plant m) on day d to no more than the outstanding orders (constraints $MXPRP_pM_mD_d$).

$$\sum_{l \in L\{l\}} ProdP_pL_lM_mD_d \leq \sum_{w \in W} OOP_pM_mW_wD_d \qquad (7)$$

each day for each product (on its designated line) at each plant.

Deliver goods from warehouse or expedite them from the plants to satisfy customer demand and acknowledge lost sales if inventory is insufficient (constraints $DLVP_pW_wD_d$).

$$DelP_pW_wD_d + IdelP_pW_wD_d + UFP_pW_wD_d = DemP_pW_wD_d \qquad (8)$$
each day for each warehouse and each PW{w}.

Limit shipments of product p from manufacturing plant m to warehouses or directly to customers as alternative shipments on day d to the amount available in plant inventory, and also limits the shipment to the maximum shipment lot size (constraint $SHP_pM_mD_d$).

$$\sum_{w \in W} ShpP_pM_mW_wD_d \leq InvP_pM_mD_d \qquad (9)$$
each day for each product.

Account for inventory balance of products at the plants at end of day d (constraint $IBPP_pM_mD_d$).

$$InvP_pM_mD_{d+1} = InvP_pM_mD_d + \sum_{l \in L\{l\}} ProdP_pL_lM_mD_d - \sum_{w \in W} ShpP_pM_mW_wD_d$$
each day for each product (on its designated line) at each plant. (10)

Account for inventory balance of products at the warehouse recognizing inbound shipping delays (constraint $IBWP_pW_wD_d$).

$$InvP_pW_wD_{d+1} = InvP_pW_wD_d - DelP_pW_wD_d - IdelP_pW_wD_d - BdelP_pW_wD_d + \sum_{m \in M\{m\}} (ShpP_pM_mW_wD_{d-\delta(w)} + ItsP_pM_mW_wD_d)$$
each day and each PW{w}. (11)

Note that the $ItsP_pW_wD_d$ variables are defined only for (p,w,d) combinations where there are goods in transit at the beginning of the planning horizon and are imposed in the model with upper and lower bounds set accordingly.

Update outstanding orders for product p at warehouse w on day d (constraint $OOUP_pM_mW_wD_d$).

$$OOP_pM_mW_wD_{d+1} = OOP_pM_mW_wD_d + OP_pM_mW_wD_d - ShpP_pM_mW_wD_{d-\delta(w)} + ItsP_pM_mW_wD_d$$
each day for product p at warehouse w. (12)

Note that $OOP_pM_MW_wD_1$ should include sum of the $ItsP_pM_mW_wD_d$ values for each day with scheduled arrivals.

Update goods in transit to reflect shipments and receipts (Constraints $GITP_pM_mW_wD_d$).

$$TrP_pM_mW_wD_{d+1} = TrP_pM_mW_wD_d + ShpP_pM_mW_wD_d - ShpP_pM_mW_wD_{d-\delta(w)} - ItsP_pM_mW_wD_d$$

each day for product p at warehouse w. (13)

Note that $TrP_pW_wD_1$ = is set to sum of the $ItsP_pW_wD_d$ values for each day with scheduled arrivals.

All variables are nonnegative and $SUP_pL_lM_mD_d$ values would binary if separate setup is required for each product. For now, we shall just assume there is a single setup required if a line at a manufacturing plant is to be activated for production during the day. $SUP_pL_lM_mD_d$ in this formulation allocates production capacity to the individual products. We therefore add a constraint that creates a single binary variable for each line at each manufacturing plant during the day that accounts for setup and cleaning time required for activating and shutting down the production line (Constraints $LSUL_lM_mD_d$) .

$$\sum_{p \in PL\{L\}} SUP_pL_lM_mD_d \leq SUL_lM_mD_d \quad (14)$$

for each line at each manufacturing plant on each day.

$SUL_lM_mD_d$ = (0,1). If setup times are negligible, these binary constraints may be relaxed.

To facilitate extraction of the solution in the report generator, we define variable $ArrP_pW_wD_d$ to be the goods that arrive at the warehouse in day d which will be shipped in this planning horizon and establish their equality in constraints that define inbound freight (Constraints $IBFP_pM_mW_wD_d$).

$$ArrP_pM_mW_wD_d = ShpP_pM_mW_wD_{d-\delta(w)} \quad (15)$$

Goods that arrive in a day may not be cross-docked and shipped out immediately. Such shipments must be placed in inventory and delayed until the next day. (constraints $CDP_pW_wD_d$)

$$DelP_pW_wD_{d+1} + IdelP_pW_wD_{d+1} + BdelP_pW_wD_{d+1} \leq InvP_pW_wD_d \quad (16)$$

The warehouse will pull goods from the manufacturing plants to fulfill orders from the warehouse i.e. the plant cannot push production to warehouse. Product is shipped the day after ordering (constraint $ORDP_pM_mW_wD_d$).

$$OP_pM_mW_wD_d \geq ShpP_pM_mW_wD_{d+1} \quad (17)$$

Create a variable to allow for extraction of the total amount of finished goods shipped from each plant across all warehouses via regular shipping (constraint $SUMSHP_pM_mD_d$).

$$TSHMP_pM_mD_d = \sum_{w \in W\{w\}} ShpP_pM_mW_wD_d \quad (18)$$

Place order for raw material r on day d to ensure desired safety stock at manufacturing plant m (constraints $MNOR_rM_mD_d$).

$\sum_{s\in S\{s\}} OR_rS_sM_mD_d + \sum_{s\in S\{s\}} OOR_rS_sM_mD_d + InvR_rM_mD_d \geq mininvR_rM_m - USMR_rM_mD_d$
each day for each raw material at each plant (19)

Restrict order of raw material r on day d to prevent overstock at manufacturing plant m (constraints $MXOR_rM_mD_d$).

$\sum_{s\in S\{s\}} OR_rS_sM_mD_d + \sum_{s\in S\{s\}} OOR_rS_sM_mD_d + InvR_rM_mD_d \leq maxinvR_rM_m + OSMR_rM_mD_d$
each day for each raw material at each plant (20)

Restrict the amount of raw material r used at manufacturing plant m on day d to the amount of product manufactured (constraints $EQR_rS_sM_mD_d$).

$UseR_rM_mD_d = \sum_{l\in L\{l\}} (recipeR_rP_pL_lM_m * ProdP_pL_lM_mD_d)$ (21)
each day for each product

Restrict the amount of raw material r used at manufacturing plant m on day d to not exceed the raw materials available at that plant at the end of the previous day (constraints $MXUR_rM_mD_d$).

$UseR_rM_mD_{d+1} \leq InvR_rM_mD_d$ (22)
for each raw material at each manufacturing plant on each day

Account for inventory balance of raw materials at the manufacturing plant recognizing inbound shipping delays (constraint $IBMR_rM_mD_d$).

$InvR_rM_m D_{d+1} = InvR_rM_mD_d + \sum_{s\in S\{s\}} ShpR_rS_sM_mD_{d-\delta(w)} - UseR_rM_mD_d$ (23)
each day

Update outstanding orders for raw material r at manufacturing plant m on day d (constraint $OOUR_rM_mD_d$).

$OOR_rS_sM_mD_{d+1} = OOR_rS_sM_mD_d + OR_rS_sM_mD_d - ShpR_rS_sM_mD_{d-\delta(w)}$ (24)
each day for raw material r at manufacturing plant m.

Update raw materials in transit to reflect shipments and receipts (Constraints $RITR_rM_mD_d$).

$TrR_rS_sM_mD_{d+1} = TrR_rS_sM_mD_d + ShpR_rS_sM_mD_d - ShpR_rS_sM_mD_{d-\delta(w)}$ (25)
each day for raw material r at manufacturing plant m.

To facilitate extraction of the solution in the report generator, we define variable $ArrR_rM_mD_d$ to be the raw materials that arrive at the plants on day d which were shipped in this planning horizon (Constraints $IBFR_rS_sM_mD_d$).

$$ArrR_rS_sM_mD_d = ShpR_rS_sM_mD_{d-\delta(w)} \tag{26}$$

Order raw materials from the suppliers to fulfill requirements at the plant. Orders to ship on a day lag at an amount equal or less than the order (constraint $ORDR_rS_sM_mD_d$).

$$OR_rS_sM_mD_d \geq ShpR_rS_sM_mD_{d+1} \tag{27}$$

Create a variable to allow for extraction of the total amount of finished goods produced in the plants across all lines (constraint $SUMPRODP_pM_mD_d$).

$$TPRDMP_pM_mD_d = \sum_{l \in L\{l\}} ProdP_pL_lM_mD \tag{28}$$

Update back ordered goods for newly unfilled orders as well as previous back orders that have just been filled (constraint $BKOP_pW_wD_d$).

$$BordP_pW_wD_{d+1} = BordP_pW_wD_d + UFP_pW_wD_d - BdelP_pW_wD_d \tag{29}$$

Ensure that the amount of finished goods delivered from back order is no more than the amount on back order the previous day, and that we begin with no goods on backorder in the system (constraint $BLDP_pW_wD_d$).

$$BdelP_pW_wD_{d+1} \leq BordP_pW_wD_d \tag{30}$$
$$BordP_pW_wD_d = 0 \text{ for } d = 1$$

Ensure that product inventory positioned at the warehouse used to satisfy customer demand does not exceed the amount positioned at the beginning of the horizon (constraint $IDLVP_pW_wD_d$).

$$\sum_{d \in D} IdelP_pW_wD_d \leq InvP_pW_wD_1 \tag{31}$$

Define a variable to capture any overstock of product inventory at the plant (constraint $MXINVP_pM_mD_d$).

$$InvP_pM_mD_d - OSMP_pM_mD_d \leq maxinvP_pM_m \tag{32}$$

Restrict production of product p (on designated line l at manufacturing plant m) on day d to prevent overstock at the plant (constraints $MXPRP_pM_mD_d$).

$$\sum_{l \in L\{l\}} ProdP_pL_lM_mD_d \leq maxinvP_pM_m + OSMP_pM_mD_d \tag{33}$$

each day for each product (on its designated line) at each plant.

Additional Pull and Hybrid Formulation Decision Variables:

To the Push formulation decision variables previously described, the following decision variables were added to create the Pull and Hybrid formulations:

$BdelP_pW_wD_d$ = deliveries of product p at warehouse w on day d that are fulfilled on backorder

$DelP_pW_wD_d$ = regular deliveries of product p at warehouse w on day d

Objective (NETCONTR) for Pull Formulation:

Pull Formulation Net Profit Contribution = (Revenue from deliveries of on-time and backordered goods – Product shipping costs – Cost of lost sales – Product in transit costs – Product inventory holding costs at plants and warehouses – Production cost – Raw material inventory holding costs at plants – Raw material inventory shortage costs at plants – Raw material inventory overstocking costs at plants – Product inventory shortage costs at plants and warehouses – Product inventory overstocking costs at plants and warehouses –Raw material shipping costs – Raw material in transit costs – Plant setup costs – Plant idle costs)

Objective (NETCONTR) for Hybrid Formulation:

Hybrid Formulation Net Profit Contribution = (Revenue from deliveries of on-time and backordered goods + Revenue from finished goods when shipped from plants but which will not arrive at the warehouses during the planning horizon – Product shipping costs – Cost of lost sales – Product in transit costs – Product inventory holding costs at plants and warehouses – Production cost – Raw material inventory holding costs at plants – Raw material inventory shortage costs at plants – Raw material inventory overstocking costs at plants – Product inventory shortage costs at plants and warehouses – Product inventory overstocking costs at plants and warehouses –Raw material shipping costs – Raw material in transit costs – Plant setup costs – Plant idle costs)

$$\text{"Pull" } Objective: \quad Max \left[\sum_{p=1}^{P} \sum_{w=1}^{W} \sum_{d=1}^{D} (revP_pW_w * \left(DelP_pW_wD_d + BdelP_pW_wD_d\right) \right.$$

$$+ (revP_pW_w - productcostP_pW_w - agrmcostP_pW_w - scP_pW_w)$$

$$* IdelP_pW_wD_d - gwloss * revP_pW_w * UFP_pW_wD_d$$

$$- icP_pW_w * InvP_pW_wD_d - itcP_pW_w * TrP_pW_wD_d - ShtPenaltyP_p * USWP_pW_wD_d$$

$$- OvrPenaltyP_p * OSWP_pW_wD_d)$$

$$- \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{d=1}^{D} scP_pM_mW_w * ShpP_pM_mW_wD_d$$

$$- \sum_{p=1}^{P} \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{d=1}^{D} pcP_pM_m * ProdP_pL_lM_mD_d$$

$$- \sum_{r=1}^{R} \sum_{s=1}^{S} \sum_{m=1}^{M} \sum_{d=1}^{D} rmcostR_rS_s * ShpR_rS_sM_mD_d$$

$$- \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{d=1}^{D} (icP_pM_m * InvP_pM_mD_d + ShtPenaltyP_pM_m * USMP_pM_mD_d$$

$$+ OvrPenaltyP_pM_m * OSMP_pM_mD_d)$$

$$- \sum_{r=1}^{R} \sum_{m=1}^{M} \sum_{d=1}^{D} (icR_rM_m * InvR_rM_mD_d + ShtPenaltyR_rM_m * USMR_rM_mD_d$$

$$+ OvrPenaltyR_rM_m * OSMR_rM_mD_d + icR_rM_m * TrR_rM_mD_d)$$

$$- \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{d=1}^{D} (idlepenL_lM_m * IdleL_lM_mD_d$$

$$\left. + idlepenL_lM_m * cleanhrsL_lM_m * SUL_lM_mD_d \,)\right]$$

"Hybrid" $Objective$: $$Max \left[\sum_{p=1}^{P} \sum_{w=1}^{W} \sum_{d=1}^{D} (revP_pW_w * \left(DelP_pW_wD_d + \ BdelP_pW_wD_d\right) \right.$$

$$+ \ (revP_pW_w - productcostP_pW_w - \ agrmcostP_pW_w - \ scP_pW_w)$$

$$* IdelP_pW_wD_d - gwloss * revP_pW_w \ * UFP_pW_wD_d$$

$$- icP_pW_w \ * InvP_pW_wD_d - itcP_pW_w \ * TrP_pW_wD_d - ShtPenaltyP_p * USWP_pW_wD_d$$

$$- OvrPenaltyP_p * OSWP_pW_wD_d)$$

$$+ \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{d=T-minlt}^{T} revP_pW_w * ShpP_pM_mW_wD_d$$

$$- \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{d=1}^{D} scP_pM_mW_w * ShpP_pM_mW_wD_d$$

$$- \sum_{p=1}^{P} \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{d=1}^{D} pcP_pM_m * ProdP_pL_lM_mD_d$$

$$- \sum_{r=1}^{R} \sum_{s=1}^{S} \sum_{m=1}^{M} \sum_{d=1}^{D} rmcostR_rS_s * ShpR_rS_sM_mD_d$$

$$- \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{d=1}^{D} (icP_pM_m * InvP_pM_mD_d + ShtPenaltyP_pM_m * USMP_pM_mD_d$$

$$+ OvrPenaltyP_pM_m * OSMP_pM_mD_d)$$

$$- \sum_{r=1}^{R} \sum_{m=1}^{M} \sum_{d=1}^{D} (icR_rM_m * InvR_rM_mD_d + ShtPenaltyR_rM_m * USMR_rM_mD_d$$

$$+ OvrPenaltyR_rM_m * OSMR_rM_mD_d + icR_rM_m * TrR_rM_mD_d)$$

$$- \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{d=1}^{D} (idlepenL_lM_m * IdleL_lM_mD_d$$

$$\left. + \ idlepenL_lM_m * cleanhrsL_lM_m * SUL_lM_mD_d \ )\right]$$

Timing of Recognition of Revenues and Costs

- Revenues: on day of shipping from manufacturing plant for the Push Formulation, and when delivered to the customer from the warehouse for the Pull Formulation.
- Production costs: on day of production at the manufacturing plant
- Shipping costs: recognized daily while finished goods and raw materials are in transit
- Inventory carrying costs: inventory holding cost recognized daily while raw materials and finished goods are in the manufacturing plant inventory and when finished goods are in warehouse inventory
- In-transit costs: inventory holding cost recognized daily while finished goods and raw materials are in transit
- Goodwill loss: 1% daily charge for loss of goodwill on all unfulfilled orders that are currently on back order

Choice of different elements in the Objective Functions

Different revenue recognition was utilized in the objective functions to drive the Push, Pull, and Hybrid strategies. Alternatively, the goal of driving different strategies could have been accomplished by applying constraints on inventory. Raw material and finished goods inventory constraints at the manufacturing plants and the warehouses could have been used to “push” product through the system to impose “leanness”. However, while such an approach would result in the desired supply chain character, it would do so without regard to the economic consequences. By embedding the elements in the objective function, the current approach allows the economic consequences to drive the inventory and production strategies thus resulting in the appropriate supply chain character.

Additional Considerations

- Supply chain level: Single level i.e. final goods are produced from raw materials with no intermediate assemblies (no parent-component relationships in the model).
- Resource constraints: Production is strictly capacitated. Inventory holding is also capacitated, but allowed to exceed capacity subject to overstock penalties.
- Set-up structure: Simple i.e. period independent.
- Demand: Static, deterministic.
- Raw material source is infinite but subject to lead times
- Product types: Bulk, high volume non-perishables. The model formulation is most appropriate for bulk or high volume non-perishables. The model would need to be modified if it were to be used for perishables. For example, an inventory aging variable with obsolescence could be introduced if perishables such as fresh food, flowers or certain medical products were under study.
- Deterioration of items: None. Consequently, neither constraints nor penalties on holding times are applied. The model would need to be adjusted (e.g. by aging of inventories) if perishability or obsolescence were product characteristics that needed to be accounted for.

Chapter 4: Optimizing Model Behavior

The first of the four research questions will be addressed in this chapter.

- Q1: Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?

Model Inputs

A sampling of the optimization model inputs includes:

Unit Revenues (per kilogram):

- Product 1 at Warehouses 1, 2, and 3 = \$4.00
- Product 1 at Warehouses 4, 5, and 6 = \$3.90
- Product 2 at all Warehouses = \$3.75
- Product 3 at Warehouses 1, 2, and 3 = \$8.25
- Product 3 at Warehouses 4, 5, and 6 = \$8.00

Cost Parameters:

- Production Cost per hour (pcP_pW_w) = \$15
- Idle cost ($idlepenL_lM_m$)= 2.5% of production cost
- Shipping cost ($scP_pM_mW_w$)= 15% of revenue
- Inventory Carrying Cost at Warehouses (icP_pW_w) = 1% of product cost charged daily
- Shortage penalty of raw material at the plant ($ShtPenaltyR_rM_m$) = 2% of product cost charged daily
- Overage penalty of product system-wide ($OvrPenaltyP_p$)= 1% of product cost charged daily
- Goodwill loss (gwloss) = 1% of revenue charged daily while goods on back order

Facilities:

- Number of plants (M_m) = 2
- Number of production lines per plant (L_l) = 3
- Maximum number of production shifts per day per plant ($maxshiftsL_lM_m$) = 2
- Maximum number of hours worked per shift per line per plant ($mxhrsL_lM_m$) = 8
- Number of warehouses (W_w) = 6
- Number of products (P_p) = 3
- Number of raw materials (R_r) = 3

Additional Inputs:

- Distinct product average demands = 18 (3 products by 6 warehouses)
- Lead times: product 1 requires a 6-day lead time when shipped from manufacturing plants to warehouses, product 2 requires a 4-day lead time, and product 3 is generally expedited and requires a 2-day lead time
- Lead times: supplier 1 ships to manufacturing plants with a 5-day lead time while supplier 2 ships with a 2-day lead time
- Production ratio ($recipeR_rP_pL_lM_m$): number of kilograms of raw material r required to produce 1 kilogram of product p on line l of manufacturing plant m
- Initial inventories ($startinvR_rM_m$, $startinvP_pM_m$, $startinvP_pW_w$)
- Initial in-transit inventories ($ItsP_pW_wD_d$)
- Inventory limits ($maxinvR_rM_m$, $maxinvP_pM_m$, $maxinvP_pW_w$)
- Production rates ($kgperhrP_pL_lM_m$)

Daily Demands at the Warehouses:

Product 1 Demands	Product 2 Demands	Product 3 Demands
$P_1W_1 = 35$	$P_2W_1 = 36$	$P_3W_1 = 40$
$P_1W_2 = 35$	$P_2W_2 = 36$	$P_3W_2 = 40$
$P_1W_3 = 35$	$P_2W_3 = 36$	$P_3W_3 = 40$
$P_1W_4 = 35$	$P_2W_4 = 36$	$P_3W_4 = 40$
$P_1W_5 = 35$	$P_2W_5 = 36$	$P_3W_5 = 40$
$P_1W_6 = 35$	$P_2W_6 = 36$	$P_3W_6 = 40$

Modeling Horizon

The optimization model was implemented with a fixed planning horizon without re-planning. Multiple planning horizons were tested, including 30-day, 60-day, 90-day and 120-day planning horizons. Given that the model was implemented without re-planning, it was necessary to ensure that the horizon was sufficiently long to allow for the combination of maximum raw material and finished goods lead times. The 90-day horizon was chosen as the most appropriate planning length.

Model/Formulation Comparisons

The output of the optimization was a set of Procurement, Production, and Distribution Plans. The following table provides a high-level summary of the resulting plans.

Raw Material	Plant	Mean Daily Shipment
1	1	124
2	1	123
3	1	131
1	2	118
2	2	117
3	2	131

Product	Plant	Mean Daily Production
1	1	71
2	1	110
3	1	149
1	2	85
2	2	110
3	2	149

Product	Warehouse	Mean Daily Deliveries
1	1	35
1	2	35
1	3	35
1	4	35
1	5	35
1	6	35
2	1	34
2	2	34
2	3	32
2	4	34
2	5	33
2	6	34
3	1	40
3	2	39
3	3	40
3	4	39
3	5	39
3	6	40

The Procurement, Production, and Distribution plans from the Push, Pull, and Hybrid formulations were compared in further detail to determine the impact of formulation on the outputs of the optimizing model.

Table 1: Summary of Push Formulation Raw Material Daily Procurement Schedule

		Raw Material Procurement Schedule (PUSH)									
		Daily New Orders					Daily Shipments				
Raw Mat	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	299	105	138	61	0	468	105	138	68
1	2	0	299	105	137	59	0	468	105	137	68
2	1	0	388	108	136	66	0	388	108	136	62
2	2	0	302	108	136	59	0	388	108	136	62
3	1	0	360	120	147	60	0	360	120	147	60
3	2	0	384	120	147	66	0	360	120	147	60

		Daily Arrivals					Daily Inventory at Plants				
Raw Mat	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	388	105	138	62	315	525	315	323	38
1	2	0	388	105	137	62	315	525	315	323	38
2	1	0	388	108	136	62	324	540	324	331	38
2	2	0	388	108	136	62	324	540	324	331	38
3	1	0	360	120	147	60	360	600	360	372	49
3	2	0	360	120	147	60	360	600	360	372	48

Table 2: Summary of Pull Formulation Raw Material Daily Procurement Schedule

		Raw Material Procurement Schedule (PULL)									
		Daily New Orders					Daily Shipments				
Raw Mat	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	299	105	95	55	0	468	105	95	59
1	2	0	299	105	95	52	0	468	105	95	59
2	1	0	302	108	97	50	0	388	108	97	51
2	2	0	302	108	97	50	0	388	108	97	51
3	1	0	360	120	108	51	0	360	120	108	48
3	2	0	360	120	108	54	0	360	120	108	48

		Daily Arrivals					Daily Inventory at Plants				
Raw Mat	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	388	105	95	53	315	525	315	324	41
1	2	0	388	105	95	53	315	525	315	324	41
2	1	0	388	108	97	51	324	540	324	332	39
2	2	0	388	108	97	51	324	540	324	332	39
3	1	0	360	120	108	48	360	600	360	372	48
3	2	0	360	120	108	48	360	600	360	372	48

Table 3: Summary of Hybrid Formulation Raw Material Daily Procurement Schedule

		Raw Material Procurement Schedule (HYBRID)									
		Daily New Orders					Daily Shipments				
Raw Mat	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	299	105	109	45	0	468	105	109	55
1	2	0	299	105	109	45	0	468	105	109	55
2	1	0	302	108	107	63	0	388	108	107	68
2	2	0	302	108	107	63	0	388	108	107	68
3	1	0	360	120	114	59	0	360	120	114	62
3	2	0	360	120	114	59	0	360	120	114	61

		Daily Arrivals at Plants					Daily Inventory at Plants				
Raw Mat	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	388	105	109	48	315	525	315	323	38
1	2	0	388	105	109	48	315	525	315	323	38
2	1	0	388	108	107	68	324	540	324	332	39
2	2	0	388	108	107	68	324	540	324	332	39
3	1	0	360	120	114	62	360	600	360	372	48
3	2	0	360	120	114	61	360	600	360	372	48

Observations:

- On average, the Push Formulation places the largest raw material orders resulting in higher shipments and inventory levels. The Hybrid Formulation is intermediate between the Push and Pull Formulations.
- The zero minimum daily raw material orders, shipment and arrival reflects the model not ordering raw materials towards the end of the horizon due to the lead time required to arrive at the plant and transform them into finished goods to generate revenues.

Table 4: Summary of Push Formulation Daily Production Schedule

		Production Schedule at the Plants (PUSH)									
		Daily Production					Daily Product Shipments				
Product	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	194	105	140	53	0	1454	105	146	150
1	2	0	194	105	140	53	0	1454	105	146	151
2	1	0	194	108	138	53	0	1490	108	144	155
2	2	0	194	108	138	53	0	1490	108	144	153
3	1	0	194	120	150	48	46	1634	120	156	166
3	2	0	194	120	150	48	46	1634	120	156	163

		Daily Product Inventory				
Product	Plant	Min	Max	Median	Mean	Std Dev
1	1	315	1575	315	602	471
1	2	315	1575	315	596	466
2	1	324	1620	324	604	468
2	2	324	1620	324	593	458
3	1	360	1800	360	724	512
3	2	360	1800	360	777	561

Table 5: Summary of Pull Formulation Daily Production Schedule

		Production Schedule at the Plants (PULL)									
		Daily Production					Daily Product Shipments				
Product	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	194	105	97	44	0	315	105	99	50
1	2	0	194	105	97	44	0	315	105	99	50
2	1	0	194	108	100	39	0	324	108	102	46
2	2	0	194	108	100	39	0	324	108	102	46
3	1	0	194	120	111	35	0	200	120	113	34
3	2	0	194	120	111	35	0	240	120	113	35

		Daily Product Inventory				
Product	Plant	Min	Max	Median	Mean	Std Dev
1	1	315	525	315	320	31
1	2	315	525	315	320	31
2	1	324	540	324	329	32
2	2	324	540	324	329	32
3	1	360	600	360	366	36
3	2	360	600	360	365	36

Table 6: Summary of Hybrid Formulation Daily Production Schedule

		Production Schedule at the Plants (HYBRID)									
		Daily Production					Daily Product Shipment				
Product	Plant	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	0	194	105	111	37	0	485	105	117	61
1	2	0	194	105	111	37	0	485	105	117	61
2	1	0	194	108	110	59	0	1490	108	116	183
2	2	0	194	108	110	59	0	1490	108	116	181
3	1	0	194	120	117	52	0	1302	120	123	156
3	2	0	194	120	117	52	0	1302	120	123	147

		Daily Product Inventory				
Product	Plant	Min	Max	Median	Mean	Std Dev
1	1	315	727	315	331	66
1	2	315	727	315	331	66
2	1	324	1,620	324	429	265
2	2	324	1,620	324	439	284
3	1	360	1,800	360	604	482
3	2	360	1800	360	594	477

Observation:

- The Push Formulation results in the largest levels of production, shipment, and finished goods inventory at the plant, with the Pull Formulation resulting in the lowest levels.

Table 7: Summary of Push Formulation Daily Distribution Schedule

		Daily Distribution Schedule (PUSH)									
		Product Orders Placed from Warehosue to Plants					Product Shipped to Warehouses from Plants				
Product	Warehouse	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	1	194	35	49	38	1	194	35	50	41
1	2	16	194	35	51	36	16	194	35	55	40
1	3	3	193	35	46	37	3	1307	35	66	147
1	4	35	159	35	46	30	35	159	35	49	32
1	5	7	232	35	48	36	16	242	35	50	38
1	6	5	219	35	48	36	16	1314	35	70	151
2	1	4	223	36	47	33	4	223	36	48	35
2	2	2	194	36	50	39	2	194	36	52	39
2	3	8	194	36	47	33	10	1474	36	69	166
2	4	6	208	36	50	33	6	208	36	51	33
2	5	0	194	36	48	33	8	194	36	50	33
2	6	11	205	36	50	31	11	1382	36	70	155
3	1	6	245	40	51	38	6	245	40	52	38
3	2	13	208	40	58	37	28	208	40	59	36
3	3	5	208	40	55	36	5	1514	40	77	172
3	4	5	184	40	51	31	5	184	40	52	31
3	5	12	194	40	52	33	12	194	40	52	33
3	6	6	175	40	52	33	6	1514	40	73	168

		Product Inventory at Warehouses					Demand Days of Product Inventory at Warehouses				
Product	Warehouse	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	105	525	105	163	115	3	15	3	4.6	3.3
1	2	105	525	105	143	84	3	15	3	4.1	2.4
1	3	105	525	105	154	113	3	15	3	4.4	3.2
1	4	105	525	105	134	82	3	15	3	3.8	2.3
1	5	105	525	105	159	115	3	15	3	4.5	3.3
1	6	105	525	105	163	106	3	15	3	4.6	3
2	1	108	540	108	147	85	3	15	3	4.1	2.3
2	2	108	540	108	160	108	3	15	3	4.4	3
2	3	108	540	108	173	114	3	15	3	4.8	3.2
2	4	108	440	108	160	85	3	12	3	4.5	2.4
2	5	108	540	108	178	128	3	15	3	4.9	3.6
2	6	108	540	108	152	97	3	15	3	4.2	2.7
3	1	120	600	120	217	167	3	15	3	5.4	4.2
3	2	120	600	120	193	118	3	15	3	4.8	2.9
3	3	120	600	120	249	164	3	15	3	6.2	4.1
3	4	120	600	120	216	156	3	15	3	5.4	3.9
3	5	120	600	120	166	107	3	15	3	4.2	2.7
3	6	120	600	120	224	143	3	15	3	5.6	3.6

Table 8: Summary of Pull Formulation Daily Distribution Schedule

		Daily Distribution Schedule (PULL)									
		Product Orders Placed from Warehosue to Plants					Product Shipped to Warehouses from Plants				
Product	Warehouse	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	35	105	35	38	13	35	105	35	38	13
1	2	35	105	35	38	13	35	105	35	38	13
1	3	3	105	35	38	14	0	105	35	38	15
1	4	35	105	35	38	12	35	105	35	38	12
1	5	35	105	35	38	13	35	105	35	38	13
1	6	35	105	35	38	13	35	105	35	38	13
2	1	36	108	36	38	12	36	108	36	38	12
2	2	14	108	36	38	13	14	108	36	38	13
2	3	36	108	36	38	12	36	108	36	38	12
2	4	14	108	36	38	13	14	108	36	38	13
2	5	36	108	36	38	12	36	108	36	38	12
2	6	36	108	36	38	12	36	108	36	38	12
3	1	6	80	40	40	7	6	80	40	40	7
3	2	40	120	40	42	11	40	120	40	42	11
3	3	40	80	40	40	4	40	80	40	40	4
3	4	40	80	40	41	6	40	80	40	41	6
3	5	40	120	40	41	10	40	120	40	41	10
3	6	6	80	40	40	7	6	80	40	40	7

		Product Inventory at Warehouses					Demand Days of Product Inventory at Warehouses				
Product	Warehouse	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	105	175	105	106	8	3	5	3	3	0.2
1	2	105	175	105	106	8	3	5	3	3	0.2
1	3	105	175	105	106	8	3	5	3	3	0.2
1	4	105	175	105	106	8	3	5	3	3	0.2
1	5	105	175	105	106	8	3	5	3	3	0.2
1	6	105	175	105	106	8	3	5	3	3	0.2
2	1	108	180	108	109	8	3	5	3	3	0.2
2	2	108	180	108	109	8	3	5	3	3	0.2
2	3	108	180	108	109	8	3	5	3	3	0.2
2	4	108	180	108	109	8	3	5	3	3	0.2
2	5	108	180	108	109	8	3	5	3	3	0.2
2	6	108	180	108	109	8	3	5	3	3	0.2
3	1	120	200	120	121	9	3	5	3	3	0.2
3	2	120	200	120	122	11	3	5	3	3.1	0.3
3	3	120	200	120	121	9	3	5	3	3	0.2
3	4	120	200	120	122	10	3	5	3	3	0.3
3	5	120	200	120	122	13	3	5	3	3.1	0.3
3	6	120	200	120	121	9	3	5	3	3	0.2

Table 9: Summary of Hybrid Formulation Daily Distribution Schedule

		Daily Distribution Schedule (HYBRID)									
		Product Orders Placed from Warehouse to Plants					Product Shipped to Warehouse from Plants				
Product	Warehouse	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	16	105	35	37	12	16	210	35	41	23
1	2	35	105	35	38	13	35	380	35	42	39
1	3	11	94	35	37	11	11	226	35	41	25
1	4	19	105	35	38	11	19	380	35	42	39
1	5	35	105	35	37	11	35	245	35	41	26
1	6	16	105	35	39	15	16	151	35	41	21
2	1	4	371	36	48	50	0	500	36	53	74
2	2	36	432	36	51	60	36	486	36	57	79
2	3	36	504	36	51	64	36	504	36	52	64
2	4	18	504	36	50	62	36	504	36	51	62
2	5	8	432	36	52	65	8	500	36	58	83
2	6	36	432	36	50	54	36	486	36	55	75
3	1	34	240	40	50	40	34	462	40	53	59
3	2	6	240	40	49	41	6	480	40	52	61
3	3	16	268	40	49	38	16	360	40	50	46
3	4	6	240	40	50	38	6	391	40	52	51
3	5	12	240	40	49	38	12	431	40	52	55
3	6	28	268	40	49	39	28	480	40	52	59

		Product Inventory at Warehouses					Demand Days of Product Inventory at Warehouses				
Product	Warehouse	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Mean	Std Dev
1	1	105	175	105	106	8	3.0	5.0	3.0	3.0	0.2
1	2	105	175	105	106	8	3.0	5.0	3.0	3.0	0.2
1	3	105	175	105	106	8	3.0	5.0	3.0	3.0	0.2
1	4	105	175	105	106	8	3.0	5.0	3.0	3.0	0.2
1	5	105	175	105	106	8	3.0	5.0	3.0	3.0	0.2
1	6	105	175	105	106	8	3.0	5.0	3.0	3.0	0.2
2	1	108	500	108	139	82	3.0	14.0	3.0	3.9	2.3
2	2	108	486	108	137	88	3.0	14.0	3.0	3.8	2.4
2	3	108	504	108	139	96	3.0	14.0	3.0	3.9	2.7
2	4	108	504	108	127	62	3.0	14.0	3.0	3.5	1.7
2	5	108	500	108	131	84	3.0	14.0	3.0	3.6	2.3
2	6	108	486	108	147	101	3.0	14.0	3.0	4.1	2.8
3	1	120	462	120	128	44	3.0	12.0	3.0	3.2	1.1
3	2	120	480	120	128	46	3.0	12.0	3.0	3.2	1.2
3	3	120	360	120	126	30	3.0	9.0	3.0	3.2	0.7
3	4	120	511	120	130	51	3.0	13.0	3.0	3.2	1.3
3	5	120	551	120	130	56	3.0	14.0	3.0	3.2	1.4
3	6	120	480	120	128	46	3.0	12.0	3.0	3.2	1.2

Observation:

- Finished goods inventory held daily at the warehouse were highest for the Push Formulation and lowest for the Pull formulation throughout the horizon, with the Hybrid Formulation intermediate between the two.

In addition to the foregoing comparison of the procurement, production and distribution schedules, the Push, Pull, and Hybrid Formulations were compared along four sets of performance metrics:

- Net Profit Contribution
- Capacity utilization
- Fill rate
- Leanness (days inventory)

<u>Capacity Utilization</u>

Capacity utilization in the plant was calculated as the amount of time that a given line is used for production divided by the total amount of time the line is available given the number of shifts available.

Table 10: Summary of Push Formulation Daily Plant Capacity Utilization

		Plant Production Capacity Utilization (PUSH)				
Plant	Line	Min	Max	Median	Mean	Std Dev
1	1	0%	100%	56%	73%	27%
1	2	0%	100%	57%	72%	26%
1	3	0%	100%	63%	78%	24%
2	1	0%	100%	56%	73%	27%
2	2	0%	100%	57%	72%	26%
2	3	0%	100%	63%	78%	24%

Table 11: Summary of Pull Formulation Daily Plant Capacity Utilization

		Plant Production Capacity Utilization (PULL)				
Plant	Line	Min	Max	Median	Mean	Std Dev
1	1	0%	100%	56%	52%	22%
1	2	0%	100%	57%	53%	20%
1	3	0%	100%	63%	58%	18%
2	1	0%	100%	56%	52%	22%
2	2	0%	100%	57%	53%	20%
2	3	0%	100%	63%	58%	18%

Table 12: Summary of Hybrid Formulation Daily Plant Capacity Utilization

		Plant Production Capacity Utilization (HYBRID)				
Plant	Line	Min	Max	Median	Mean	Std Dev
1	1	0%	100%	56%	58%	19%
1	2	0%	100%	57%	58%	30%
1	3	0%	100%	63%	61%	26%
2	1	0%	100%	56%	58%	19%
2	2	0%	100%	57%	58%	30%
2	3	0%	100%	63%	61%	26%

Observation:

- The Push Formulation has significantly higher plant production capacity utilization compared to the Pull and Hybrid Formulations. This is due to the Push Formulation producing final goods up to the maximum inventory capacity, while the Pull Formulation seeks to produce enough to meet demand.

Fill Rate

Fill rate was used as the measure of service level, where fill rate was defined as the ratio of deliveries to demand.

Table 13: Summary of Push Formulation Daily Warehouse Fill Rates

Daily Product Fill Rates at Warehouses (PUSH)				
Product	Warehouse	Median	Mean	Std Dev
1	1	100%	94%	23%
1	2	100%	94%	23%
1	3	100%	94%	23%
1	4	100%	94%	23%
1	5	100%	94%	23%
1	6	100%	94%	23%
2	1	100%	78%	40%
2	2	100%	74%	43%
2	3	100%	72%	42%
2	4	100%	76%	41%
2	5	100%	77%	42%
2	6	100%	72%	43%
3	1	100%	83%	37%
3	2	100%	87%	34%
3	3	100%	84%	36%
3	4	100%	83%	37%
3	5	100%	86%	34%
3	6	100%	84%	36%

Table 14: Summary of Pull Formulation Daily Warehouse Fill Rates

Daily Product Fill Rates at Warehouses (PULL)				
Product	Warehouse	Median	Mean	Std Dev
1	1	100%	94%	23%
1	2	100%	94%	23%
1	3	100%	94%	23%
1	4	100%	94%	23%
1	5	100%	94%	23%
1	6	100%	94%	23%
2	1	100%	78%	40%
2	2	100%	74%	43%
2	3	100%	72%	42%
2	4	100%	76%	41%
2	5	100%	77%	42%
2	6	100%	72%	43%
3	1	100%	83%	37%
3	2	100%	87%	34%
3	3	100%	84%	36%
3	4	100%	83%	37%
3	5	100%	86%	34%
3	6	100%	84%	36%

Table 15: Summary of Hybrid Formulation Daily Warehouse Fill Rates

Daily Product Fill Rates at Warehouses (HYBRID)				
Product	Warehouse	Median	Mean	Std Dev
1	1	100%	94%	23%
1	2	100%	94%	23%
1	3	100%	94%	23%
1	4	100%	94%	23%
1	5	100%	94%	23%
1	6	100%	94%	23%
2	1	100%	78%	40%
2	2	100%	74%	43%
2	3	100%	72%	42%
2	4	100%	76%	41%
2	5	100%	77%	42%
2	6	100%	72%	43%
3	1	100%	83%	37%
3	2	100%	87%	34%
3	3	100%	84%	36%
3	4	100%	83%	37%
3	5	100%	86%	34%
3	6	100%	84%	36%

Observation:

- In aggregate, the Push Formulation resulted in the highest fill rates. This is largely because the Push Formulation produced and shipped goods to the warehouses up to the maximum capacity, even when it would have been operationally preferable to hold inventory in the plant either as finished goods, work in process, or raw material.

Leanness

The amount of inventory in the system reflects the level of leanness of the supply chain and is measured as the number of days' worth of inventory on hand i.e. given the average daily demand for a given product, the number of days of demand that can be satisfied out of current inventory at the warehouses.

Given that inventory placement is an experimental variable in the simulation component of this analysis, we set the inventory reorder point for raw materials at plants, finished goods at plants, as well as finished goods at warehouses at zero. These levels will be varied in the computational experiments.

Absent any overrides, an available optimal solution would be for the optimizing model to find a solution with zero ending inventories. To ensure modeling of the supply chain as a going concern at the end of the planning horizon, minimum inventory constraints are introduced in the model.

Table 16: Push Formulation Ending Raw Material Inventory at Manufacturing Plants

Ending Raw Material Inventory (PUSH)			
Raw Mat	Plant	Day	Inventory
1	1	90	315
1	2	90	315
2	1	90	324
2	2	90	324
3	1	90	360
3	2	90	360

Table 17: Pull Formulation Ending Raw Material Inventory at Manufacturing Plants

Ending Raw Material Inventory (PULL)			
Raw Mat	Plant	Day	Inventory
1	1	90	315
1	2	90	315
2	1	90	324
2	2	90	324
3	1	90	360
3	2	90	360

Table 18: Hybrid Formulation Ending Raw Material Inventory at Manufacturing Plants

Ending Raw Material Inventory (HYBRID)			
Raw Mat	Plant	Day	Inventory
1	1	90	315
1	2	90	315
2	1	90	324
2	2	90	324
3	1	90	360
3	2	90	360

Observation:

- As expected, the ending raw material inventories in all three Formulations are at the minimum inventory level.

Table 19: Push Formulation Ending Product Inventory at Manufacturing Plants

Ending Product Inventory at Plants (PUSH)				
Product	Plant	Day	Inventory	Shipment
1	1	90	315	315
1	2	90	315	315
2	1	90	324	324
2	2	90	324	324
3	1	90	360	360
3	2	90	360	360

Table 20: Pull Formulation Ending Product Inventory at Manufacturing Plants

Ending Product Inventory at Plants (PULL)				
Product	Plant	Day	Inventory	Shipment
1	1	90	315	0
1	2	90	315	0
2	1	90	324	0
2	2	90	324	0
3	1	90	360	0
3	2	90	360	0

Table 21: Hybrid Formulation Ending Product Inventory at Manufacturing Plants

Ending Product Inventory at Plants (HYBRID)				
Product	Plant	Day	Inventory	Shipment
1	1	90	436	436
1	2	90	436	436
2	1	90	906	906
2	2	90	906	906
3	1	90	526	526
3	2	90	526	526

Observation:

- The Push Formulation had a large non-zero finished goods inventory level at the end of the horizon which was then shipped on that day to recognize revenue. The Hybrid Formulation, likewise, had a large non-zero finished goods inventory as product could still be shipped and revenue recognized as long as it arrived at the warehouse on horizon end plus lead time. As expected, the Pull Formulation had zero inventory at the end of the horizon as the lead time would not allow for goods shipped towards the end of the planning horizon to arrive at the warehouse within the planning horizon to allow for recognition of the revenue.

Table 22: Push Formulation Ending Product Inventory at Warehouses

Daily Product Fill Rates at Warehouses (PUSH)							
Product	Warehouse	Day	Inventory	DaysInv	InTransit	DaysInTransit	DaysMaxInv
1	1	90	525	15.0	75	2.1	15.0
1	2	90	525	15.0	75	2.1	15.0
1	3	90	525	15.0	75	2.1	15.0
1	4	90	495	14.1	75	2.1	15.0
1	5	90	525	15.0	75	2.1	15.0
1	6	90	525	15.0	75	2.1	15.0
2	1	90	532	14.8	30	0.8	15.0
2	2	90	540	15.0	30	0.8	15.0
2	3	90	540	15.0	30	0.8	15.0
2	4	90	524	14.6	30	0.8	15.0
2	5	90	484	13.4	30	0.8	15.0
2	6	90	512	14.2	30	0.8	15.0
3	1	90	600	15.0	0	0.0	15.0
3	2	90	600	15.0	0	0.0	15.0
3	3	90	600	15.0	0	0.0	15.0
3	4	90	600	15.0	0	0.0	15.0
3	5	90	600	15.0	0	0.0	15.0
3	6	90	600	15.0	0	0.0	15.0

Table 23: Pull Formulation Ending Product Inventory at Warehouses

Daily Product Fill Rates at Warehouses (PULL)							
Product	Warehouse	Day	Inventory	DaysInv	InTransit	DaysInTransit	DaysMaxInv
1	1	90	105	3.0	75	2.1	15.0
1	2	90	105	3.0	75	2.1	15.0
1	3	90	105	3.0	75	2.1	15.0
1	4	90	105	3.0	75	2.1	15.0
1	5	90	105	3.0	75	2.1	15.0
1	6	90	105	3.0	75	2.1	15.0
2	1	90	108	3.0	30	0.8	15.0
2	2	90	108	3.0	30	0.8	15.0
2	3	90	108	3.0	30	0.8	15.0
2	4	90	108	3.0	30	0.8	15.0
2	5	90	108	3.0	30	0.8	15.0
2	6	90	108	3.0	30	0.8	15.0
3	1	90	120	3.0	0	0.0	15.0
3	2	90	120	3.0	0	0.0	15.0
3	3	90	120	3.0	0	0.0	15.0
3	4	90	120	3.0	0	0.0	15.0
3	5	90	120	3.0	0	0.0	15.0
3	6	90	120	3.0	0	0.0	15.0

Table 24a: Hybrid Formulation Ending Product Inventory at Warehouses at Day 90

Daily Product Fill Rates at Warehouses (HYBRID)							
Product	Warehouse	Day	Inventory	DaysInv	InTransit	DaysInTransit	DaysMaxInv
1	1	90	105	3.0	75	2.1	15.0
1	2	90	105	3.0	75	2.1	15.0
1	3	90	105	3.0	75	2.1	15.0
1	4	90	105	3.0	75	2.1	15.0
1	5	90	105	3.0	75	2.1	15.0
1	6	90	105	3.0	75	2.1	15.0
2	1	90	108	3.0	30	0.8	15.0
2	2	90	108	3.0	30	0.8	15.0
2	3	90	108	3.0	30	0.8	15.0
2	4	90	108	3.0	30	0.8	15.0
2	5	90	108	3.0	30	0.8	15.0
2	6	90	108	3.0	30	0.8	15.0
3	1	90	320	8.0	0	0.0	15.0
3	2	90	240	6.0	0	0.0	15.0
3	3	90	308	7.7	0	0.0	15.0
3	4	90	332	8.3	0	0.0	15.0
3	5	90	240	6.0	0	0.0	15.0
3	6	90	296	7.4	0	0.0	15.0

Table 24b: Hybrid Formulation Ending Product Inventory at Warehouses at Day 100

Daily Product Fill Rates at Warehouses (HYBRID)							
Product	Warehouse	Day	Inventory	DaysInv	InTransit	DaysInTransit	DaysMaxInv
1	1	100	525	15.0	75	2.1	15.0
1	2	100	525	15.0	75	2.1	15.0
1	3	100	525	15.0	75	2.1	15.0
1	4	100	525	15.0	75	2.1	15.0
1	5	100	525	15.0	75	2.1	15.0
1	6	100	525	15.0	75	2.1	15.0
2	1	100	540	15.0	30	0.8	15.0
2	2	100	540	15.0	30	0.8	15.0
2	3	100	540	15.0	30	0.8	15.0
2	4	100	540	15.0	30	0.8	15.0
2	5	100	540	15.0	30	0.8	15.0
2	6	100	540	15.0	30	0.8	15.0
3	1	100	600	15.0	0	0.0	15.0
3	2	100	600	15.0	0	0.0	15.0
3	3	100	600	15.0	0	0.0	15.0
3	4	100	600	15.0	0	0.0	15.0
3	5	100	600	15.0	0	0.0	15.0
3	6	100	600	15.0	0	0.0	15.0

Observation:

- The Push Formulation leads to significant finished goods inventory at the warehouses at the end of the horizon (day 90). Pull Formulation results in minimal finished goods inventory at the end of the horizon. The Hybrid Formulation reflects similar inventory to the Pull Formulation at day 90, but those inventories balloon to similar to Push levels at day 100 (note that lead times in the model range from 2-6 days).

Table 25: Net Contribution to Profit

Cash Flow Income Statement (in $K)			
Component	**Push**	**Pull**	**Hybrid**
Revenue	232,921	235,551	235,551
Raw Material Cost	-102,224	-72,875	-80,170
Production Cost	-123,229	-88,445	-97,148
Outbound Shipping Cost	-19,056	-13,280	-15,224
Line Cleaning Cost	-10,134	-10,134	-10,134
Net Contribution to Profit	**-21,722**	**50,817**	**32,875**
Accrual Income Statement (in $K)			
Component	**Push**	**Pull**	**Hybrid**
Revenue	232,921	235,551	235,551
Raw Material Cost	-102,224	-72,875	-80,170
Production Cost	-123,229	-88,445	-97,148
Outbound Shipping Cost	-19,056	-13,280	-15,224
Line Cleaning Cost	-10,134	-10,134	-10,134
Raw Material Carrying Cost	-1,847	-1,850	-1,852
Product at Plant Carrying Cost	-5,795	-2,920	-3,540
Product In-Transit Carrying Cost	-4,633	-3,541	-3,708
Product at Warehouse Carrying Cost	-4,410	-2,912	-3,219
Product Inventory Value Change at Plant	-4,129	-4,129	2,819
Product Inventory Value Change In-Transit	41,863	0	19,736
Product Inventory Value Change at Warehouse	21,954	-4,442	-1,275
Net Contribution to Profit	**21,281**	**31,023**	**41,836**

Observations:

- When recognizing revenues and costs using the cash flow method, the Pull Formulation results in the highest net contribution to profit. This is because (i) the Push Formulation manufactures and ships the maximum amount of finished goods subject to maximum inventory levels at the warehouse thus incurring expenses, but not recognizing revenues since some of the inventory is not delivered to meet customer demand; (ii) the Hybrid Formulation manufactures and ships finished goods towards the end of the planning horizon to keep the system viable, but does not recognize the revenues associated with that production. The Pull Formulation only produces and ships finished goods which will be delivered to customers to recognize revenue. However, it depletes the system and does not leave the supply chain as a going concern.

- When recognizing revenues and costs using the accrual method, the Hybrid Formulation results in the highest net contribution to profit. Unlike the cash flow method, the accrual method accounts for all the expenses and costs including such non-cash costs as inventory carrying costs. The Hybrid Formulation outperforms the Pull formulation primarily because the Hybrid Formulation accounts for the changes in the value of inventory. The Hybrid Formulation manufactures and ships product towards the end of the horizon to keep the system viable which is valued and recognized in the Accrual method as inventory value change.

Summary Findings from the Optimizing Model

Given the cost structures in the supply chain setting laid out in this dissertation, the following optimization findings were obtained:

- The Pull Formulation results in lower expected profitability primarily because revenue is recognized only upon receipt of finished goods at the warehouse and the model stops producing and shipping product that would not reach the warehouse before the end of the planning horizon. It can leave the firm with insufficient inventory to meet demand at the end of the planning horizon unless explicit constraints on ending inventories are added to the model to ensure sufficient safety stocks.

- The Pull Formulation leads to a much leaner supply chain with respect to inventory.
- The choice of accounting standard (cash flow versus accrual) provides a different signal as to the relative merits of the push, pull, and hybrid formulations.
- Analysis of the optimization model results answers Research Question 1 (Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?) in the affirmative, consistent with Xu and Smith (2018). While Xu and Smith implemented a rolling horizon planning model, the current work is a fixed horizon planning model.

Chapter 5: Simulation Model Behavior

Model Description

Simulation is a methodology that is well suited for accounting for the stochastic nature of deviation and disruption risks. The simulation model takes as its initial inputs, among other factors, the procurement plan, the production plan, and the distribution plan that were outputs of the optimization model.

Raw material orders are shipped in accordance with the Procurement Plan that is an output of the optimization model and arrive randomly pursuant to stochastic lead times. Production occurs as capacity and raw materials are available and as demand dictates. Finished goods inventory is shipped daily as necessary with consideration of current product shortages at the warehouse. Arrival dates are generated randomly pursuant to stochastic lead times when the shipments are released. Shipment receipts at warehouses are processed on the day they arrive with updates to stock in transit and warehouse inventories.

Steps in simulation model:

1. Read in model parameters and initial conditions
    a. Channel information (for each warehouse and product combination)
        i. Average daily demand
        ii. Average time for delivery from plant to warehouse
        iii. Current amount on order
        iv. Current amount in transit
        v. Production line at the plant used to produce the product
    b. Production rates (for each production line and product produced on the line)
    c. Product changeover and cleaning times between product runs (for each line)

2. Set number of days to be simulated and initial conditions (for each production line)
    a. Current setup (product in process or cleaning) on each production line at beginning of the day
    b. Maximum number of 8-hour shifts to be operated
3. Generate daily demands at each warehouse for each product (i.e., for each channel)
4. Deliver product to customers from warehouse inventories in response to demand
    a. Ship up to amount ordered (with partial orders if allowed)
    b. Record lost sales for any unmet demands
5. Update inventory
6. Accumulate orders for each product at the plant
7. Update Plant inventories with the day's production and reduce raw materials by amount used in production
8. Release shipments to a warehouse and set the arrival date based on lead time variates.
9. Update plant raw material inventories, plant finished goods inventories, and goods in shipment to warehouses to reflect shipments that are released
10. Identify raw material shipment arrivals at plants and finished goods arrivals at warehouses for the day
11. Update plant raw material inventory, warehouse finished goods inventories, and goods in transit to reflect raw materials and goods received
12. If simulation limit (in days) is reached, terminate simulation and generate performance reports; otherwise return to step 3

Simulation Type

The simulation type chosen for this study was a terminating simulation rather than a steady-state simulation. This type of simulation was chosen because this study investigates the behavior of a firm's supply chain over a particular period of time. The simulation begins on Day 1 and terminates on Day 90 which is the end of the planning horizon. Numerous replications of the terminating simulations are run to simulate performance under different environments. This is in contrast with a steady-state implementation which would have no specific starting and ending conditions, but would have a ramp up period and model performance would be extracted once the model arrived at stability. The terminating approach was selected as it better emulates the most common corporate planning and performance-reporting practices which typically follow a quarterly cadence.

Multivariate Normal Generation Process

The simulation model contains 48 stochastic demand and lead time variables. There are 3 products fulfilled at each of 6 warehouses leading to 18 unique demand variables. There are 2 manufacturing plants, with each plant assigned to fulfil 3 warehouses with the products. This leads to 18 unique product lead times. Lastly, the 2 manufacturing plants each source 3 raw materials from 2 suppliers for a total of 12 unique raw material lead times.

The stochastic variables are generated from a multivariate normal distribution. Three key inputs are used to generate the distribution: (i) the average values of the variables as obtained from the deterministic Optimizing Model, (ii) a coefficient of variation (which is itself an experimental variable in the model), and (iii) correlation coefficients (also experimental variables in the simulation model). In this research, the same correlation coefficients are used for all pairs of variables. A sample size is selected reflecting the number of observations of each variable to be generated. The 48 variables are generated such that each is expected to have a mean across the sample equal to the input average value from the Optimizing Model, expected to have a sample standard deviation equal to the product of the input coefficient of variation and the input average value, and the sample correlation coefficient between any two variables is expected to be equal to the input correlation coefficient.

Statistical Analysis of Simulation Variables – Correlation Structure

The 48 simulated variables were analyzed to investigate their fidelity to the input correlation structure. For ease of presentation, given that a 48x48 matrix would be difficult to fit on one page, the correlation matrices of the sample variables are reported in the following charts as scatterplots. Each dot in the scatterplots represents an element in the correlation matrix. Specifically, there are 48 columns in the scatterplot (x-axis) each of which has 48 dots (along the y-axis). The 2,304 dots in the scatterplot represent the elements in the 48x48 correlation matrix. In each of the scatterplots, "rho" is the correlation coefficient.

Chart 1: Scatterplot of Correlation Matrix with Rho 0.1 run for 90 observations

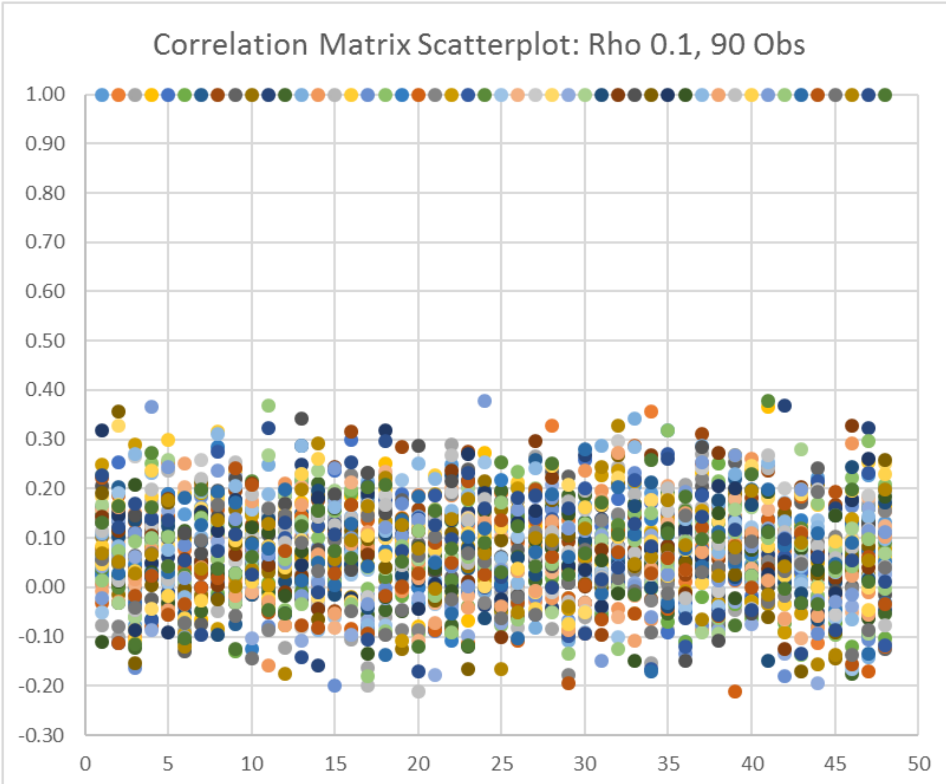


Chart 2: Scatterplot of Correlation Matrix with Rho 0.1 run for 500 observations

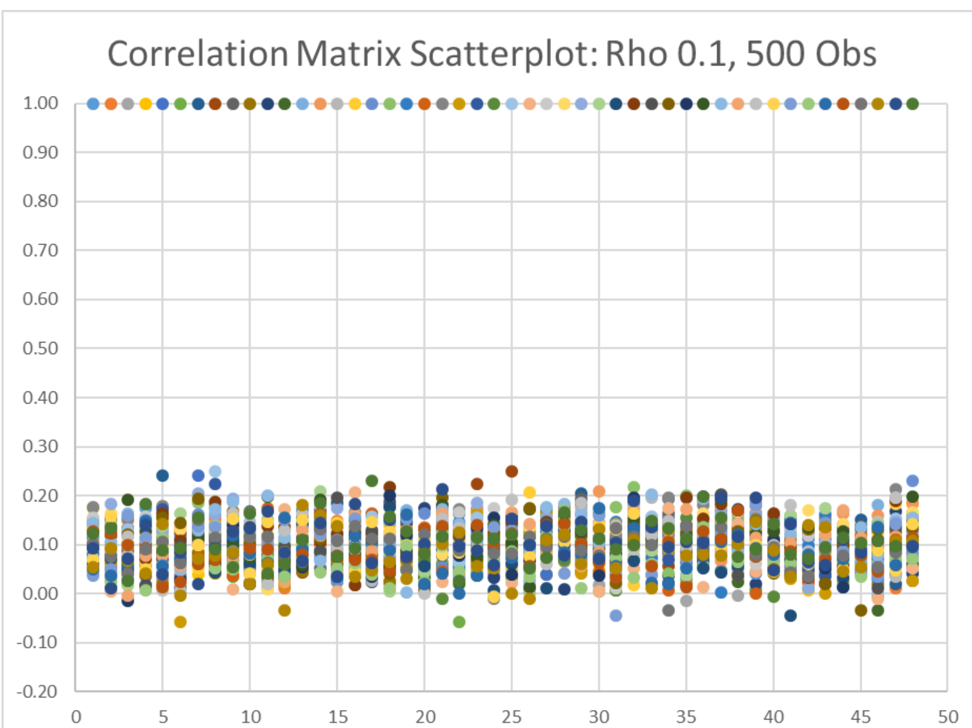
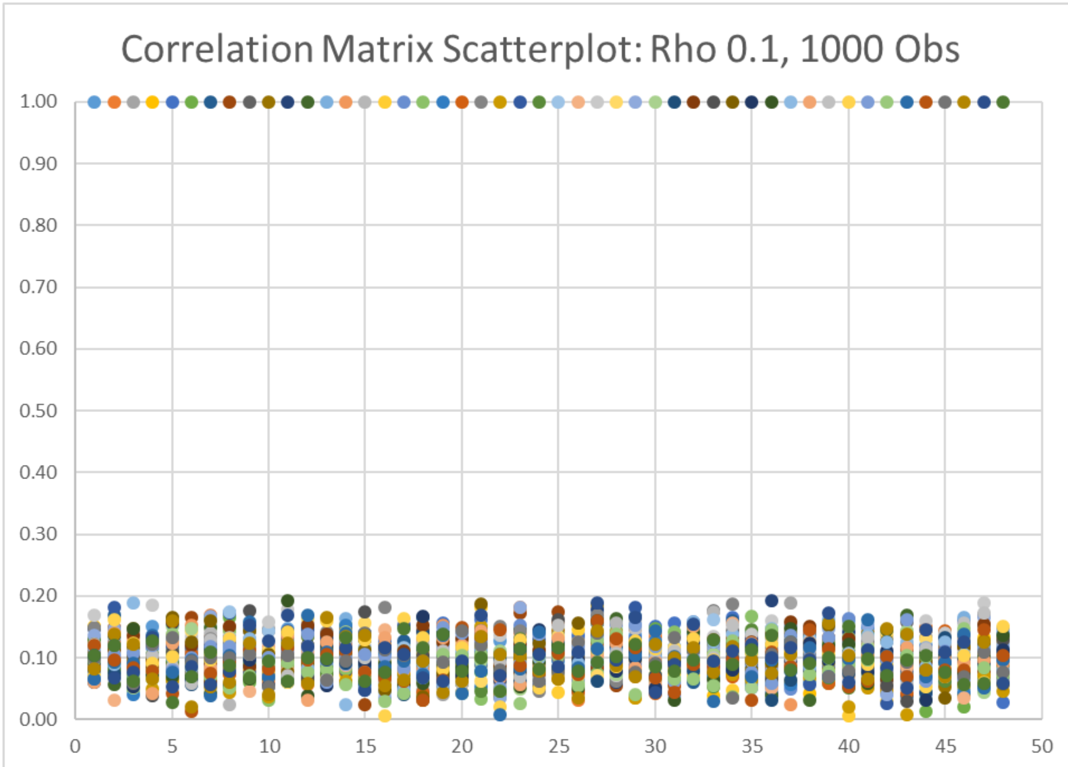


Chart 3: Scatterplot of Correlation Matrix with Rho 0.1 run for 1,000 observations



Observation:

- It takes numerous iterations for the multivariate normal generation process to converge to the input correlation parameter. That is, given an input correlation parameter of 0.1, the observed correlations from the multivariate normal process ranged from -0.2 to 0.4 for a 90 day iteration run, from -0.14 to 0.24 for a 500 day iteration run, and from 0 to 0.2 for a 1,000 day iteration run.

Chart 4: Scatterplot of Correlation Matrix with Rho 0.5 run for 90 observations

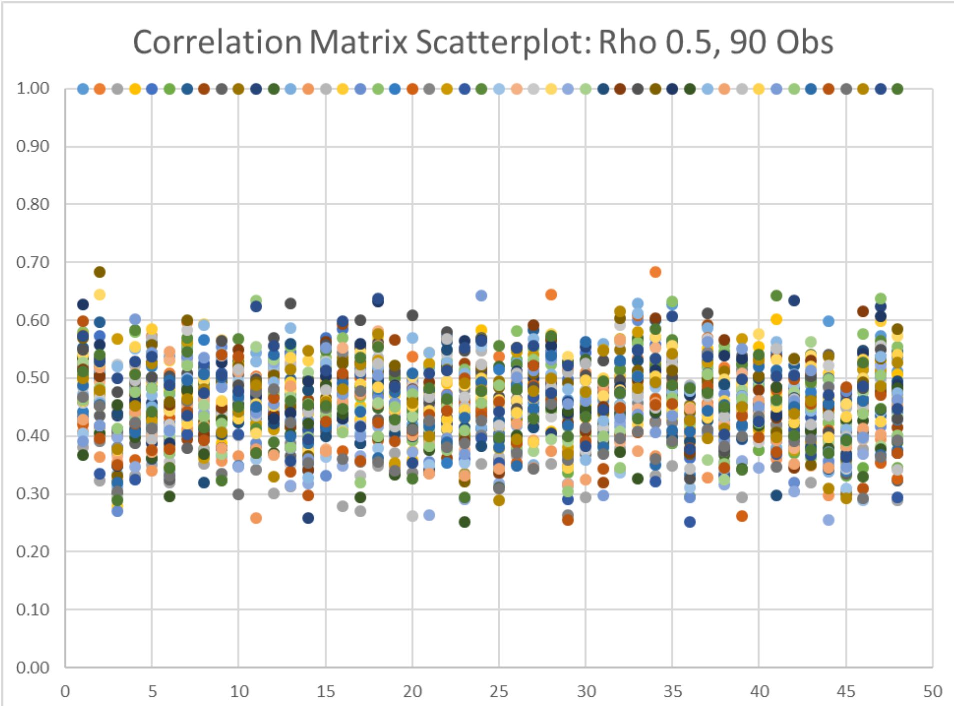


Chart 5: Scatterplot of Correlation Matrix with Rho 0.5 run for 500 observations

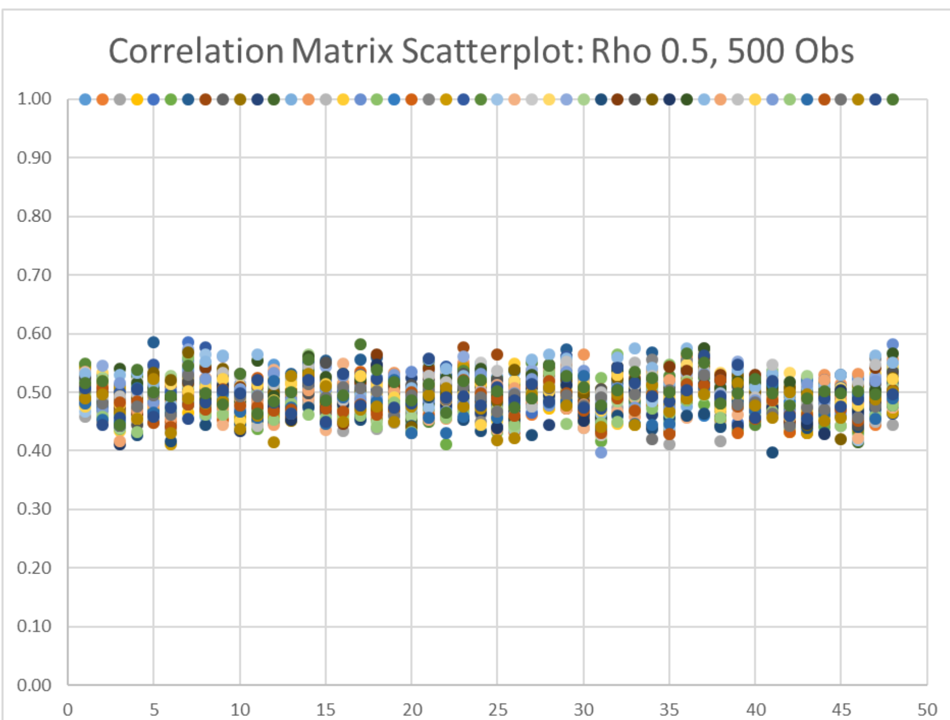
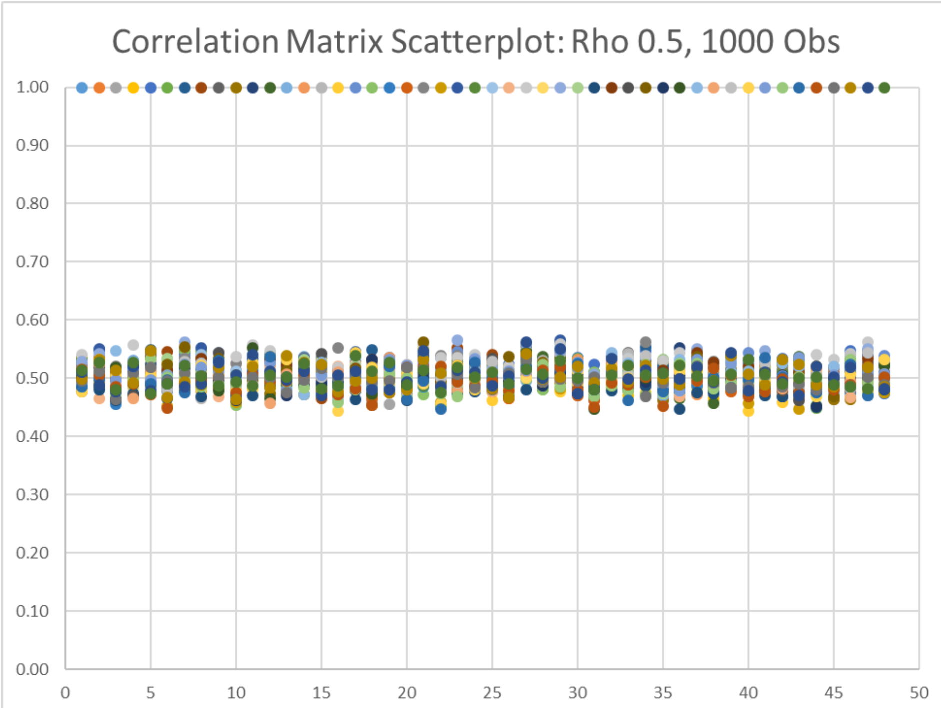


Chart 6: Scatterplot of Correlation Matrix with Rho 0.5 run for 1,000 observations



Observation:

- It takes numerous iterations for the multivariate normal generation process to converge to the input correlation parameter. Given an input correlation parameter of 0.5, the observed correlations from the multivariate normal process ranged from 0.24 to 0.68 for a 90 day iteration run, from 0.4 to 0.59 for a 500 day iteration run, and from 0.45 to 0.56 for a 1,000 day iteration run.

Chart 7: Scatterplot of Correlation Matrix with Rho 0.9 run for 90 observations

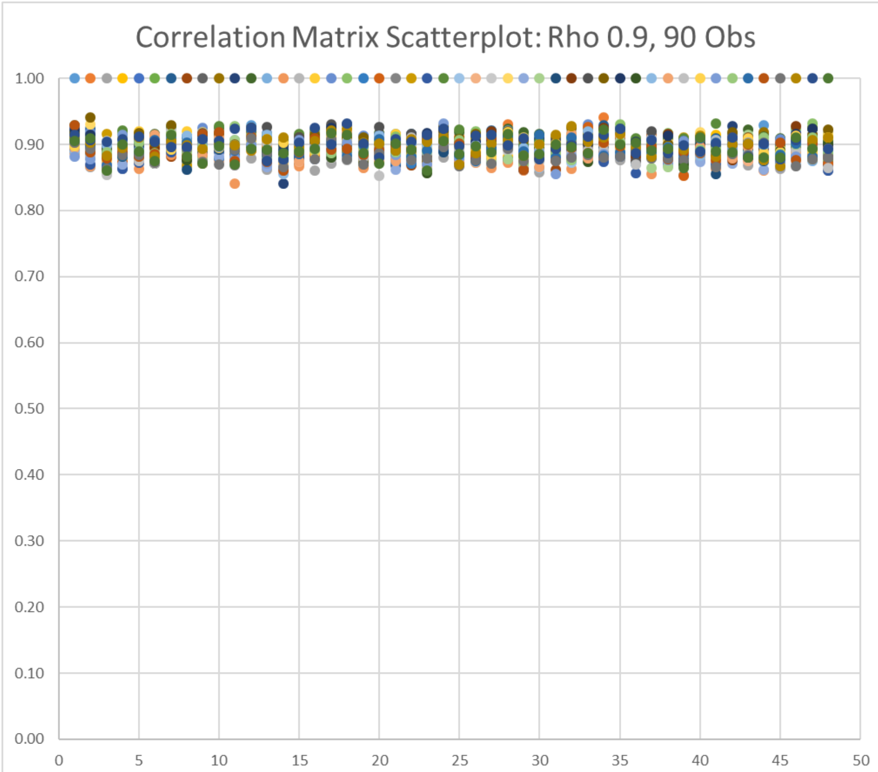


Chart 8: Scatterplot of Correlation Matrix with Rho 0.9 run for 500 observations

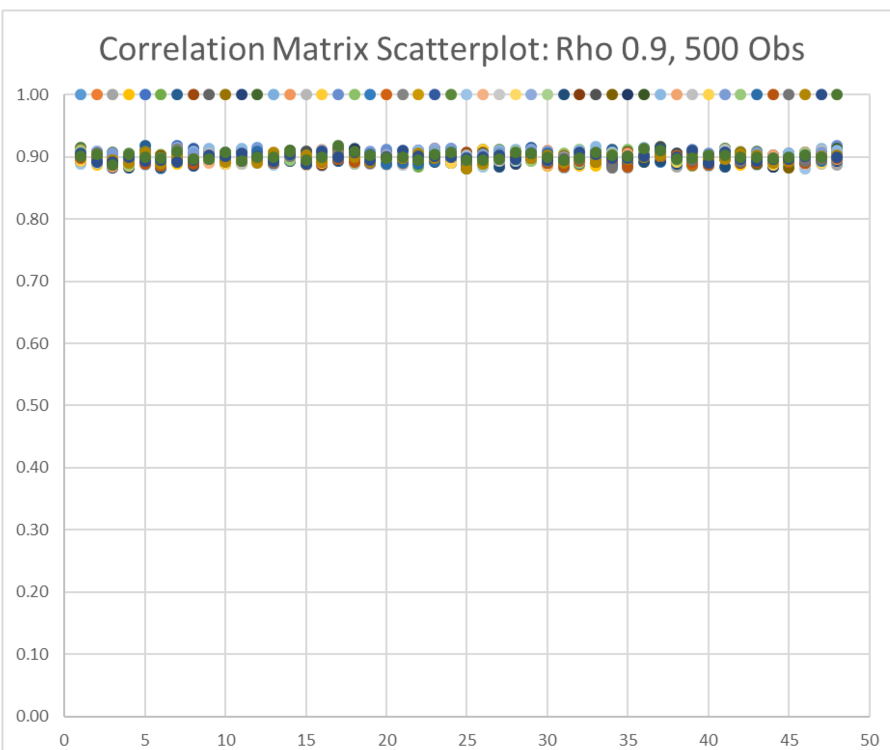
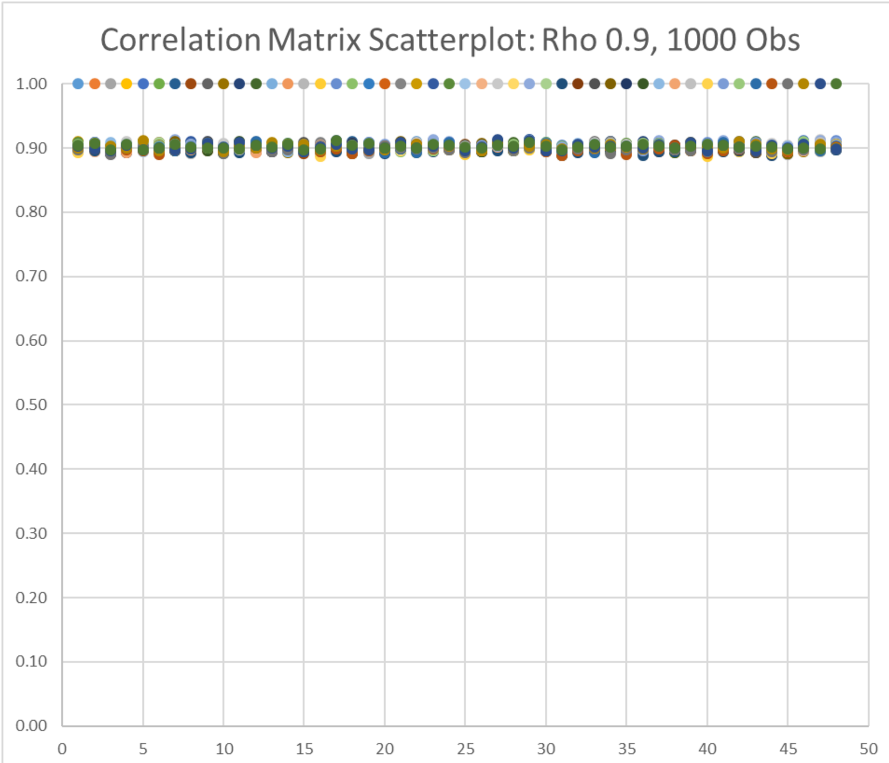


Chart 9: Scatterplot of Correlation Matrix with Rho 0.9 run for 1,000 observations



Observations:

- It takes numerous iterations for the multivariate normal generation process to converge to the input correlation parameter. Given an input correlation parameter of 0.9, the observed correlations from the multivariate normal process ranged from 0.83 to 0.94 for a 90 day iteration run, from 0.88 to 0.92 for a 500 day iteration run, and from 0.89 to 0.91 for a 1,000 day iteration run.
- The higher correlation runs (0.9) converge quicker than the lower correlation runs (0.1).
- The 90 day planning horizon chosen for this dissertation has the limitation of having observed correlations that can deviate significantly from the input

correlation parameter. To mitigate this limitation, the 90 day planning horizon used in the simulation model is run for 200 iterations (see next section for justification of the number of iterations) which results in better convergence.

Convergence of Net Profit Contribution to steady state

The correlated normal variates were analyzed to determine their statistical properties. Three levels of coefficient of variation and correlation coefficients were jointly tested: (i) 0.1, (ii) 0.5, and (iii) 0.9. To obtain a sense of the time required to reach "steady state" for the multivariate normal relationships, three sample sizes were tested: (i) a 90 observation sample, (ii) a 500 observation sample, and (iii) a 1,000 observation sample.

Convergence tests were run to determine the appropriate number of iterations to run in each simulation. A large number of 1,000 was selected *a priori* as the baseline number of iterations. The simulation was run at 1,000 iterations and certain important outputs, primarily income statement performance metrics, were obtained. The absolute percentage error between the model output at 1,000 iterations and at various iterations from 50 to 950 in multiples of 50 were calculated and graphed.

Chart 10: Average Absolute Percentage Deviation of Net Profit Contribution from the 1,000-iteration result (Push Formulation – CV 0.5 – Correlation Coefficient 0.5)

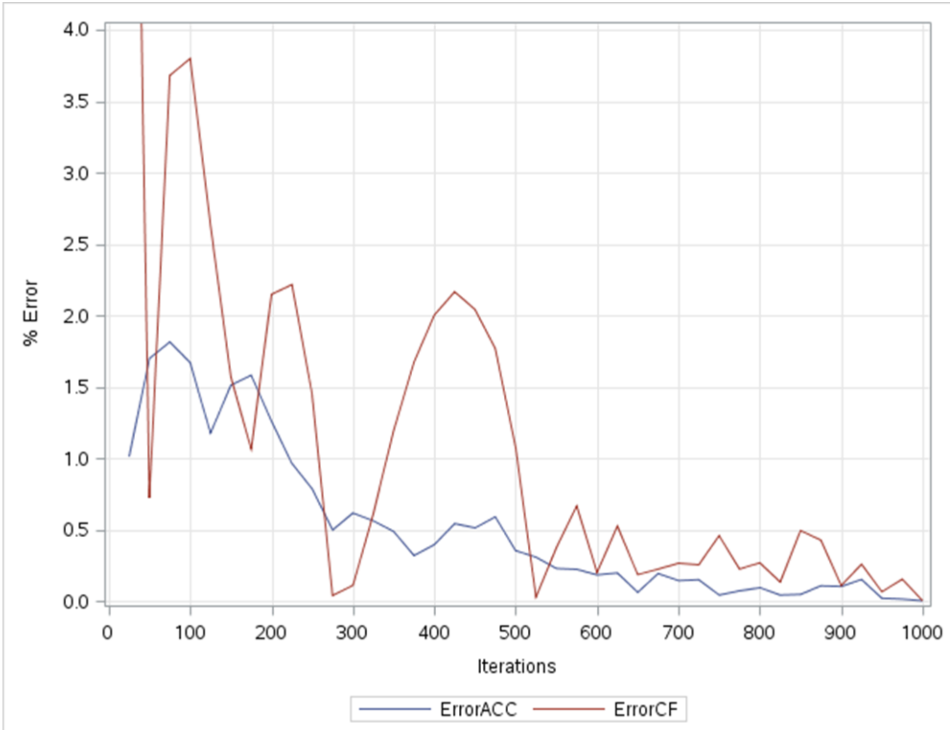


Chart 11: Net Profit Contribution Solution Error for 1,000 iterations (Pull Formulation – CV 0.5 – Correlation Coefficient 0.5)

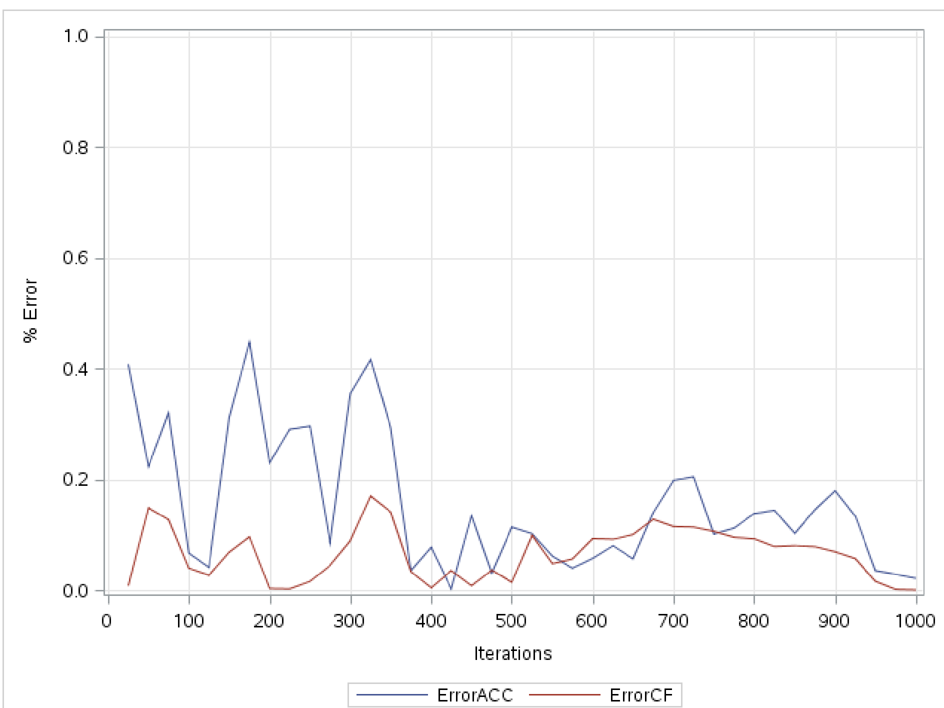
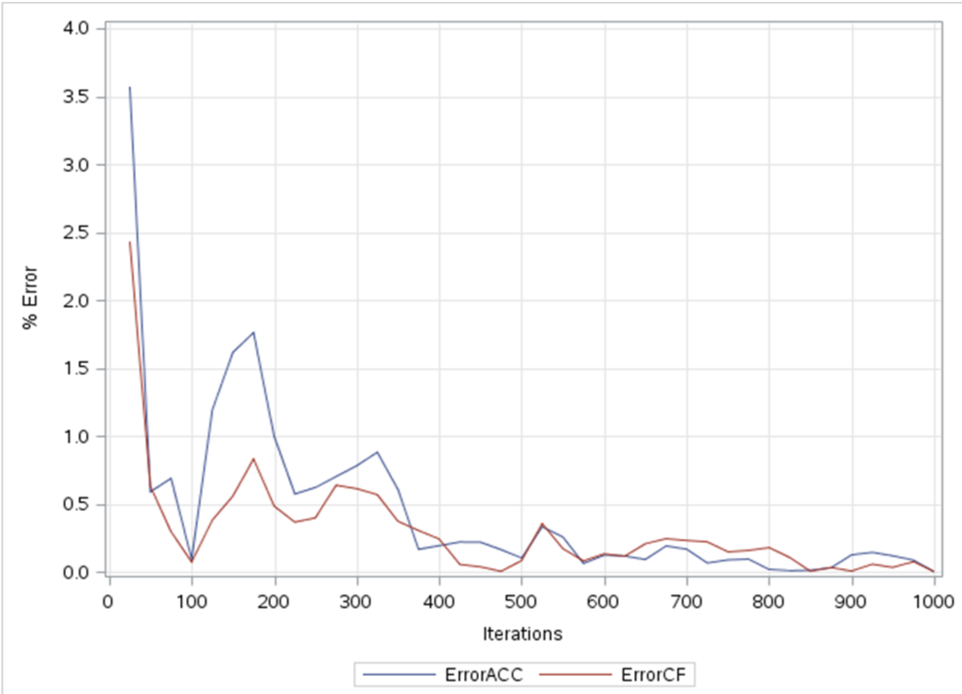


Chart 12: Net Profit Contribution Solution Error for 1,000 iterations (Hybrid Formulation – CV 0.5 – Correlation Coefficient 0.5)



Observation:

- The income statement performance metrics largely converged by 200 iterations, with the absolute percentage error relative to 1,000 iterations decreasing from approximately 3% at 50 iterations to approximately 0.5% at 200 iterations (Hybrid Formulation).

Income Statements from Simulation Model

Table 26: Net Contribution to Profit

Cash Flow Income Statement (in $K)			
Component	**Push**	**Pull**	**Hybrid**
Revenue	236,555	221,924	235,781
Raw Material Cost	-101,891	-73,236	-79,691
Production Cost	-116,711	-83,843	-92,073
Outbound Shipping Cost	-18,072	-12,561	-14,459
Line Cleaning Cost	-10,134	-10,134	-10,134
Net Contribution to Profit	**-10,253**	**42,150**	**39,424**
Accrual Income Statement (in $K)			
Component	**Push**	**Pull**	**Hybrid**
Revenue	236,555	221,924	235,781
Raw Material Cost	-101,891	-73,236	-79,691
Production Cost	-116,711	-83,843	-92,073
Outbound Shipping Cost	-18,072	-12,561	-14,459
Line Cleaning Cost	-10,134	-10,134	-10,134
Raw Material Carrying Cost	-4,040	-3,867	-3,587
Product at Plant Carrying Cost	-5,165	-3,013	-3,645
Product In-Transit Carrying Cost	-4,615	-3,414	-3,933
Product at Warehouse Carrying Cost	-2,982	-1,608	-1,653
Product Inventory Value Change at Plant	-2,717	-2,009	1,777
Product Inventory Value Change In-Transit	34,011	1,068	14,242
Product Inventory Value Change at Warehouse	15,128	-9,977	-4,776
Net Contribution to Profit	**19,367**	**19,330**	**37,849**

Observations:

- The Hybrid Formulation is most stable and provides results that are superior to the Push and the Pull Formulations. Thus, it will be used as the basis of the stochastic experiments.

Summary Findings from the Simulation Model

Simulation Findings:

- Results tend to converge as the number of observations (iterations) increases. Results thus have more reliability when they are arrived at when running large sample sizes. However, there is a trade-off between reliability and the time and computational resources needed.

- The higher the assumed input variability (coefficient of variation) the larger the number of observations (iterations) needed in order to converge. Thus, for a given number of iterations higher coefficient of variation scenarios are less reliable than lower ones.
- Analysis of the simulation model income statements affirms the optimization model answer to Research Question 1 (Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?) as "yes".

Chapter 6: Supply Chain Risk Analysis

Computational Experiments

Several computational experiments were conducted to determine the impact of risk on the modelled supply chain. The experiments involved introducing variability in a number of key factors in the model.

Deviations

Deviations are realized in the model as what Hajmohammad and Vachon (2016) refer to as "speculative risks". These are risks which can result in a gain relative to the starting position.

- Demand: Average daily product demand at the warehouses is an input into the model (there are 3 products and 6 warehouses for 18 channel combinations. The 18-daily product-warehouse demands are subject to variation. Their variations are studied as an experimental factor. The variations are investigated at a low setting (coefficient of variation = 0.3) and at a high setting (coefficient of variation = 0.7). Additionally, the correlations of the variations of the product demands, as well as the product and raw material lead times are investigated at a low setting (correlation coefficient = 0.3) and at a high setting (correlation coefficient = 0.7). The distribution from which demands are selected is adjusted-normal as the left tail is truncated to ensure no negative demands. An adjusted-normal distribution was selected for demands over a Poisson distribution for ease of implementation and to allow for more straightforward and tractable correlations with the lead time variables.

- Lead times: There are two sets of lead times in the model. First, the delivery of raw materials from suppliers to manufacturing plants requires a lead time. Second, the delivery of finished goods from the manufacturing plants to the warehouses requires a separate lead time. 18-daily manufacturing plant to warehouse lead times, as well as the 12-daily supplier to manufacturing plant lead times are generated. Their variations are investigated at a low setting (coefficient of variation = 0.3) and at a high setting (coefficient of variation = 0.7). Additionally, the correlations of the variations of the product demands, as well as the product and raw material lead times are investigated at a low setting (correlation coefficient = 0.3) and at a high setting (correlation coefficient = 0.7). The distribution from which lead times are selected is adjusted-normal as the left tail is truncated to a minimum of 1 day lead time. An adjusted-normal distribution was selected for lead times over a lognormal distribution for ease of implementation and to allow for more straightforward and tractable correlations with the demand variables.

Disruptions

Disruptions are realized in the model as what Hajmohammad and Vachon (2016) refer to as "pure risks". These are risks which cannot result in a gain relative to the starting position.

- Production: The probability of a production disruption occurring is selected from a binomial distribution. Low probability reflects a 1% chance of occurrence on any given day while high probability reflects a 5% chance. When a production disruption occurs, the severity can either be low (1 day) or high (5 days). For production that means that no transformation of raw materials to finished goods can occur for the specified period. This is implemented by setting the production capacity to zero for the relevant period.

- Distribution: The probability of a distribution disruption occurring is selected from a binomial distribution. Low probability reflects a 1% chance of occurrence on any given day while high probability reflects a 5% chance. When a distribution disruption occurs, the severity can either be low (1 day) or high (5 days). Distribution disruptions are implemented as an additional lead time of the specified severity being added to the lead time obtained from the multivariate normal generation process.

The disruption variables (probability and severity) are selected independently of the deviation variables (demand and lead time) i.e. the disruption variables are not introduced into the multi-variate normal generation process. Thus, no correlation between the disruption variables and deviation variables is enforced.

Simulation Process

The simulation process is initialized with the deterministic Procurement, Production, and Distribution Plans. Briefly, the simulation model begins with the Procurement plan from the MILP, which determines the expected amount of raw materials ordered and shipped on each day of the planning horizon. While the MILP had deterministic lead times from suppliers to the manufacturing plant, the simulation model obtains stochastic lead times generated from the Multi Variate Normal (MVN) process. Consequently, with respect to “deviation risk” raw materials in the simulation model have different arrival times at the manufacturing plants compared to the MILP. Additionally, with respect to "disruption risk" supplier disruptions are introduced following a binomial probability distribution each for probability of occurrence (low =1%, high = 5%) and severity of occurrence (low =1 day, high = 5 days). For example, in the instance where a supplier disruption occurs and it is of a high severity level, then 5 days are added to the lead-time for that shipment that was drawn from the MVN process.

For production, the simulation model takes the MILP Production Plan as the starting point. For any day where there are sufficient resources (raw materials, production capacity) to produce according to the deterministic Production Plan, production will follow that plan. However, if there are insufficient resources e.g. raw materials are running low, then production on that day will occur up to the level supported by available resources. Given the stochastic arrival of raw materials at the manufacturing plant, actual manufacturing output may deviate from the MILP plan. Additionally, "disruption risk" is introduced into production following a binomial probability distribution each for probability of occurrence (low =1%, high = 5%) and severity of occurrence (low =1 day, high = 5 days). For example, in the instance where a production disruption occurs and it is of a low severity level, then production capacity is eliminated for 1 day thus no transformation of raw materials to finished goods occurs during the disruption.

For outbound distribution, the simulation model begins with the MILP Distribution plan. For any day where there are sufficient finished goods at the manufacturing plant to ship according to the deterministic Distribution Plan, shipping will follow that plan. However, if the finished goods inventory is running low, quantity shipped on that day will occur up to the level supported by the amount of available inventory. The simulation model will obtain that shipment's lead-time from the manufacturing plant to the warehouse from the MVN process. Further, "disruption risk" is introduced following a binomial probability distribution each for probability of occurrence (low =1%, high = 5%) and severity of occurrence (low =1 day, high = 5 days). For example, in the instance where an outbound shipping disruption occurs and it is of a high severity level, then 5 days are added to the lead-time for that shipment that was drawn from the MVN process. For delivery of finished goods at the warehouse, final demand is obtained from the MVN process. Simulated demand thus deviates from the MILP plan and is satisfied to the extent that sufficient inventory exists at the warehouse. Otherwise, unfilled demand is placed on backorder. Backorders are given priority in fulfillment on subsequent days relative to regular orders as finished goods arrive at the warehouse from the manufacturing plants.

Simulation Experimental Plan

To get a baseline understanding of the impact of variation in demand and lead time, the correlation of these variables, as well as the random introduction of disruption, a set of stochastic scenarios was defined. The multivariate normal process generated variables such that they would either have a low level of correlation (correlation coefficient of 0.3 among all variables) or a high level of correlation (correlation coefficient of 0.7 among all variables). Additionally, disruption of the daily production plan was introduced either at a probability of 0 (no disruption), 1% (low disruption), and 5% (high disruption). Independently, severity of disruption was modelled as days to recovery with one of three values: 0, 1 (low), or 5 (high). From the foregoing, a set of eight distinct scenarios was defined as in Tables 27a and 27b capturing various combinations of volatility, correlation, and disruption. While this less-than-full-factorial design left open the possibility of confounding variables affecting the results in ways that were not controlled for and therefore not explicitly studied, the large number of parameters in the simulation model made a full factorial design impracticable. That is, given the trade-off between modeling the supply chain as realistically as possible (with as many parameters as were necessary) versus implementing a design of experiment that eliminated all confounding factors, the choice was made to privilege the realistic modeling of the supply chain. All observations and findings ensuing from the upcoming computational experiments are to be understood in light of the limitation that interactions among various factors in the simulation model cannot be explicitly disentangled.

Table 27a: Description of Computational Experiments

Scenario Mnemonic	Description
Sim 1	Low volatility of demand, raw material lead times, and finished goods lead times, with low correlation among them. No disruptions. ($\text{Vol}_{Low}\text{Corr}_{Low}\text{Disrupt}_{None}$)
Sim 2	High volatility of demand, raw material lead times, and finished goods lead times, with low correlation among them. No disruptions. ($\text{Vol}_{High}\text{Corr}_{Low}\text{Disrupt}_{None}$)

Sim 3	Low volatility of demand, raw material lead times, and finished goods lead times, with high correlation among them. No disruptions. ($Vol_{Low}Corr_{High}Disrupt_{None}$)
Sim 4	High volatility of demand, raw material lead times, and finished goods lead times, with high correlation among them. No disruptions. ($Vol_{High}Corr_{High}Disrupt_{None}$)
Sim 5	Low volatility of demand, raw material lead times, and finished goods lead times, with low correlation among them. Low disruptions. ($Vol_{Low}Corr_{Low}Disrupt_{Low}$)
Sim 6	Low volatility of demand, raw material lead times, and finished goods lead times, with low correlation among them. High disruptions. ($Vol_{Low}Corr_{Low}Disrupt_{High}$)
Sim 7	High volatility of demand, raw material lead times, and finished goods lead times, with high correlation among them. Low disruptions. ($Vol_{High}Corr_{High}Disrupt_{Low}$)
Sim 8	High volatility of demand, raw material lead times, and finished goods lead times, with high correlation among them. High disruptions. ($Vol_{High}Corr_{High}Disrupt_{High}$)

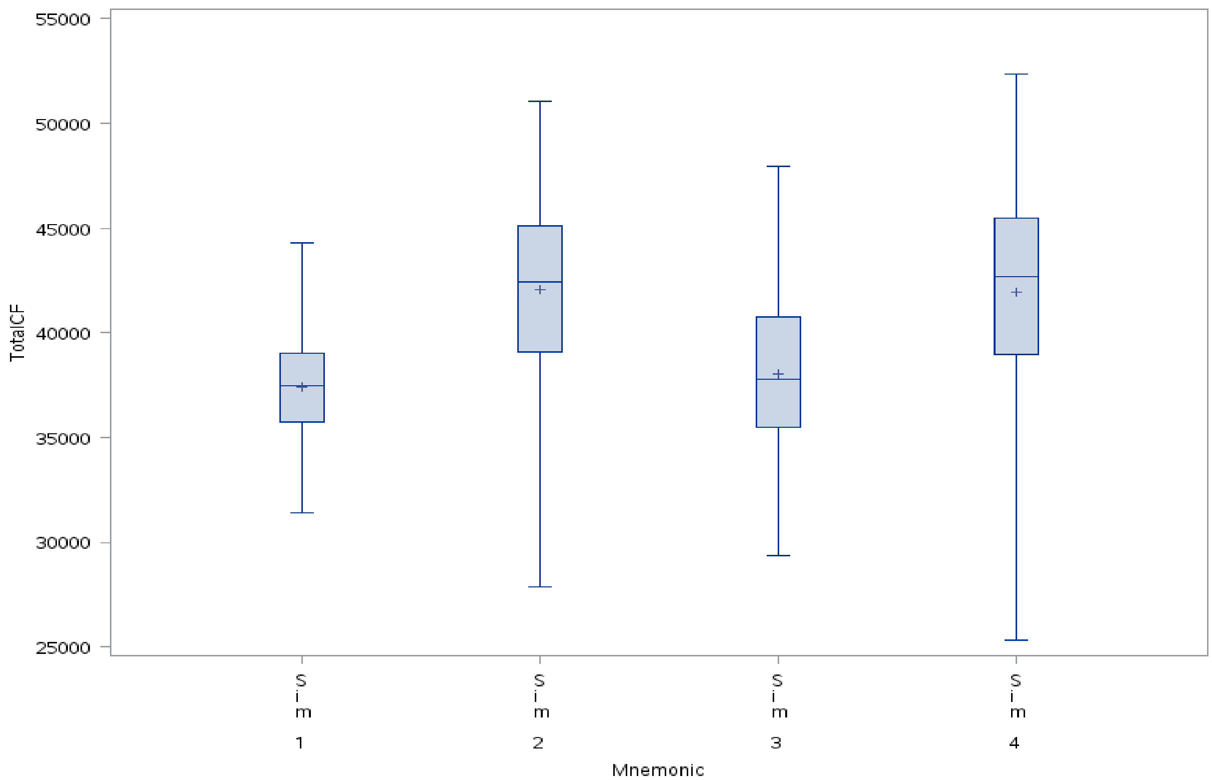
Table 27b: Select Input Values for the Computational Experiments

Mne-monic	***Descriptor***	***CV of Demand***	***CV of Product Lead Time***	***CV of Raw Mat Lead Time***	***Corr Co-efficient***	***Disruption Probability***	***Severity / Time to Recover***
Sim 1	$Vol_{Low}Corr_{Low}Disrupt_{None}$	0.3	0.3	0.3	0.3	0	0
Sim 2	$Vol_{High}Corr_{Low}Disrupt_{None}$	0.7	0.7	0.7	0.3	0	0
Sim 3	$Vol_{Low}Corr_{High}Disrupt_{None}$	0.3	0.3	0.3	0.7	0	0
Sim 4	$Vol_{High}Corr_{High}Disrupt_{None}$	0.7	0.7	0.7	0.7	0	0
Sim 5	$Vol_{Low}Corr_{Low}Disrupt_{Low}$	0.3	0.3	0.3	0.3	1%	1 day

Sim 6	$Vol_{Low}Corr_{Low}Disrupt_{High}$	0.3	0.3	0.3	0.3	5%	5 days
Sim 7	$Vol_{High}Corr_{High}Disrupt_{Low}$	0.7	0.7	0.7	0.7	1%	1 day
Sim 8	$Vol_{High}Corr_{High}Disrupt_{High}$	0.7	0.7	0.7	0.7	5%	5 days

Computational Experiments Results: Deviations

Chart 13: Cash Flow Net Profit Contribution: Simulations 1-4 (No disruptions)



In reading the boxplot, note that the bottom of the box reflects the lower quartile (Q1) value while the top of the box reflects the upper quartile (Q3) value. The median is marked by the horizontal line in the box. The whiskers, the two lines outside the box, extend to the highest and lowest observed values.

Table 28a: Cash Flow Net Profit Contribution by Scenario – No disruptions

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 1	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$	37,403	2,495	31,395	44,283
Sim 2	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$	42,081	3,870	27,840	51,017
Sim 3	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$	38,007	3,577	29,325	47,946
Sim 4	Vol_{High} $Corr_{High}$ $Disrupt_{None}$	41,942	4,960	25,316	52,377

Chart 14: Accrual Net Profit Contribution: Simulations 1-4 (No disruptions)

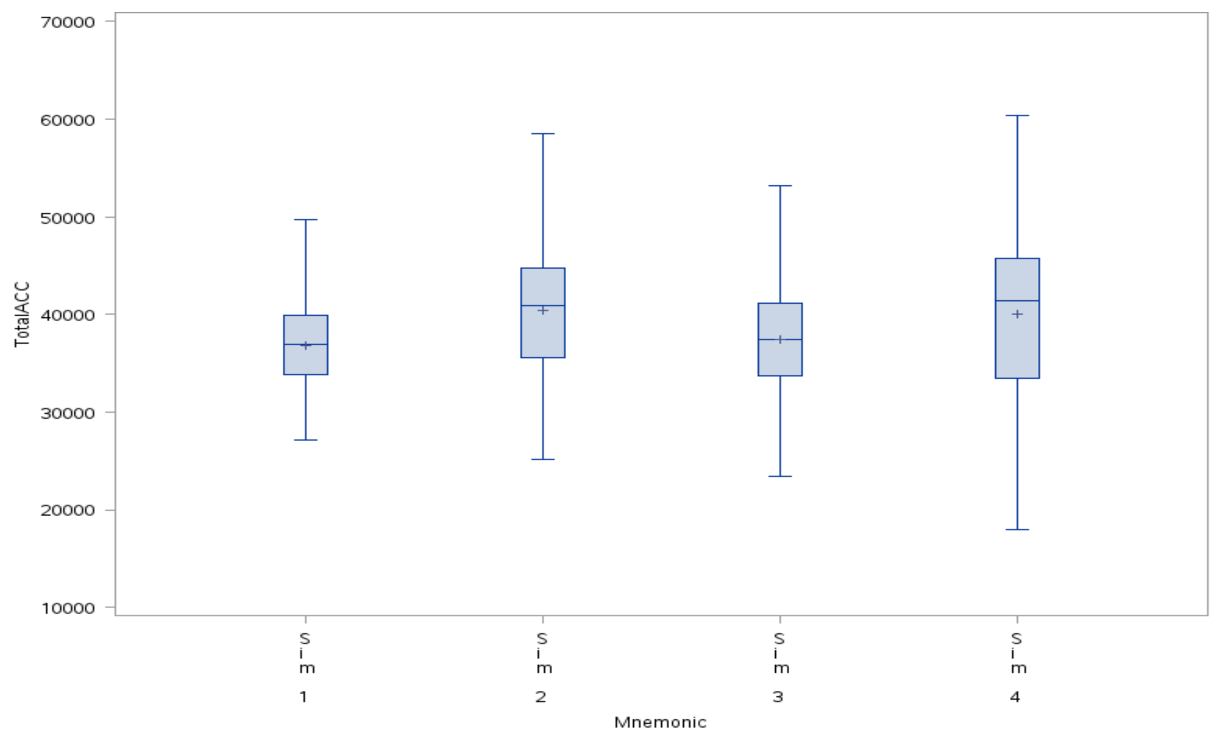


Table 28b: Accrual Net Profit Contribution by Scenario – No disruptions

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 1	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$	36,769	4,175	27,070	49,748
Sim 2	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$	40,449	6,184	25,162	58,436
Sim 3	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$	37,428	5,844	23,391	53,198
Sim 4	Vol_{High} $Corr_{High}$ $Disrupt_{None}$	40,067	8,268	17,994	60,364

Observations:

- Holding the correlation coefficient constant, both the mean net profit contribution and the standard deviation of the net profit contribution increase with the coefficient of variation. This is likely attributable to the positive skew introduced in the demand distribution by the adjusted normal distribution.
- Holding the coefficient of variation constant, the correlation coefficient has modest impact on net profit contribution under both Cash Flow and Accrual Accounting.

Computational Experiments Results: Disruptions

Chart 15: Cash Flow Net Profit Contribution: Simulations 5-8

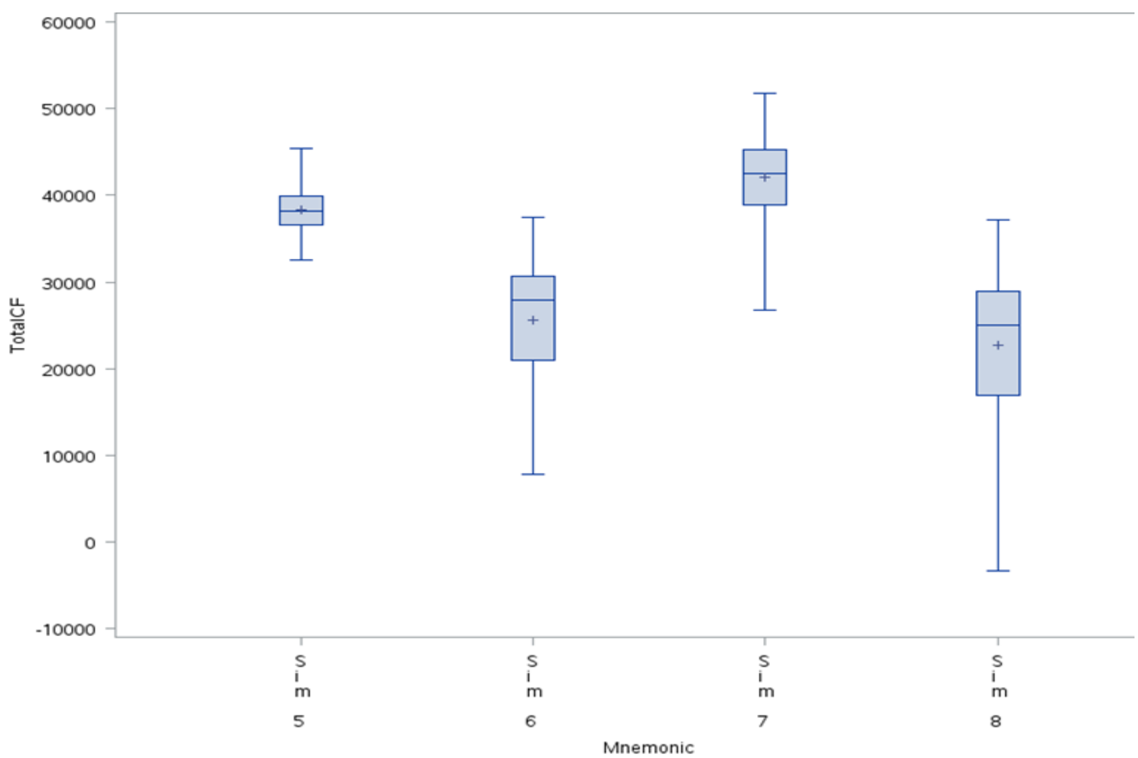


Table 29a: Cash Flow Net Profit Contribution by Scenario – with disruptions

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 5	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$	38,353	2,445	32,603	45,376
Sim 6	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$	25,586	7,397	7,842	37,432
Sim 7	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$	42,027	4,659	26,748	51,852
Sim 8	Vol_{High} $Corr_{High}$ $Disrupt_{High}$	22,658	8,565	-3,286	37,241

Chart 16: Accrual Net Profit Contribution: Simulations 5-8

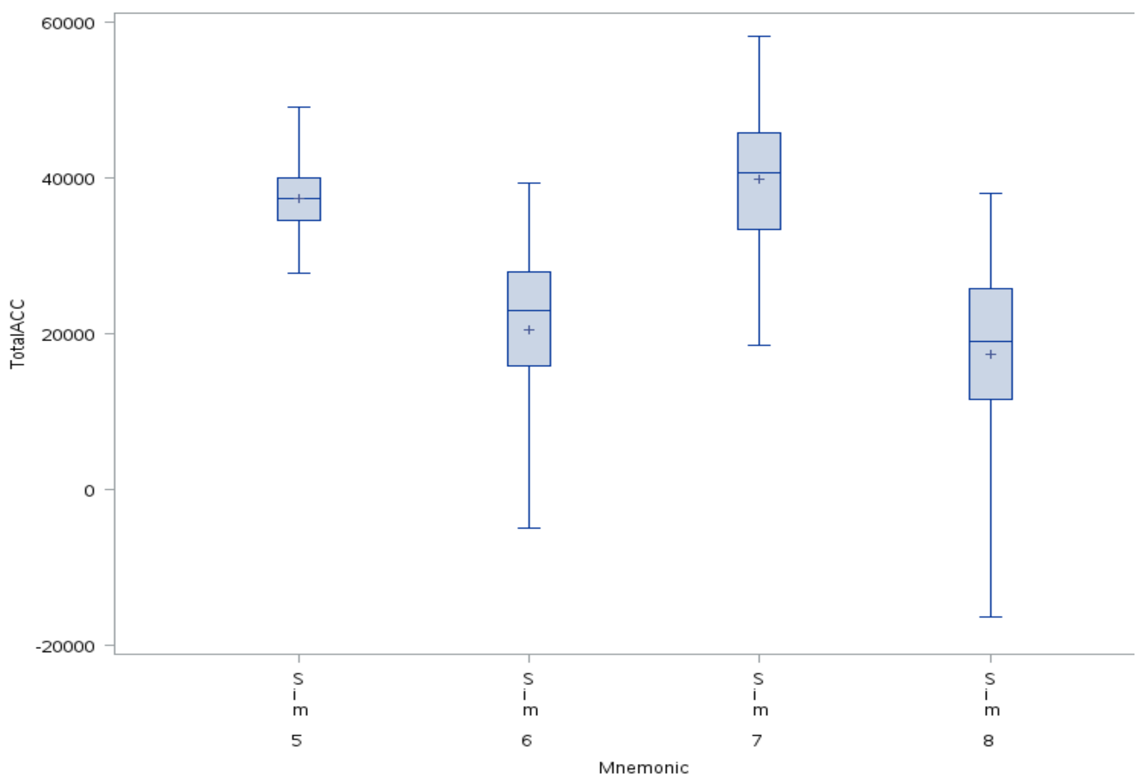


Table 29b: Accrual Net Profit Contribution by Scenario – with disruptions

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 5	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$	37,338	4,113	27,730	49,060
Sim 6	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$	20,486	10,224	-5,010	39,444
Sim 7	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$	39,802	8,067	18,555	58,196
Sim 8	Vol_{High} $Corr_{High}$ $Disrupt_{High}$	17,357	11,309	-16,280	38,062

Observation:

- The scenario with the highest disruption had significantly lower net profit contribution and higher standard deviation of net profit contribution. Disruption effects dominate the effects due to the coefficient of variation and the correlation coefficient.

Computational Experiments Findings

Given the cost structures in the supply chain setting laid out in this dissertation, the following simulation findings were obtained:

- Absent disruptions, the mean value of supply chain performance (mean net contribution to profit) and the variability of net contribution to profit increase with both coefficient of variation and with the correlation of coefficient, consistent with the expectation of "speculative" risks.
- Disruptions decrease the mean net contribution to profit and increase the variability of net contribution to profit, consistent with the expectation of "pure" risks.

Chapter 7: Supply Chain Risk Mitigation

The remaining three research questions are addressed in this chapter:

- Q2: Are the best risk mitigation strategies contingent on the nature of the particular risks (frequency, severity, correlation)? Or, alternatively, are certain risk mitigation strategies globally optimal (dominate all others)?
- Q3: Is there a portfolio effect among risk mitigation strategies? That is, on a risk-adjusted basis, will a combination of mitigation strategies outperform each individual mitigation strategy?
- Q4: Can a blend of risk mitigation strategies be constructed that constitute a Pareto efficient frontier with respect to the performance measure (net profit contribution) versus the risk measure (standard deviation of net profit contribution) thus providing a basis for trading off risk versus performance?

The introduction of risk due to variability in demand, lead times, and disruptions leads to significant variability in performance. Specifically, net profit contribution, service level, leanness, and capacity utilization vary considerably in the various iterations in each simulation. To determine the impact of various risk mitigation strategies on the performance metrics, four strategies were investigated: (i) inventory placement, (ii) expediting, (iii) production flexibility, and (iv) a combination of inventory placement, expediting, and production flexibility.

Inventory Placement

- Finished goods: Two locations for holding finished goods inventory were studied: (i) the manufacturing plants, and (ii) the warehouses.
- Raw materials: raw materials inventory may be stored in the manufacturing plants over and above the amount determined to be optimal by the optimization model.

Flexibility

- *Expediting*: One way of implementing supply chain flexibility in the model is allowing for deliveries to reach either the manufacturing plant (raw materials) or the warehouses (finished goods) much faster than the standard lead times. A higher shipping cost is imposed on expedited raw materials and finished goods.
- *Production flexibility*: Another way of implementing supply chain flexibility in the model is allowing for production plan pre-emption i.e. the goods to be produced on any given day will be determined, in part, by the relative level of inventory of the various finished goods inventories at the warehouses with the goal of changing production plans to prioritize finished goods that are at low inventory levels in the simulations. In the model this risk management strategy is implemented by beginning with the production plan from the optimizing model and revising it depending on the level of stochastic demand with consideration given to available production capacity.

Description of Risk Mitigation Heuristics

The introduction of deviation and disruption risks can significantly reduce the amount of finished goods available at the warehouse for delivery to satisfy demand. To study the impact of risk mitigation strategies, inventory placement, expediting, and production flexibility are introduced as follows:

Inventory Placement:

The simulation model begins with the MILP solution, which includes a given level of safety stock inventory for raw materials at the manufacturing plant, finished goods at the manufacturing plant, and finished goods at the warehouse (these were all initialized at 5 days' worth of inventory). To study the impact of inventory placement, each of the safety stock levels was raised by 3 days' worth of inventory to investigate how well the increased inventory would cover the stochastic lead times and disruption events. The cost of the additional inventory was also captured in the simulation.

Expediting:

Expediting was modelled as the shipment of finished goods from the manufacturing plant to the warehouse for delivery with a 1-day lead-time. An expediting trigger was defined and was an experimental factor. For example, an expediting trigger of 3 meant that expediting was allowed when the On backorder orders at the warehouse from unmet demand reached 3 times the average daily demand. When triggered, stochastic lead times as well as any potential disruption lead times that would otherwise be assigned to that shipment were overridden and expedited such that the shipment arrived at the warehouse for delivery to meet customer demand 1 day after it was shipped from the manufacturing plant. Shipping costs on expedited shipments were modelled as twice those of regular shipments.

Production Flexibility:

Production flexibility allowed the transformation of raw materials to finished goods to significantly deviate from the MILP Production plan. Production flexibility was triggered when there was unmet demand at the warehouse that was leading to orders being placed on backorder. Flexibility was implemented by allowing the production process to increase beyond the MILP plan subject to not exceeding overall plant capacity. Additionally, if there was one product that was primarily low and on backorder while other products had inventory above their safety stock then production capacity was allocated to the low product in order to increase its production and increase its inventory levels.

Risk Management Experimental Plan

The four risk mitigation strategies were implemented to determine their impact on supply chain performance in the face of risk and were applied in each of the eight risk scenarios (scenarios are described in Tables 27a and 27b). The objective was to determine (i) the impact of each risk mitigation strategy on the various stochastic scenarios, and (ii) to compare the relative performance of the risk mitigation strategies. Eight case studies, as described in Table 30, were designed as the basis for investigating the risk mitigation strategies.

Table 30: Description of Case Studies

Case #	Simulation #	Description
I	Sim 1	Low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them. No disruptions.
II	Sim 2	High volatility of demand, raw material lead times and finished goods lead times, with low correlation among them. No disruptions.
III	Sim 3	Low volatility of demand, raw material lead times and finished goods lead times, with high correlation among them. No disruptions.
IV	Sim 4	High volatility of demand, raw material lead times and finished goods lead times, with high correlation among them. No disruptions.
V	Sim 5	Low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them. Low disruptions.
VI	Sim 6	Low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them. High disruptions.
VII	Sim 7	High volatility of demand, raw material lead times and finished goods lead times, with high correlation among them. Low disruptions.
VIII	Sim 8	High volatility of demand, raw material lead times and finished goods lead times, with high correlation among them. High disruptions.

NOTE: Simulation # in Table 30 reflects the simulation identifier in Tables 27a and 27b

The risk mitigation strategies were applied as treatments to the various cases as summarized below.

Treatment A

- Inventory placement: raw materials and finished goods at production plants, and finished goods at warehouses

Treatment B

- Expediting

Treatment C

- Production re-planning

Treatment D

- Inventory placement: raw materials and finished goods at production plants, and finished goods at warehouses
- Expediting
- Production re-planning

Risk Mitigation Results

Simulations 1, 2, 3, 4, 5, 6, 7, and 8 were the foundations of the stochastic experiments. These eight scenarios reflected risk acceptance because they do not involve the implementation of any risk mitigation strategies. The results of each base simulation experiment were obtained and formed the basis for comparison to the results of each of the four risk mitigation strategies. The risk mitigation strategies were implemented under the same conditions as the base simulation experiments. The objective was to determine the impact of risk mitigation on the stochastic scenarios. The mean net profit contribution and the standard deviation of the net profit contribution for each base scenario were compared to the performance metrics of the appropriate risk mitigation strategies to determine the impact of the various risk mitigation strategies on the performance metrics.

Statistical Analysis

Statistical analysis was employed to study the results for each of the eight case studies (each of which contains five scenarios – the base scenario plus the four risk mitigation scenarios). Specifically, the objective was to test whether the mean Net Profit Contributions of the risk mitigation scenarios were statistically different from the mean Net Profit Contributions of the base case scenarios. This would provide evidence for or against the hypothesis that the various risk mitigation scenarios had an impact on the supply chain in the face of deviation and disruption risks. Prior to selecting an appropriate statistical analysis technique to test whether the mean performance metric was different across treatments, a number of observations of the data were made. First, the Net Profit Contribution was deemed the continuous, response variable while the mnemonic that identified each scenario was the classification, independent variable. Second, variances were recognized to be heterogeneous across scenarios. The differences in variances were a result of (i) the input assumption (coefficient of variation was different across scenarios), (ii) random incidence and severity of disruption risk, and (iii) the consequence of the risk mitigation strategies. Third, the data was balanced, with 200 observations for each scenario. Given the foregoing data characteristics, especially its heterogeneity, three sets of statistical analyses were performed.

First, the parametric procedure Analysis of Variance (ANOVA) was used to test whether the risk mitigation results were statistically different. Despite the heterogeneity of the complete set of data, ANOVA was appropriate given that the data was studied in subsets whose differences in variance was much lower than that of the entire data set. For example, Case I (simulations 1, 9, 10, 11, and 12) consisted of data obtained from simulations exposed to low coefficient of variation, low correlation, and no disruptions while case VIII (simulations 8, 37, 38, 39, and 40) consisted of data obtained from simulations exposed to high coefficient of variation, high correlation, and high disruption. ANOVA allowed us to determine whether any of the means of the scenarios in a given case were different (there were five scenarios in each case – the base scenario plus the four risk mitigation scenarios). Additionally, the Waller-Duncan post hoc means comparison test was conducted. This range test can identify which set of means among the various scenarios are significantly different from which other set and which sets of scenarios have means which are not significantly different. This provided additional information beyond the F-test in the ANOVA. The ANOVA F-test can lead us to conclude that the means of the various scenarios in the ANOVA are significantly different if even one pair is different. The F-test does not identifying which pair or set is different. The Waller-Duncan test groups the various scenarios so that we can tell which scenarios are significantly different and which ones are not significantly different from each other. The ANOVA results are reported in Tables 31a through 32h.

Second, to confirm that the results of the ANOVA test were not biased by the heterogeneity of the data, a non-parametric procedure for analyzing the risk management results was also employed. The procedure selected was the Kruskal-

Wallis one-way analysis of variance. This procedure is a generalization of the Wilcoxon rank-sum test where the response variables from test groups are aggregated and ranked without regard to group membership. The ranks are then summed by group. The test is computed by comparing the ranked sums. In the current analysis, five groups (scenarios) of results are compared at a time. The null hypothesis of the Kruskal-Wallis test is that the five scenarios are drawn at random from identical populations and so the summed ranks are expected to be similar. Failing to reject the null hypothesis would suggest that there is no significant difference in the data distribution among the five samples. In that case, the conclusion may be drawn that the various risk mitigation strategies do not have a differential impact on the stochastic scenarios. Rejecting the null hypothesis, by contrast, would call for the conclusion that the risk mitigation strategies lead to different Net Profit Contribution performance. The Kruskal-Wallis one-way analysis of variance results are reported in Tables 33a through 34h.

Third, in order to compare the results of the individual risk mitigation strategies to the base case (risk acceptance), pairwise T-test analyses were run to study the means of the various simulation results with allowance for unequal variances. The goal was to identify which individual risk mitigation strategies were statistically significantly different from risk acceptance. The “Sattertwaite” approximation of the standard errors does not assume that the variances of the two samples are equal and is thus the appropriate reading in cases of heterogeneity. The T-test results are reported in Table 35.

Cases I-IV: Cash Flow Accounting

Cases I-IV reflect "speculative" risk scenarios where variation is introduced in demand and lead time, but with no disruptions. The objective was to test the impact of risk mitigation in the face of different levels of deviations (demand volatility, lead time volatility, and different levels of correlation coefficients). Case I reflects low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and no disruptions. Case II reflects high volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and no disruptions. Case III reflects low volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and no disruptions, while Case IV reflects high volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and no disruptions. The results for each case with the base simulation scenario and the four risk management treatments were as follows:

Table 31a: Cash Flow Net Profit Contributions for Case I

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 1	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$	37,403	2,495	31,395	44,283
Sim 9	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	33,118	2,904	26,177	40,336
Sim 10	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	38,910	2,596	32,660	46,067
Sim 11	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	31,763	2,325	25,714	38,555
Sim 12	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	25,929	2,307	20,280	32,410

Case I					
ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	20,992,328,946	5,248,082,236	817	<.0001
Error	995	6,393,465,373	6,425,593		
Corrected Total	999	27,385,794,319			
R-Square	Coeff Var	Root MSE	TotalCF Mean		
0.77	7.58	2,535	33,425		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
Mnemonic	4	20,992,328,946	5,248,082,236	817	<.0001

Table 31b: Cash Flow Net Profit Contributions for Case II

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 2	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$	42,081	3,870	27,840	51,017
Sim 13	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	39,478	5,635	22,964	53,273
Sim 14	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	44,080	4,054	29,162	53,441
Sim 15	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	36,077	4,569	17,545	48,476
Sim 16	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	30,620	4,670	13,733	42,745

Case II					
ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	22,577,007,045	5,644,251,761	267	<.0001
Error	995	21,064,311,415	21,170,162		
Corrected Total	999	43,641,318,460			
R-Square	Coeff Var	Root MSE	TotalCF Mean		
0.52	11.96	4,601	38,467		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
Mnemonic	4	22,577,007,045	5,644,251,761	267	<.0001

Table 31c: Cash Flow Net Profit Contributions for Case III

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 3	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$	38,007	3,577	29,325	47,946
Sim 17	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	33,559	4,206	23,689	46,345
Sim 18	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	40,361	3,799	31,141	50,915
Sim 19	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	32,290	3,254	24,718	40,103
Sim 20	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	26,453	3,347	18,882	34,796

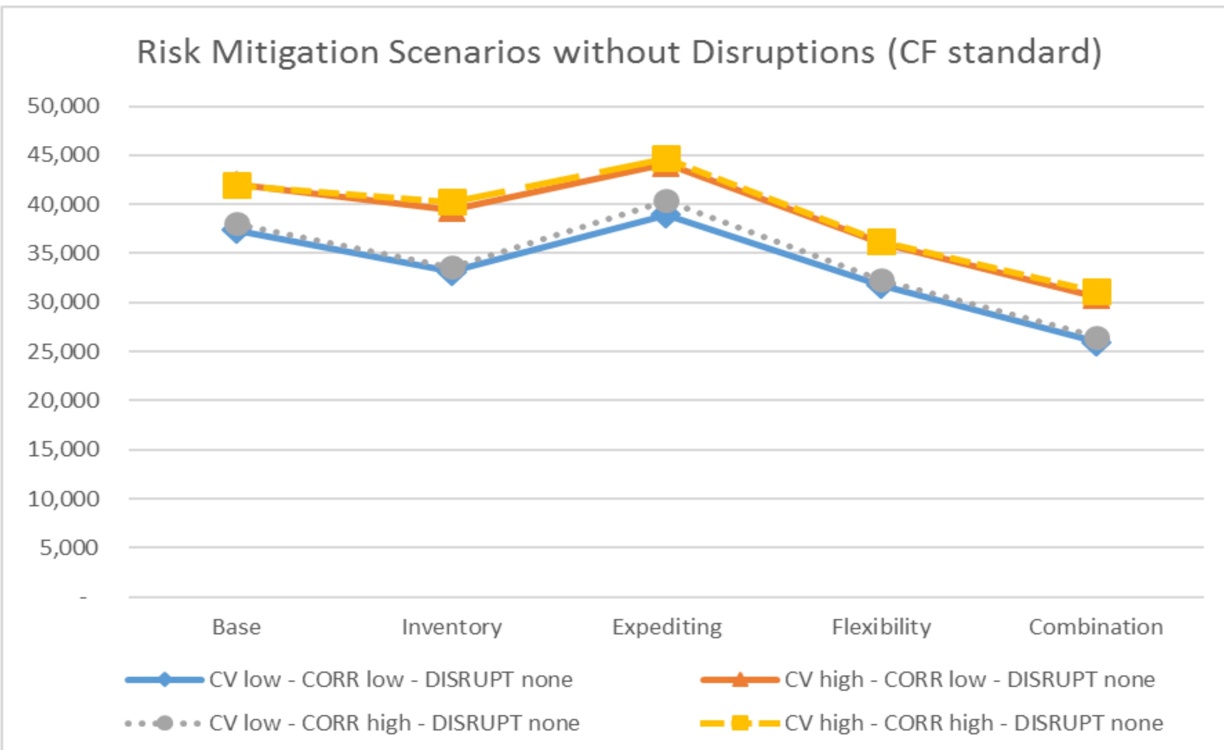
Case III ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	23,299,824,863	5,824,956,216	437	<.0001
Error	995	13,276,597,693	13,343,314		
Corrected Total	999	36,576,422,556			
R-Square	**Coeff Var**	**Root MSE**	**TotalCF Mean**		
0.64	10.70	3,653	34,134		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	23,299,824,863	5,824,956,216	437	<.0001

Table 31d: Cash Flow Net Profit Contributions for Case IV

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 4	Vol_{High} $Corr_{High}$ $Disrupt_{None}$	41,942	4,960	25,316	52,377
Sim 21	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	40,231	7,842	20,063	57,712
Sim 22	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	44,712	5,287	26,988	55,836
Sim 23	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	36,219	6,146	21,133	49,994
Sim 24	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	31,091	6,460	15,641	47,747

Case IV					
ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	22,588,524,673	5,647,131,168	146	<.0001
Error	995	38,517,900,392	38,711,458		
Corrected Total	999	61,106,425,065			
R-Square	**Coeff Var**	**Root MSE**	**TotalCF Mean**		
0.37	16.02	6,222	38,839		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	22,588,524,673	5,647,131,168	146	<.0001

Chart 17: Comparison of Risk Mitigation Scenarios



Observations:

- In each case, the distribution of the Net Profit Contribution of the five scenarios, in aggregate, are significantly different.

- In the presence of deviations (and absent disruptions), expediting as a risk management strategy dominates other alternatives.

Cases V-VIII: Cash Flow Accounting

Cases V-VIII reflect a combination of "speculative" and "pure" risk scenarios where variation is introduced in demand and lead time as well as disruptions. The objective is to test the impact of risk mitigation in the face of different levels of deviations (demand volatility, lead time volatility, and different levels of correlation coefficients) as well as different levels of disruptions. Case V reflects low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and low disruptions. Case VI reflects low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and high disruptions. Case VII reflects high volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and low disruptions, while Case VIII reflects high volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and high disruptions. The results for each case with the base simulation scenario and the four risk management treatments were as follows:

Table 31e: Cash Flow Net Profit Contributions for Case V

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 5	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$	38,353	2,445	32,603	45,376
Sim 25	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	34,242	2,987	27,178	41,511
Sim 26	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	35,220	2,292	29,844	41,193
Sim 27	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	32,832	2,418	26,050	40,059
Sim 28	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	27,445	2,159	22,594	33,487

Case V					
ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	12,820,102,904	3,205,025,726	523	<.0001
Error	995	6,101,156,601	6,131,816		
Corrected Total	999	18,921,259,506			
R-Square	**Coeff Var**	**Root MSE**	**TotalCF Mean**		
0.68	7.37	2,476	33,618		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	12,820,102,904	3,205,025,726	523	<.0001

Table 31f: Cash Flow Net Profit Contributions for Case VI

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 6	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$	25,586	7,397	7,842	37,432
Sim 29	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	38,751	5,967	23,631	50,073
Sim 30	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	29,132	6,649	9,515	38,794
Sim 31	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	30,392	6,886	12,480	42,464
Sim 32	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	38,432	4,609	26,745	47,452

Case VI					
ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	27,570,867,884	6,892,716,971	170	<.0001
Error	995	40,434,897,741	40,638,088		
Corrected Total	999	68,005,765,626			
R-Square	**Coeff Var**	**Root MSE**	**TotalCF Mean**		
0.41	19.64	6,375	32,459		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	27,570,867,884	6,892,716,971	170	<.0001

Table 31g: Cash Flow Net Profit Contributions for Case VII

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 7	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$	42,027	4,659	26,748	51,852
Sim 33	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	41,147	7,703	20,910	58,156
Sim 34	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	38,939	6,067	21,253	49,279
Sim 35	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	37,061	6,056	22,171	49,365
Sim 36	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	29,262	5,794	11,806	46,466

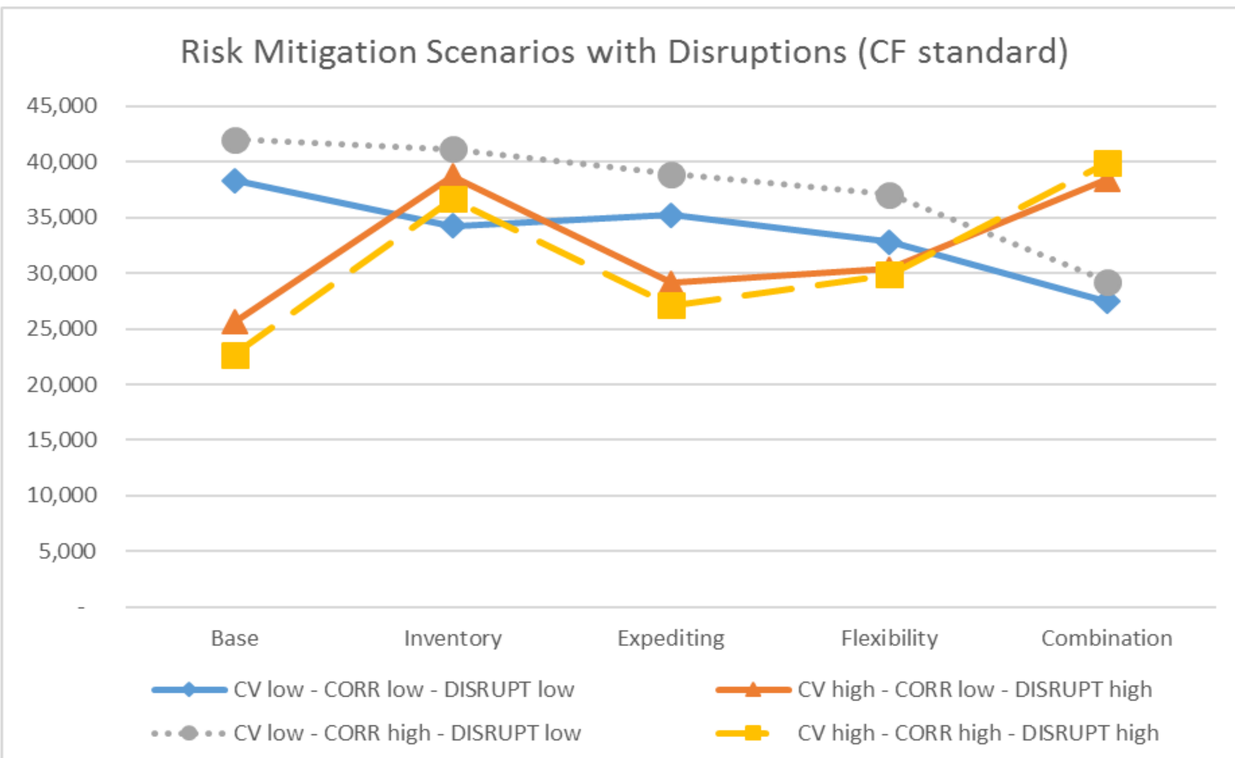
Case VII **ANOVA of Cash Flow Net Contribution** The ANOVA Procedure Dependent Variable: TotalCF					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	20,750,851,390	5,187,712,848	138	<.0001
Error	995	37,429,378,669	37,617,466		
Corrected Total	999	58,180,230,059			
R-Square	**Coeff Var**	**Root MSE**	**TotalCF Mean**		
0.36	16.27	6,133	37,687		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	20,750,851,390	5,187,712,848	138	<.0001

Table 31h: Cash Flow Net Profit Contributions for Case VIII

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 8	Vol_{High} $Corr_{High}$ $Disrupt_{High}$	22,658	8,565	-3,286	37,241
Sim 37	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	36,643	7,528	12,826	51,024
Sim 38	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	27,133	7,930	-3,278	39,010
Sim 39	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	29,848	6,881	14,129	43,567
Sim 40	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	39,936	5,984	20,546	50,228

Case VIII					
ANOVA of Cash Flow Net Contribution The ANOVA Procedure Dependent Variable: TotalCF					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	39,454,545,442	9,863,636,360	179	<.0001
Error	995	54,937,952,757	55,214,023		
Corrected Total	999	94,392,498,198			
R-Square	**Coeff Var**	**Root MSE**	**TotalCF Mean**		
0.42	23.78	7,431	31,243		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	39,454,545,442	9,863,636,360	179	<.0001

Chart 18: Comparison of Risk Mitigation Scenarios



Observations:

- In each case, the distribution of the Net Profit Contribution of the five scenarios, in aggregate, are significantly different.

- Under high disruption, every risk management strategy dominates risk acceptance.
- Under low disruption, risk acceptance dominates risk mitigation.

Cases I-IV: Accrual Accounting

Cases I-IV reflect "speculative" scenarios where variation is introduced in demand and lead time, but with no disruptions. The objective is to test the impact of risk mitigation in the face of different levels of deviations (demand volatility, lead time volatility, and different levels of correlation coefficients). Case I reflects low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and no disruptions. Case II reflects high volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and no disruptions. Case III reflects low volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and no disruptions, while Case IV reflects high volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and no disruptions. The results for each case with the base simulation scenario and the four risk management treatments were as follows:

Table 32a: Accrual Net Profit Contributions for Case I

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 1	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$	36,769	4,175	27,070	49,748
Sim 9	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	33,700	3,986	25,024	48,104
Sim 10	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	39,300	2,622	32,987	46,528
Sim 11	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	30,677	2,347	25,760	39,109
Sim 12	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	32,090	1,786	27,817	37,602

Case I					
ANOVA of Accrual Net Contribution The ANOVA Procedure Dependent Variable: TotalACC					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	9,849,397,407	2,462,349,352	252	<.0001
Error	995	9,728,526,652	9,777,414		
Corrected Total	999	19,577,924,059			
R-Square	Coeff Var	Root MSE	TotalACC Mean		
0.50	9.06	3,127	34,507		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
Mnemonic	4	9,849,397,407	2,462,349,352	252	<.0001

Table 32b: Accrual Net Profit Contributions for Case II

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 2	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$	40,449	6,184	25,162	58,436
Sim 13	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	38,674	6,773	23,877	60,026
Sim 14	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	44,653	4,107	29,542	54,136
Sim 15	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	34,217	4,368	24,735	51,319
Sim 16	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	34,607	3,184	26,342	45,728

Case II					
ANOVA of Accrual Net Contribution The ANOVA Procedure Dependent Variable: TotalACC					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	15,037,925,065	3,759,481,266	144	<.0001
Error	995	25,910,174,580	26,040,376		
Corrected Total	999	40,948,099,645			
R-Square	Coeff Var	Root MSE	TotalACC Mean		
0.37	13.25	5,103	38,520		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
Mnemonic	4	15,037,925,065	3,759,481,266	144	<.0001

Table 32c: Accrual Net Profit Contributions for Case III

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 3	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$	37,428	5,844	23,391	53,198
Sim 17	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	34,164	5,387	21,108	50,994
Sim 18	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	41,571	3,913	32,075	52,443
Sim 19	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	31,064	3,357	24,106	43,368
Sim 20	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	32,212	2,345	25,941	39,248

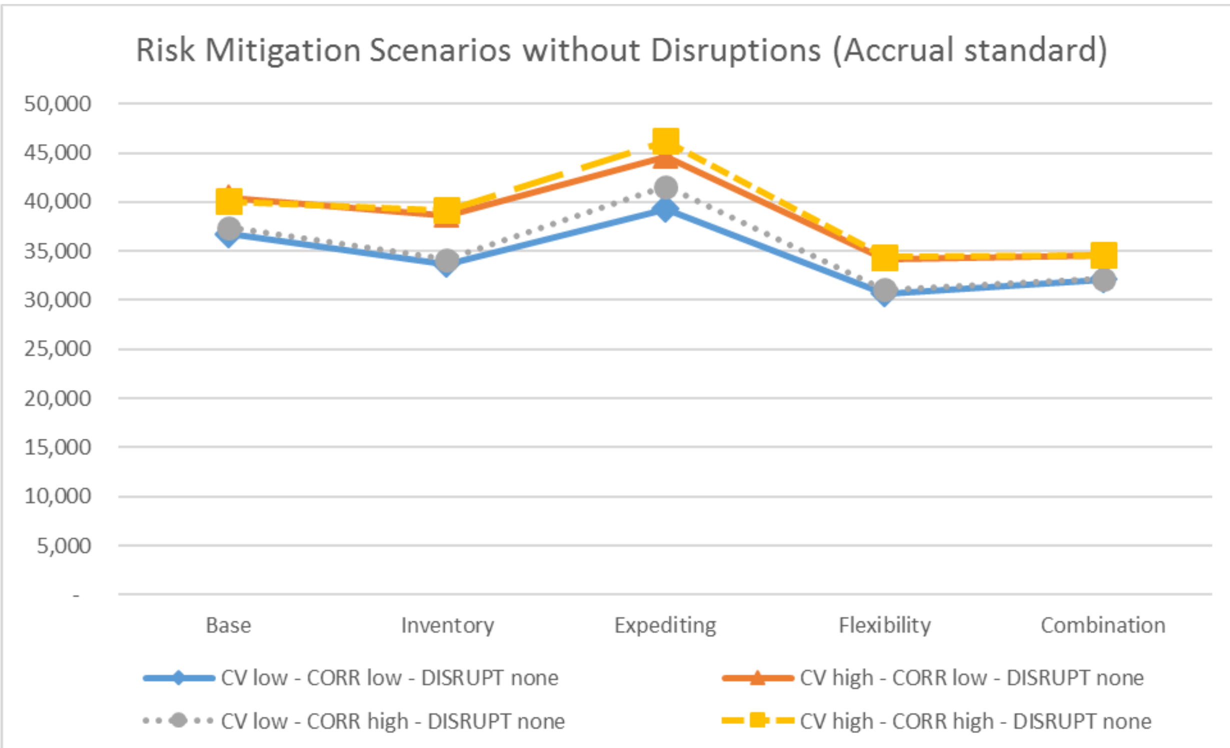
Case III					
ANOVA of Accrual Net Contribution **The ANOVA Procedure** **Dependent Variable: TotalACC**					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	14,526,403,666	3,631,600,917	191	<.0001
Error	995	18,955,099,561	19,050,351		
Corrected Total	999	33,481,503,227			
R-Square	**Coeff Var**	**Root MSE**	**TotalACC Mean**		
0.43	12.37	4,365	35,288		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	14,526,403,666	3,631,600,917	191	<.0001

Table 32d: Accrual Net Profit Contributions for Case IV

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 4	Vol_{High} $Corr_{High}$ $Disrupt_{None}$	40,067	8,268	17,994	60,364
Sim 21	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	39,187	9,542	19,976	69,124
Sim 22	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	46,232	5,467	27,906	57,734
Sim 23	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	34,409	6,163	21,196	58,213
Sim 24	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	34,586	4,641	22,753	53,438

Case IV					
ANOVA of Accrual Net Contribution **The ANOVA Procedure** **Dependent Variable: TotalACC**					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	18,795,600,183	4,698,900,046	94	<.0001
Error	995	49,514,001,330	49,762,815		
Corrected Total	999	68,309,601,513			
R-Square	**Coeff Var**	**Root MSE**	**TotalACC Mean**		
0.28	18.14	7,054	38,896		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	18,795,600,183	4,698,900,046	94	<.0001

Chart 19: Comparison of Risk Mitigation Scenarios



Observations:

- In each case, the distribution of the Net Profit Contribution of the five scenarios, in aggregate, are significantly different.

- In the presence of deviations (and absent disruptions), expediting as a risk management strategy dominates other alternatives.

Cases V-VII: Accrual Accounting

Cases V-VII reflect a combination of "speculative" and "pure" risk scenarios where variation is introduced in demand and lead time as well as disruptions. The objective is to test the impact of risk mitigation in the face of different levels of deviations (demand volatility, lead time volatility, and different levels of correlation coefficients) as well as different levels of disruptions. Case V reflects low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and low disruptions. Case VI reflects low volatility of demand, raw material lead times and finished goods lead times, with low correlation among them and high disruptions. Case VII reflects high volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and low disruptions, while Case VIII reflects high volatility of demand, raw material lead times and finished goods lead times, with high correlation among them and high disruptions. The results for each case with the base simulation scenario and the four risk management treatments were as follows:

Table 32e: Accrual Net Profit Contributions for Case V

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 5	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$	37,338	4,113	27,730	49,060
Sim 25	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	34,053	3,914	25,115	47,989
Sim 26	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	24,498	1,108	21,615	27,277
Sim 27	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	30,957	2,456	25,981	40,026
Sim 28	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	25,489	992	22,641	28,673

Case V					
ANOVA of Accrual Net Contribution The ANOVA Procedure Dependent Variable: TotalACC					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	24,143,823,443	6,035,955,861	746	<.0001
Error	995	8,053,432,133	8,093,902		
Corrected Total	999	32,197,255,576			
R-Square	Coeff Var	Root MSE	TotalACC Mean		
0.75	9.34	2,845	30,467		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
Mnemonic	4	24,143,823,443	6,035,955,861	746	<.0001

Table 32f: Accrual Net Profit Contributions for Case VI

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 6	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$	20,486	10,224	-5,010	39,444
Sim 29	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	31,855	8,935	8,725	49,111
Sim 30	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	25,126	9,213	681	41,639
Sim 31	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	25,126	9,213	681	41,639
Sim 32	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	20,805	5,974	5,713	28,150

Case VI					
ANOVA of Accrual Net Contribution The ANOVA Procedure Dependent Variable: TotalACC					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	37,424,526,441	9,356,131,610	130	<.0001
Error	995	71,687,770,542	72,048,011		
Corrected Total	999	109,112,296,983			
R-Square	Coeff Var	Root MSE	TotalACC Mean		
0.34	38.06	8,488	22,300		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
Mnemonic	4	37,424,526,441	9,356,131,610	130	<.0001

Table 32g: Accrual Net Profit Contributions for Case VII

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 7	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$	39,802	39,802	39,802	39,802
Sim 33	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	39,264	39,264	39,264	39,264
Sim 34	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	25,628	25,628	25,628	25,628
Sim 35	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	34,632	34,632	34,632	34,632
Sim 36	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	27,101	27,101	27,101	27,101

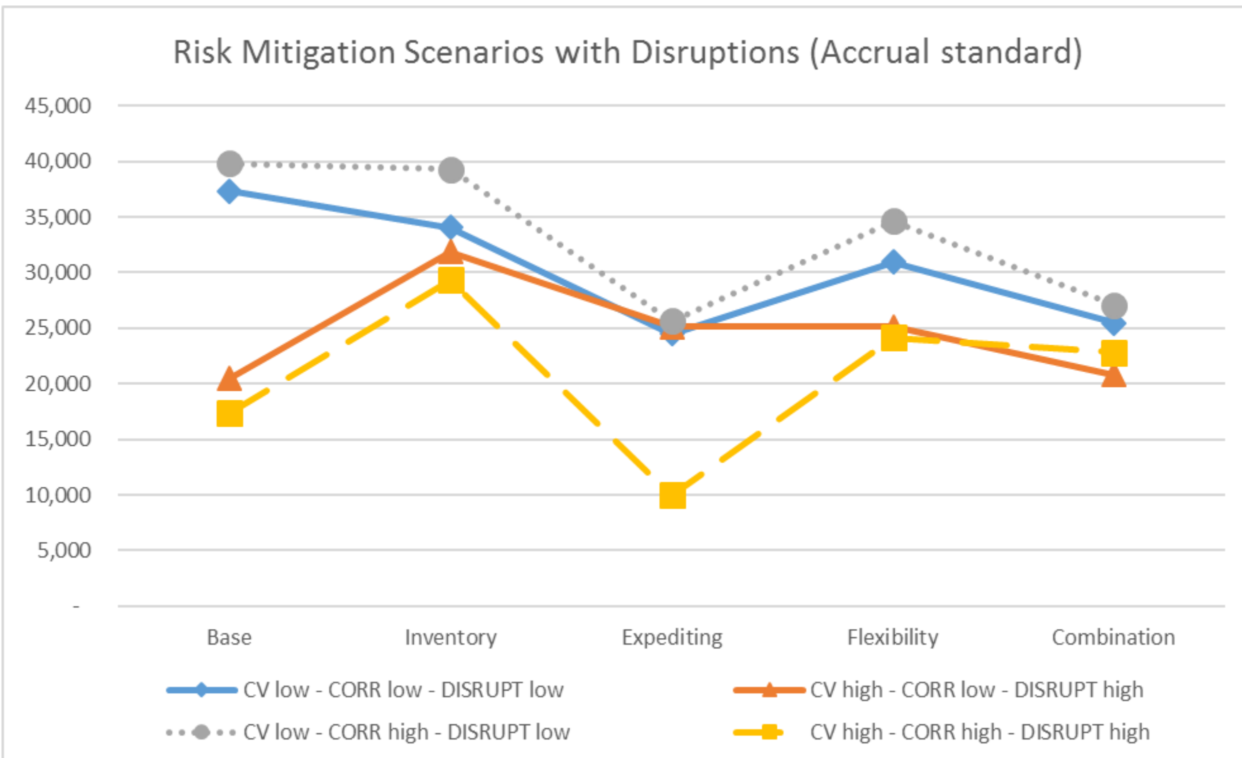
Case VII **ANOVA of Accrual Net Contribution** The ANOVA Procedure Dependent Variable: TotalACC					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	35,380,796,968	8,845,199,242	208	<.0001
Error	995	42,306,912,124	42,519,510		
Corrected Total	999	77,687,709,092			
R-Square	**Coeff Var**	**Root MSE**	**TotalACC Mean**		
0.46	19.59	6,521	33,285		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	35,380,796,968	8,845,199,242	208	<.0001

Table 32h: Accrual Net Profit Contributions for Case VIII

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 8	Vol_{High} $Corr_{High}$ $Disrupt_{High}$	17,357	11,309	-16,280	38,062
Sim 37	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	29,336	10,544	-2,555	52,101
Sim 38	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	10,006	8,986	-26,215	25,230
Sim 39	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	24,135	9,005	373	42,105
Sim 40	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	22,842	6,122	4,060	30,986

Case VIII					
ANOVA of Accrual Net Contribution **The ANOVA Procedure** **Dependent Variable: TotalACC**					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	43,299,974,479	10,824,993,620	123	<.0001
Error	995	87,234,398,949	87,672,763		
Corrected Total	999	130,534,373,428			
R-Square	**Coeff Var**	**Root MSE**	**TotalACC Mean**		
0.33	45.16	9,363	20,735		
Source	**DF**	**Anova SS**	**Mean Square**	**F Value**	**Pr > F**
Mnemonic	4	43,299,974,479	10,824,993,620	123	<.0001

Chart 20: Comparison of Risk Mitigation Scenarios



Observations:

- In each case, the distribution of the Net Profit Contribution of the five scenarios, in aggregate, are significantly different.
- Under low disruption, risk acceptance dominates risk mitigation.

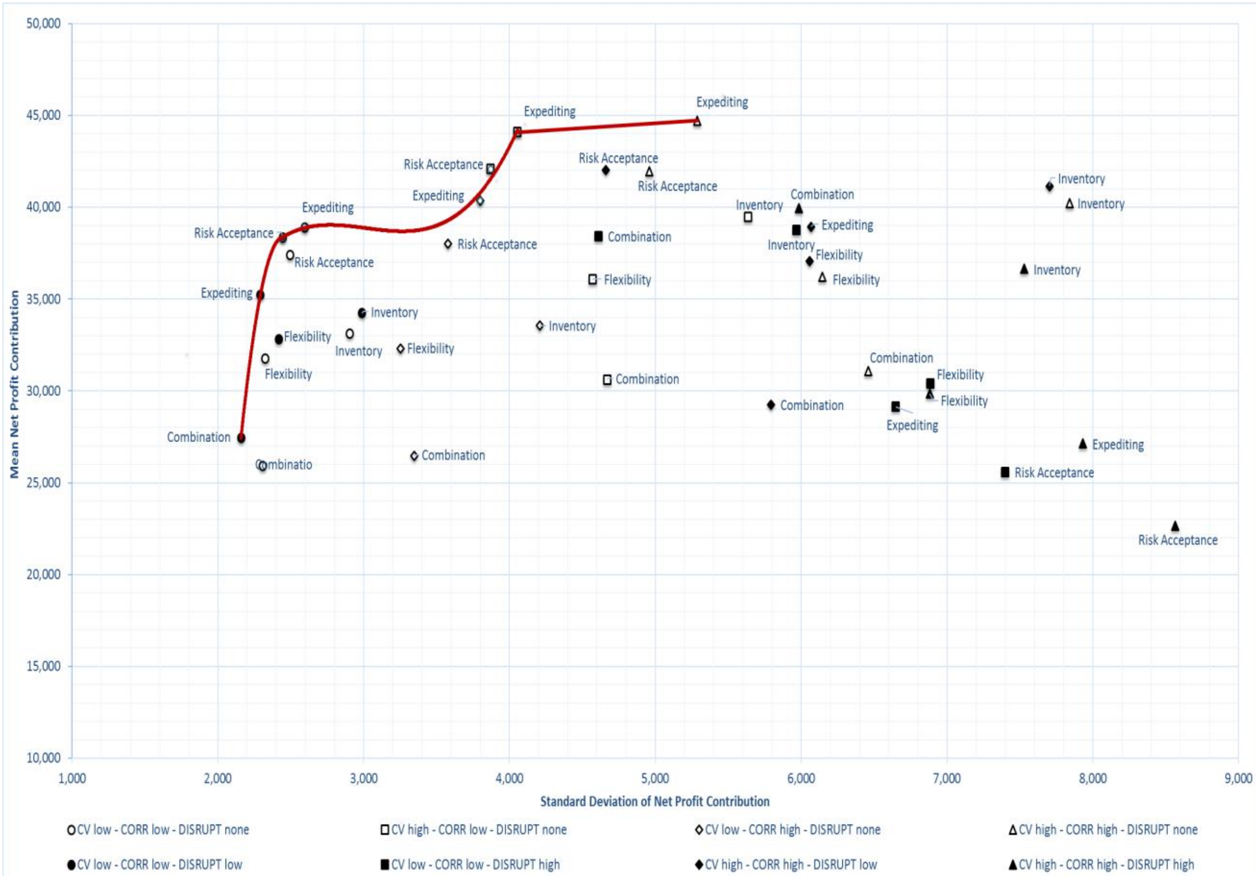
- Under high disruption, risk mitigation dominates risk acceptance except for the expediting strategy under conditions of high correlation and coefficient of variation.

Efficient Frontier Analysis

Assuming a trade-off between risk and return, a Pareto-efficient frontier can be constructed to investigate whether certain risk mitigation strategies provide the best combination of risk and return characteristics. In this analysis, the net profit contribution performance measure (return) is graphed against the standard deviation of net profit contribution (risk). To the extent that a risk-return trade-off exists, the efficient frontier will be upward sloping. The scenarios (whether risk-mitigated or risk-accepted) that form the outer edge of the frontier will possess the best combination of risk and return characteristics.

For each of the forty scenarios - 8 base risk-accepted scenarios and 32 (8x4) risk- mitigation scenarios – the mean Net Profit Contribution and the Variance of the Net Profit Contribution were obtained in order to graph an efficient frontier.

Chart 21: Efficient Frontier – Cash Flow Net Profit Contribution



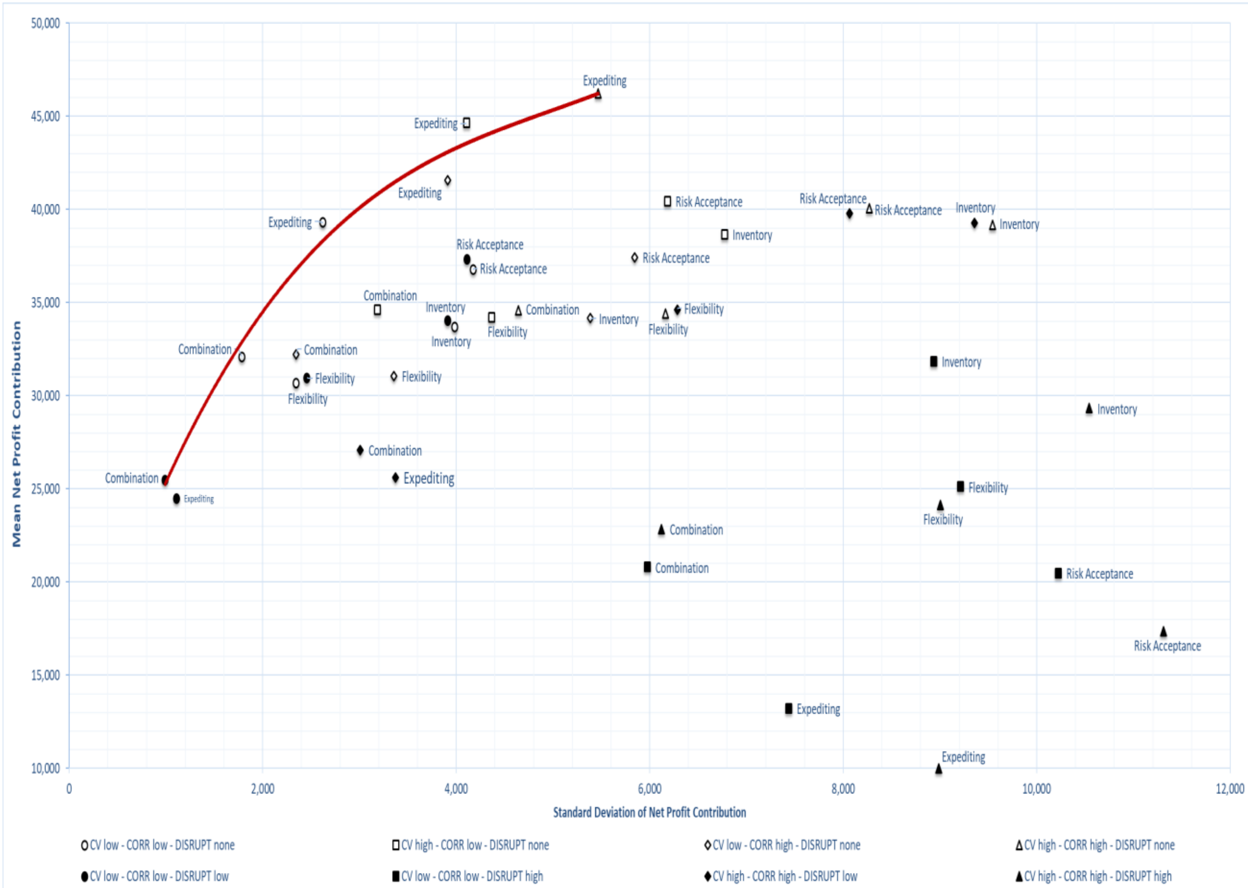
Non-dominated Scenarios: Cash Flow Accounting

Mnemonic	Descriptor
Sim 28	Vol$_{Low}$ Corr$_{Low}$ Disrupt$_{Low}$ - Inv$_{yes}$ Exp$_{yes}$ Flex$_{yes}$
Sim 26	Vol$_{Low}$ Corr$_{Low}$ Disrupt$_{Low}$ - Inv$_{no}$ Exp$_{yes}$ Flex$_{no}$
Sim 5	Vol$_{Low}$ Corr$_{Low}$ Disrupt$_{Low}$
Sim 10	Vol$_{Low}$ Corr$_{Low}$ Disrupt$_{None}$ - Inv$_{no}$ Exp$_{yes}$ Flex$_{no}$
Sim 18	Vol$_{Low}$ Corr$_{High}$ Disrupt$_{None}$ - Inv$_{no}$ Exp$_{yes}$ Flex$_{no}$
Sim 2	Vol$_{High}$ Corr$_{Low}$ Disrupt$_{None}$
Sim 14	Vol$_{High}$ Corr$_{Low}$ Disrupt$_{None}$ - Inv$_{no}$ Exp$_{yes}$ Flex$_{no}$
Sim 22	Vol$_{High}$ Corr$_{High}$ Disrupt$_{None}$ - Inv$_{no}$ Exp$_{yes}$ Flex$_{no}$

Observations:

- The non-dominated scenarios form an upward-sloping efficient frontier.
- Expediting as a risk mitigating strategy appears to be the most efficient as it is the most common strategy on the frontier

Chart 22: Efficient Frontier – Accrual Net Profit Contribution



Non-dominated Scenarios: Accrual Accounting

Mnemonic	Descriptor
Sim 28	$Vol_{Low}\,Corr_{Low}\,Disrupt_{Low}$ - $Inv_{yes}\,Exp_{yes}\,Flex_{yes}$
Sim 12	$Vol_{Low}\,Corr_{Low}\,Disrupt_{None}$ - $Inv_{yes}\,Exp_{yes}\,Flex_{yes}$
Sim 10	$Vol_{Low}\,Corr_{Low}\,Disrupt_{None}$ - $Inv_{no}\,Exp_{yes}\,Flex_{no}$
Sim 18	$Vol_{Low}\,Corr_{High}\,Disrupt_{None}$ - $Inv_{no}\,Exp_{yes}\,Flex_{no}$
Sim 14	$Vol_{High}\,Corr_{Low}\,Disrupt_{None}$ - $Inv_{no}\,Exp_{yes}\,Flex_{no}$
Sim 22	$Vol_{High}\,Corr_{High}\,Disrupt_{None}$ - $Inv_{no}\,Exp_{yes}\,Flex_{no}$

Observations:

- The non-dominated scenarios form an upward-sloping efficient frontier.

- Expediting as a risk mitigating strategy appears to be the most efficient as it is the most common strategy on the frontier. The combination of all risk mitigation strategies is the only other scenario that appears on the frontier.
- All base scenarios (i.e. without risk mitigation) are dominated.

Risk Management Findings

Given the cost structures in the supply chain setting laid out in this dissertation, the following risk management findings were obtained:

- In response to Research Question 2 (Are the best risk mitigation strategies contingent on the nature of the particular risks - frequency, severity, correlation? Or, alternatively, are certain risk mitigation strategies globally optimal?), the results uphold contingency theory, suggesting that the best risk management strategy depends on the type of risk being faced. Specifically, "speculative" risks are best risk accepted while "pure" risks are best risk mitigated.
- In response to Research Question 3 (Is there a portfolio effect among risk mitigation strategies? That is, on a risk-adjusted basis, will a combination of mitigation strategies outperform each individual mitigation strategy?), the results do not support a portfolio effect among risk mitigation strategies. The efficient frontier suggests that expediting as a single risk management strategy outperforms the combination of all risk mitigation strategies on a risk-adjusted basis.
- In response to Research Question 4 (Can a blend of risk mitigation strategies be constructed that constitute a Pareto efficient frontier with respect to the

performance measure versus the risk measure thus providing a basis for trading off risk versus performance?), the results reveal that the risk mitigation outcomes form an efficient frontier.

- Risk mitigation strategies are robust to accounting standard.

Chapter 8: Summary of Research Findings

The objective of this dissertation has been to develop and test an approach that will quantify the level of disruption risk in the supply chain, evaluate the cost and impact of risk mitigation strategies, validate event management protocols pre-implementation, and optimize across a portfolio of risk mitigation strategies. The following questions have been addressed:

- Q1: Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?
- Q2: Are the best risk mitigation strategies contingent on the nature of the particular risks (frequency, severity, correlation)? Or, alternatively, are certain risk mitigation strategies globally optimal (dominate all others)?
- Q3: Is there a portfolio effect among risk mitigation strategies? That is, on a risk-adjusted basis, will a combination of mitigation strategies outperform each individual mitigation strategy?
- Q4: Can a blend of risk mitigation strategies be constructed that constitute a Pareto efficient frontier with respect to the performance measure (net profit contribution) versus the risk measure (standard of net profit contribution) thus providing a basis for trading off risk versus performance?

The specific results of this type of analysis depend on the cost structure of the firm and on the costs of implementing the set of selected risk mitigation strategies. Given the cost structures in the supply chain setting laid out in this dissertation, the results have demonstrated:

- Q1: Yes, accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions.
- Q2: Yes, contingency theory is upheld.
- Q3: No, there is no clear portfolio effect among risk mitigation strategies
- Q4: Yes, risk mitigation results constitute an upward-sloping Pareto-efficient frontier.

Specifically, this research has identified the following set of findings:

<u>Optimization Findings</u>

- The Pull Formulation results in lower expected profitability primarily because revenue is recognized only upon receipt of finished goods at the warehouse and the model stops producing and shipping product that would not reach the warehouse before the end of the planning horizon. It can leave the firm with insufficient inventory to meet demand at the end of the planning horizon unless explicit constraints on ending inventories are added to the model to ensure sufficient safety stocks.
- The Pull Formulation leads to a much leaner supply chain with respect to inventory.
- The choice of accounting standard (cash flow versus accrual) provides a different signal as to the relative merits of the push, pull, and hybrid formulations.

- Analysis of the optimization model results answers Research Question 1 (Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?) in the affirmative, consistent with Xu and Smith (2018). While Xu and Smith implemented a rolling horizon planning model, the current work is a fixed horizon planning model.

Simulation Findings

- Results tend to converge as the number of observations (iterations) increases. Results thus have more reliability when they are arrived at when running large sample sizes. However, there is a trade-off between reliability and the time and computational resources needed.
- The higher the assumed input variability (coefficient of variation) the larger the number of observations (iterations) needed in order to converge. Thus, for a given number of iterations higher coefficient of variation scenarios are less reliable than lower ones.
- Analysis of the simulation model income statements affirms the optimization model answer to Research Question 1 (Do accounting policy and value-added metrics significantly affect production strategy and optimizing model solutions?) as "yes".

Stochastic Experiment Findings

- Absent disruptions, the mean value of supply chain performance (mean net contribution to profit) and the variability of net contribution to profit increase with both coefficient of variation and with the correlation of coefficient, consistent with the expectation of "speculative" risks.

- Disruptions decrease the mean net contribution to profit and increase the variability of net contribution to profit, consistent with the expectation of “pure” risks.

<u>Risk Management Findings</u>

- In response to Research Question 2 (Are the best risk mitigation strategies contingent on the nature of the particular risks - frequency, severity, correlation? Or, alternatively, are certain risk mitigation strategies globally optimal?), the results uphold contingency theory, suggesting that the best risk management strategy depends on the type of risk being faced. Specifically, “speculative” risks are best risk accepted while “pure” risks are best risk managed
- In response to Research Question 3 (Is there a portfolio effect among risk mitigation strategies? That is, on a risk-adjusted basis, will a combination of mitigation strategies outperform each individual mitigation strategy?), the results do not support a portfolio effect among risk mitigation strategies. The efficient frontier suggests that expediting as a single risk management strategy outperforms the combination of all risk mitigation strategies on a risk-adjusted basis.
- In response to Research Question 4 (Can a blend of risk mitigation strategies be constructed that constitute a Pareto efficient frontier with respect to the performance measure versus the risk measure thus providing a basis for trading off risk versus performance?), the results reveal that the risk management outcomes form an efficient frontier.

- Risk mitigation strategies are robust to accounting standard.

The current work and foregoing findings are of importance to supply chain practitioners and academics alike. Recognizing the dependence of the specific findings on the cost structure of the supply chain, practitioners will take note of the benefits of value-added metrics in the optimization modeling as well as the impact of accounting policy on decision making, while academics will be interested to note that certain foundational theoretical frameworks (contingency theory) are supported by numerical analysis of realistic supply chains while others (portfolio theory) are not supported.

Future Work

- The current model tests the impact of risk mitigation strategies via discrete event simulation. Future work will plan on testing the impact of risk mitigation strategies in the optimization model by adding deterministic buffers to delivery lead times and safety stocks, and investigating deterministic sensitivities to the buffers.
- Current work has been limited to investigating four risk mitigation strategies, namely inventory placement, expediting, production flexibility, and their combination. Future work will examine a wider set of strategies. For example, diversification (both geographic and organizational) can be introduced by limiting the shares of business allocated to the suppliers in the current model.
- Risk mitigation strategies were implemented without regard to budget constraints and manager risk tolerances. Future work will study whether the

introduction of explicit budget constraints alters the relative merits of the various risk mitigation strategies.

- The optimizing model could be reformulated to optimize on a rolling horizon (rather than the current fixed horizon). Such a reformulated rolling horizon model could revise plans stochastically and allow for comparison of performance with solutions obtained using the heuristic rules for reallocating productive resources and managing inventory in the simulation component of the current model.
- The optimizing and simulation models could be reformulated to be more generally applicable to a wider set of product types. The current models are formulated to handle non-perishable products. The models could be modified (e.g. by introducing the aging of inventory and penalty obsolescence costs) to handle perishable products.
- Choi, Chiu, and Chan (2016) called for more studies on the "value of risk reduction" (VRR) to help companies estimate the feasibility of their risk mitigation strategies. They argue that there are very few studies in the literature that fit this bill. The pair-wise comparison between the risk and performance of the base simulations and the risk mitigation scenarios in the current work begins to address this issue. Further extensions will be designed to more frontally address this challenge.

Appendix

Table 33a: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case I

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 1	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$	37,403	2,495	31,395	44,283
Sim 9	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	33,118	2,904	26,177	40,336
Sim 10	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	38,910	2,596	32,660	46,067
Sim 11	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	31,763	2,325	25,714	38,555
Sim 12	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	25,929	2,307	20,280	32,410

Kruskal-Wallis Test - Cash Flow Net Contribution For Case I					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	**N**	**Sum of Scores**	**Expected Under H0**	**Std Dev Under H0**	**Mean Score**
Sim 1	200	146,424	100,100	3,653	732
Sim 10	200	162,823	100,100	3,653	814
Sim 11	200	75,865	100,100	3,653	379
Sim 12	200	22,544	100,100	3,653	113
Sim 9	200	92,844	100,100	3,653	464

Kruskal-Wallis Test	
Chi-Square	763.3
DF	4
Pr > Chi-Square	<.0001

Table 33b: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case II

Net Cash Flow Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 2	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$	42,081	3,870	27,840	51,017
Sim 13	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	39,478	5,635	22,964	53,273
Sim 14	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	44,080	4,054	29,162	53,441
Sim 15	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	36,077	4,569	17,545	48,476
Sim 16	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	30,620	4,670	13,733	42,745

Kruskal-Wallis Test - Cash Flow Net Contribution For Case II					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 13	200	106,673	100,100	3,653	533
Sim 14	200	150,918	100,100	3,653	755
Sim 15	200	75,396	100,100	3,653	377
Sim 16	200	34,430	100,100	3,653	172
Sim 2	200	133,083	100,100	3,653	665

Kruskal-Wallis Test	
Chi-Square	517.7
DF	4
Pr > Chi-Square	<.0001

Table 33c: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case III

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 3	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$	38,007	3,577	29,325	47,946
Sim 17	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	33,559	4,206	23,689	46,345
Sim 18	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	40,361	3,799	31,141	50,915
Sim 19	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	32,290	3,254	24,718	40,103
Sim 20	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	26,453	3,347	18,882	34,796

Kruskal-Wallis Test - Cash Flow Net Contribution For Case III					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 17	200	93,268	100,100	3,653	466
Sim 18	200	159,875	100,100	3,653	799
Sim 19	200	79,104	100,100	3,653	396
Sim 20	200	28,633	100,100	3,653	143
Sim 3	200	139,620	100,100	3,653	698

Kruskal-Wallis Test	
Chi-Square	643.2
DF	4
Pr > Chi-Square	<.0001

Table 33d: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case IV

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 4	Vol_{High} $Corr_{High}$ $Disrupt_{None}$	41,942	4,960	25,316	52,377
Sim 21	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	40,231	7,842	20,063	57,712
Sim 22	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	44,712	5,287	26,988	55,836
Sim 23	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	36,219	6,146	21,133	49,994
Sim 24	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	31,091	6,460	15,641	47,747

Kruskal-Wallis Test - Cash Flow Net Contribution For Case IV					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 21	200	107,852	100,100	3,653	539
Sim 22	200	145,710	100,100	3,653	729
Sim 23	200	77,980	100,100	3,653	390
Sim 24	200	44,957	100,100	3,653	225
Sim 4	200	124,001	100,100	3,653	620

Kruskal-Wallis Test	
Chi-Square	374.1
DF	4
Pr > Chi-Square	<.0001

Table 33e: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case V

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 5	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$	38,353	2,445	32,603	45,376
Sim 25	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	34,242	2,987	27,178	41,511
Sim 26	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	35,220	2,292	29,844	41,193
Sim 27	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	32,832	2,418	26,050	40,059
Sim 28	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	27,445	2,159	22,594	33,487

Kruskal-Wallis Test - Cash Flow Net Contribution For Case V					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 25	200	106,061	100,100	3,653	530
Sim 26	200	121,808	100,100	3,653	609
Sim 27	200	84,297	100,100	3,653	421
Sim 28	200	23,354	100,100	3,653	117
Sim 5	200	164,980	100,100	3,653	825

Kruskal-Wallis Test	
Chi-Square	650.7
DF	4
Pr > Chi-Square	<.0001

Table 33f: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case VI

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 6	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$	25,586	7,397	7,842	37,432
Sim 29	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	38,751	5,967	23,631	50,073
Sim 30	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	29,132	6,649	9,515	38,794
Sim 31	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	30,392	6,886	12,480	42,464
Sim 32	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	38,432	4,609	26,745	47,452

Kruskal-Wallis Test - Cash Flow Net Contribution For Case VI					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 29	200	146,756	100,100	3,653	734
Sim 30	200	74,168	100,100	3,653	371
Sim 31	200	83,896	100,100	3,653	419
Sim 32	200	144,890	100,100	3,653	724
Sim 6	200	50,790	100,100	3,653	254

Kruskal-Wallis Test	
Chi-Square	452.5
DF	4
Pr > Chi-Square	<.0001

Table 33g: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case VII

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 7	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$	42,027	4,659	26,748	51,852
Sim 33	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	41,147	7,703	20,910	58,156
Sim 34	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	38,939	6,067	21,253	49,279
Sim 35	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	37,061	6,056	22,171	49,365
Sim 36	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	29,262	5,794	11,806	46,466

Kruskal-Wallis Test - Cash Flow Net Contribution For Case VII					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 33	200	123,449	100,100	3,653	617
Sim 34	200	109,225	100,100	3,653	546
Sim 35	200	93,514	100,100	3,653	468
Sim 36	200	38,453	100,100	3,653	192
Sim 7	200	135,859	100,100	3,653	679

Kruskal-Wallis Test	
Chi-Square	344.7
DF	4
Pr > Chi-Square	<.0001

Table 33h: Kruskal-Wallis Test of Cash Flow Net Profit Contributions for Case VIII

Net Cash Flow Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 8	Vol_{High} $Corr_{High}$ $Disrupt_{High}$	22,658	8,565	-3,286	37,241
Sim 37	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	36,643	7,528	12,826	51,024
Sim 38	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	27,133	7,930	-3,278	39,010
Sim 39	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	29,848	6,881	14,129	43,567
Sim 40	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	39,936	5,984	20,546	50,228

Kruskal-Wallis Test - Cash Flow Net Contribution For Case VIII					
Wilcoxon Scores (Rank Sums) for Variable TotalCF Classified by Variable Mnemonic					
Mnemonic	**N**	**Sum of Scores**	**Expected Under H0**	**Std Dev Under H0**	**Mean Score**
Sim 37	200	133,751	100,100	3,653	669
Sim 38	200	73,780	100,100	3,653	369
Sim 39	200	88,663	100,100	3,653	443
Sim 40	200	154,958	100,100	3,653	775
Sim 8	200	49,348	100,100	3,653	247

Kruskal-Wallis Test	
Chi-Square	452.0
DF	4
Pr > Chi-Square	<.0001

Table 34a: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case I

Net Accrual Profit Contribution					
Mnemonic	**Descriptor**	**Mean**	**Std Dev**	**Min**	**Max**
Sim 1	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$	36,769	4,175	27,070	49,748
Sim 9	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	33,700	3,986	25,024	48,104
Sim 10	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	39,300	2,622	32,987	46,528
Sim 11	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	30,677	2,347	25,760	39,109
Sim 12	Vol_{Low} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	32,090	1,786	27,817	37,602

Kruskal-Wallis Test - Accrual Net Contribution For Case I					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	**N**	**Sum of Scores**	**Expected Under H0**	**Std Dev Under H0**	**Mean Score**
Sim 1	200	130,440	100,100	3,653	652
Sim 10	200	162,640	100,100	3,653	813
Sim 11	200	46,740	100,100	3,653	234
Sim 12	200	69,632	100,100	3,653	348
Sim 9	200	91,048	100,100	3,653	455

Kruskal-Wallis Test	
Chi-Square	520.8
DF	4
Pr > Chi-Square	<.0001

Table 34b: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case II

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 2	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$	40,449	6,184	25,162	58,436
Sim 13	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	38,674	6,773	23,877	60,026
Sim 14	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	44,653	4,107	29,542	54,136
Sim 15	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	34,217	4,368	24,735	51,319
Sim 16	Vol_{High} $Corr_{Low}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	34,607	3,184	26,342	45,728

Kruskal-Wallis Test - Accrual Net Contribution For Case II					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 13	200	101,408	100,100	3,653	507
Sim 14	200	156,625	100,100	3,653	783
Sim 15	200	60,164	100,100	3,653	301
Sim 16	200	63,931	100,100	3,653	320
Sim 2	200	118,372	100,100	3,653	592

Kruskal-Wallis Test	
Chi-Square	385.6
DF	4
Pr > Chi-Square	<.0001

Table 34c: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case III

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 3	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$	37,428	5,844	23,391	53,198
Sim 17	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	34,164	5,387	21,108	50,994
Sim 18	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	41,571	3,913	32,075	52,443
Sim 19	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	31,064	3,357	24,106	43,368
Sim 20	Vol_{Low} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	32,212	2,345	25,941	39,248

Kruskal-Wallis Test - Accrual Net Contribution For Case III					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 17	200	90,690	100,100	3,653	453
Sim 18	200	162,107	100,100	3,653	811
Sim 19	200	55,158	100,100	3,653	276
Sim 20	200	69,955	100,100	3,653	350
Sim 3	200	122,590	100,100	3,653	613

Kruskal-Wallis Test	
Chi-Square	441.6
DF	4
Pr > Chi-Square	<.0001

Table 34d: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case IV

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 4	Vol_{High} $Corr_{High}$ $Disrupt_{None}$	40,067	8,268	17,994	60,364
Sim 21	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{no} $Flex_{no}$	39,187	9,542	19,976	69,124
Sim 22	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{yes} $Flex_{no}$	46,232	5,467	27,906	57,734
Sim 23	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{no} Exp_{no} $Flex_{yes}$	34,409	6,163	21,196	58,213
Sim 24	Vol_{High} $Corr_{High}$ $Disrupt_{None}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	34,586	4,641	22,753	53,438

Kruskal-Wallis Test - Accrual Net Contribution For Case IV					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 21	200	101,007	100,100	3,653	505
Sim 22	200	153,031	100,100	3,653	765
Sim 23	200	67,731	100,100	3,653	339
Sim 24	200	69,438	100,100	3,653	347
Sim 4	200	109,293	100,100	3,653	546

Kruskal-Wallis Test	
Chi-Square	292.2
DF	4
Pr > Chi-Square	<.0001

Table 34e: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case V

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 5	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$	37,338	4,113	27,730	49,060
Sim 25	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	34,053	3,914	25,115	47,989
Sim 26	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	24,498	1,108	21,615	27,277
Sim 27	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	30,957	2,456	25,981	40,026
Sim 28	Vol_{Low} $Corr_{Low}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	25,489	992	22,641	28,673

Kruskal-Wallis Test - Accrual Net Contribution For Case V					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 25	200	140,666	100,100	3,653	703
Sim 26	200	30,297	100,100	3,653	151
Sim 27	200	113,323	100,100	3,653	567
Sim 28	200	50,621	100,100	3,653	253
Sim 5	200	165,593	100,100	3,653	828

Kruskal-Wallis Test	
Chi-Square	805.0
DF	4
Pr > Chi-Square	<.0001

Table 34f: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case VI

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 6	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$	20,486	10,224	-5,010	39,444
Sim 29	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	31,855	8,935	8,725	49,111
Sim 30	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	25,126	9,213	681	41,639
Sim 31	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	25,126	9,213	681	41,639
Sim 32	Vol_{Low} $Corr_{Low}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	20,805	5,974	5,713	28,150

Kruskal-Wallis Test - Accrual Net Contribution For Case VI					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 29	200	152,567	100,100	3,653	763
Sim 30	200	47,081	100,100	3,653	235
Sim 31	200	119,018	100,100	3,653	595
Sim 32	200	88,704	100,100	3,653	444
Sim 6	200	93,130	100,100	3,653	466

Kruskal-Wallis Test	
Chi-Square	365.6
DF	4
Pr > Chi-Square	<.0001

Table 34g: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case VII

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 7	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$	39,802	39,802	39,802	39,802
Sim 33	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{no} $Flex_{no}$	39,264	39,264	39,264	39,264
Sim 34	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{yes} $Flex_{no}$	25,628	25,628	25,628	25,628
Sim 35	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{no} Exp_{no} $Flex_{yes}$	34,632	34,632	34,632	34,632
Sim 36	Vol_{High} $Corr_{High}$ $Disrupt_{Low}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	27,101	27,101	27,101	27,101

Kruskal-Wallis Test - Accrual Net Contribution For Case VII					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 33	200	137,322	100,100	3,653	687
Sim 34	200	44,359	100,100	3,653	222
Sim 35	200	116,982	100,100	3,653	585
Sim 36	200	57,894	100,100	3,653	289
Sim 7	200	143,943	100,100	3,653	720

Kruskal-Wallis Test	
Chi-Square	508.4
DF	4
Pr > Chi-Square	<.0001

Table 34h: Kruskal-Wallis Test of Accrual Net Profit Contributions for Case VIII

Net Accrual Profit Contribution					
Mnemonic	Descriptor	Mean	Std Dev	Min	Max
Sim 8	Vol_{High} $Corr_{High}$ $Disrupt_{High}$	17,357	11,309	-16,280	38,062
Sim 37	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{no} $Flex_{no}$	29,336	10,544	-2,555	52,101
Sim 38	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{yes} $Flex_{no}$	10,006	8,986	-26,215	25,230
Sim 39	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{no} Exp_{no} $Flex_{yes}$	24,135	9,005	373	42,105
Sim 40	Vol_{High} $Corr_{High}$ $Disrupt_{High}$ - Inv_{yes} Exp_{yes} $Flex_{yes}$	22,842	6,122	4,060	30,986

Kruskal-Wallis Test - Accrual Net Contribution For Case VIII					
Wilcoxon Scores (Rank Sums) for Variable TotalACC Classified by Variable Mnemonic					
Mnemonic	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Sim 37	200	144,246	100,100	3,653	721
Sim 38	200	44,540	100,100	3,653	223
Sim 39	200	118,263	100,100	3,653	591
Sim 40	200	109,264	100,100	3,653	546
Sim 8	200	84,187	100,100	3,653	421

Kruskal-Wallis Test	
Chi-Square	341.8
DF	4
Pr > Chi-Square	<.0001

Table 35: Pairwise T-Test Analyses

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 1	200	36,769	4,175	295	27,070	49,748	
Sim 9	200	33,700	3,986	282	25,024	48,104	
Diff (1-2)		3,069	4,081	408			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 1		36,769	36,187	37,351	4,175	3,802	4,630
Sim 9		33,700	33,144	34,256	3,986	3,630	4,420
Diff (1-2)	Pooled	3,069	2,267	3,872	4,081	3,817	4,386
Diff (1-2)	Satterthwaite	3,069	2,267	3,872			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	398.0	7.5	<.0001
Satterthwaite	Unequal	397.2	7.5	<.0001

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 1	200	36,769	4,175	295	27,070	49,748	
Sim 10	200	39,300	2,622	185	32,987	46,528	
Diff (1-2)		-2,530	3,486	349			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 1		36,769	36,187	37,351	4,175	3,802	4,630
Sim 10		39,300	38,934	39,665	2,622	2,388	2,907
Diff (1-2)	Pooled	-2,530	-3,216	-1,845	3,486	3,260	3,746
Diff (1-2)	Satterthwaite	-2,530	-3,216	-1,845			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-7.3	<.0001			
Satterthwaite	Unequal	334.8	-7.3	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 1	200	36,769	4,175	295	27,070	49,748	
Sim 11	200	30,677	2,347	166	25,760	39,109	
Diff (1-2)		6,092	3,387	339			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 1		36,769	36,187	37,351	4,175	3,802	4,630
Sim 11		30,677	30,350	31,004	2,347	2,137	2,603
Diff (1-2)	Pooled	6,092	5,427	6,758	3,387	3,167	3,639
Diff (1-2)	Satterthwaite	6,092	5,426	6,759			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	18.0	<.0001			
Satterthwaite	Unequal	313.4	18.0	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 1	200	36,769	4,175	295	27,070	49,748	
Sim 12	200	32,090	1,786	126	27,818	37,602	
Diff (1-2)		4,679	3,211	321			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 1		36,769	36,187	37,351	4,175	3,802	4,630
Sim 12		32,090	31,841	32,339	1,786	1,626	1,980
Diff (1-2)	Pooled	4,679	4,048	5,310	3,211	3,002	3,451
Diff (1-2)	Satterthwaite	4,679	4,047	5,311			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	14.6	<.0001			
Satterthwaite	Unequal	269.5	14.6	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 13	200	38,674	6,773	479	23,877	60,026	
Sim 2	200	40,449	6,184	437	25,162	58,436	
Diff (1-2)		-1,775	6,485	649			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 13		38,674	37,730	39,619	6,773	6,168	7,511
Sim 2		40,449	39,587	41,311	6,184	5,632	6,858
Diff (1-2)	Pooled	-1,775	-3,050	-500	6,485	6,065	6,970
Diff (1-2)	Satterthwaite	-1,775	-3,050	-500			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-2.7	0.01			
Satterthwaite	Unequal	394.8	-2.7	0.01			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 14	200	44,653	4,107	290	29,542	54,136	
Sim 2	200	40,449	6,184	437	25,162	58,436	
Diff (1-2)		4,204	5,249	525			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 14		44,653	44,081	45,226	4,107	3,740	4,554
Sim 2		40,449	39,587	41,311	6,184	5,632	6,858
Diff (1-2)	Pooled	4,204	3,172	5,236	5,249	4,909	5,641
Diff (1-2)	Satterthwaite	4,204	3,172	5,237			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	8.0	<.0001			
Satterthwaite	Unequal	345.9	8.0	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 15	200	34,217	4,368	309	24,735	51,319	
Sim 2	200	40,449	6,184	437	25,162	58,436	
Diff (1-2)		-6,232	5,354	535			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 15		34,217	33,608	34,826	4,368	3,977	4,843
Sim 2		40,449	39,587	41,311	6,184	5,632	6,858
Diff (1-2)	Pooled	-6,232	-7,284	-5,179	5,354	5,006	5,753
Diff (1-2)	Satterthwaite	-6,232	-7,285	-5,179			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-11.6	<.0001			
Satterthwaite	Unequal	358.0	-11.6	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 16	200	34,607	3,184	225	26,342	45,728	
Sim 2	200	40,449	6,184	437	25,162	58,436	
Diff (1-2)		-5,842	4,919	492			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 16		34,607	34,163	35,051	3,184	2,900	3,531
Sim 2		40,449	39,587	41,311	6,184	5,632	6,858
Diff (1-2)	Pooled	-5,842	-6,809	-4,875	4,919	4,599	5,286
Diff (1-2)	Satterthwaite	-5,842	-6,810	-4,874			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-11.9	<.0001			
Satterthwaite	Unequal	297.6	-11.9	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 17	200	34,164	5,387	381	21,108	50,994	
Sim 3	200	37,428	5,844	413	23,391	53,198	
Diff (1-2)		-3,264	5,620	562			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 17		34,164	33,413	34,915	5,387	4,906	5,974
Sim 3		37,428	36,613	38,243	5,844	5,322	6,480
Diff (1-2)	Pooled	-3,264	-4,369	-2,159	5,620	5,255	6,040
Diff (1-2)	Satterthwaite	-3,264	-4,369	-2,159			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-5.8	<.0001			
Satterthwaite	Unequal	395.4	-5.8	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 18	200	41,572	3,913	277	32,075	52,443	
Sim 3	200	37,428	5,844	413	23,391	53,198	
Diff (1-2)		4,144	4,973	497			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 18		41,572	41,026	42,117	3,913	3,563	4,339
Sim 3		37,428	36,613	38,243	5,844	5,322	6,480
Diff (1-2)	Pooled	4,144	3,166	5,121	4,973	4,650	5,344
Diff (1-2)	Satterthwaite	4,144	3,166	5,122			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	8.3	<.0001			
Satterthwaite	Unequal	347.6	8.3	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 19	200	31,064	3,357	237	24,106	43,368	
Sim 3	200	37,428	5,844	413	23,391	53,198	
Diff (1-2)		-6,364	4,766	477			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 19		31,064	30,596	31,532	3,357	3,058	3,723
Sim 3		37,428	36,613	38,243	5,844	5,322	6,480
Diff (1-2)	Pooled	-6,364	-7,301	-5,427	4,766	4,456	5,121
Diff (1-2)	Satterthwaite	-6,364	-7,302	-5,426			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-13.4	<.0001			
Satterthwaite	Unequal	317.5	-13.4	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 20	200	32,212	2,345	166	25,941	39,249	
Sim 3	200	37,428	5,844	413	23,391	53,198	
Diff (1-2)		-5,216	4,452	445			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 20		32,212	31,885	32,539	2,345	2,135	2,600
Sim 3		37,428	36,613	38,243	5,844	5,322	6,480
Diff (1-2)	Pooled	-5,216	-6,092	-4,341	4,452	4,163	4,785
Diff (1-2)	Satterthwaite	-5,216	-6,093	-4,340			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-11.7	<.0001			
Satterthwaite	Unequal	261.5	-11.7	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 21	200	39,187	9,542	675	19,976	69,124	
Sim 4	200	40,067	8,268	585	17,994	60,364	
Diff (1-2)		-880	8,928	893			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 21		39,187	37,857	40,518	9,542	8,689	10,581
Sim 4		40,067	38,914	41,220	8,268	7,529	9,169
Diff (1-2)	Pooled	-880	-2,635	875	8,928	8,348	9,594
Diff (1-2)	Satterthwaite	-880	-2,636	875			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-1.0	0.32			
Satterthwaite	Unequal	390.1	-1.0	0.32			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 22	200	46,232	5,467	387	27,906	57,735	
Sim 4	200	40,067	8,268	585	17,994	60,364	
Diff (1-2)		6,165	7,009	701			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 22		46,232	45,470	46,994	5,467	4,979	6,063
Sim 4		40,067	38,914	41,220	8,268	7,529	9,169
Diff (1-2)	Pooled	6,165	4,787	7,543	7,009	6,554	7,532
Diff (1-2)	Satterthwaite	6,165	4,786	7,543			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	8.8	<.0001			
Satterthwaite	Unequal	345.1	8.8	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 23	200	34,409	6,163	436	21,196	58,213	
Sim 4	200	40,067	8,268	585	17,994	60,364	
Diff (1-2)		-5,658	7,292	729			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 23		34,409	33,550	35,269	6,163	5,612	6,834
Sim 4		40,067	38,914	41,220	8,268	7,529	9,169
Diff (1-2)	Pooled	-5,658	-7,092	-4,225	7,292	6,819	7,836
Diff (1-2)	Satterthwaite	-5,658	-7,092	-4,224			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-7.8	<.0001			
Satterthwaite	Unequal	368.0	-7.8	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 24	200	34,587	4,641	328	22,753	53,438	
Sim 4	200	40,067	8,268	585	17,994	60,364	
Diff (1-2)		-5,481	6,705	670			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 24		34,587	33,939	35,234	4,641	4,227	5,147
Sim 4		40,067	38,914	41,220	8,268	7,529	9,169
Diff (1-2)	Pooled	-5,481	-6,799	-4,163	6,705	6,269	7,205
Diff (1-2)	Satterthwaite	-5,481	-6,800	-4,162			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-8.2	<.0001			
Satterthwaite	Unequal	313.1	-8.2	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 25	200	34,053	3,914	277	25,115	47,990	
Sim 5	200	37,338	4,113	291	27,730	49,060	
Diff (1-2)		-3,285	4,014	401			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 25		34,053	33,507	34,599	3,914	3,564	4,340
Sim 5		37,338	36,764	37,911	4,113	3,745	4,561
Diff (1-2)	Pooled	-3,285	-4,074	-2,496	4,014	3,754	4,314
Diff (1-2)	Satterthwaite	-3,285	-4,074	-2,496			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-8.2	<.0001			
Satterthwaite	Unequal	397.0	-8.2	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 26	200	24,498	1,108	78	21,615	27,277	
Sim 5	200	37,338	4,113	291	27,730	49,060	
Diff (1-2)		-12,840	3,012	301			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 26		24,498	24,343	24,652	1,108	1,009	1,228
Sim 5		37,338	36,764	37,911	4,113	3,745	4,561
Diff (1-2)	Pooled	-12,840	-13,432	-12,248	3,012	2,816	3,237
Diff (1-2)	Satterthwaite	-12,840	-13,434	-12,247			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-42.6	<.0001			
Satterthwaite	Unequal	227.7	-42.6	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 27	200	30,957	2,456	174	25,981	40,026	
Sim 5	200	37,338	4,113	291	27,730	49,060	
Diff (1-2)		-6,380	3,387	339			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 27		30,957	30,615	31,300	2,456	2,236	2,723
Sim 5		37,338	36,764	37,911	4,113	3,745	4,561
Diff (1-2)	Pooled	-6,380	-7,046	-5,715	3,387	3,167	3,640
Diff (1-2)	Satterthwaite	-6,380	-7,047	-5,714			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-18.8	<.0001			
Satterthwaite	Unequal	324.9	-18.8	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 28	200	25,489	992	70	22,641	28,673	
Sim 5	200	37,338	4,113	291	27,730	49,060	
Diff (1-2)		-11,849	2,991	299			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 28		25,489	25,351	25,627	992	903	1,100
Sim 5		37,338	36,764	37,911	4,113	3,745	4,561
Diff (1-2)	Pooled	-11,849	-12,437	-11,261	2,991	2,797	3,215
Diff (1-2)	Satterthwaite	-11,849	-12,438	-11,259			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-39.6	<.0001			
Satterthwaite	Unequal	222.1	-39.6	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 29	200	31,855	8,935	632	8,725	49,111	
Sim 6	200	20,486	10,224	723	-5,010	39,444	
Diff (1-2)		11,369	9,601	960			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 29		31,855	30,609	33,101	8,935	8,137	9,908
Sim 6		20,486	19,061	21,912	10,224	9,310	11,337
Diff (1-2)	Pooled	11,369	9,481	13,256	9,601	8,978	10,318
Diff (1-2)	Satterthwaite	11,369	9,481	13,256			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	11.8	<.0001			
Satterthwaite	Unequal	391.0	11.8	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 30	200	13,227	7,437	526	-8,904	25,440	
Sim 6	200	20,486	10,224	723	-5,010	39,444	
Diff (1-2)		-7,259	8,940	894			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 30		13,227	12,190	14,264	7,437	6,773	8,247
Sim 6		20,486	19,061	21,912	10,224	9,310	11,337
Diff (1-2)	Pooled	-7,259	-9,017	-5,502	8,940	8,360	9,607
Diff (1-2)	Satterthwaite	-7,259	-9,017	-5,501			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-8.1	<.0001			
Satterthwaite	Unequal	363.5	-8.1	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 31	200	25,126	9,213	652	681	41,639	
Sim 6	200	20,486	10,224	723	-5,010	39,444	
Diff (1-2)		4,640	9,732	973			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 31		25,126	23,841	26,411	9,213	8,390	10,217
Sim 6		20,486	19,061	21,912	10,224	9,310	11,337
Diff (1-2)	Pooled	4,640	2,727	6,553	9,732	9,100	10,458
Diff (1-2)	Satterthwaite	4,640	2,726	6,553			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	4.8	<.0001			
Satterthwaite	Unequal	393.8	4.8	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 32	200	20,805	5,974	422	5,713	28,150	
Sim 6	200	20,486	10,224	723	-5,010	39,444	
Diff (1-2)		319	8,373	837			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 32		20,805	19,972	21,638	5,974	5,441	6,625
Sim 6		20,486	19,061	21,912	10,224	9,310	11,337
Diff (1-2)	Pooled	319	-1,327	1,965	8,373	7,830	8,998
Diff (1-2)	Satterthwaite	319	-1,328	1,966			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	0.4	0.70			
Satterthwaite	Unequal	320.7	0.4	0.70			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 33	200	39,264	9,357	662	21,272	67,432	
Sim 7	200	39,802	8,068	571	18,555	58,197	
Diff (1-2)		-539	8,736	874			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 33		39,264	37,959	40,568	9,357	8,521	10,376
Sim 7		39,802	38,678	40,927	8,068	7,347	8,946
Diff (1-2)	Pooled	-539	-2,256	1,179	8,736	8,169	9,388
Diff (1-2)	Satterthwaite	-539	-2,256	1,179			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-0.6	0.54			
Satterthwaite	Unequal	389.6	-0.6	0.54			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 34	200	25,628	3,372	239	16,053	32,937	
Sim 7	200	39,802	8,068	571	18,555	58,197	
Diff (1-2)		-14,174	6,183	618			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 34		25,628	25,158	26,099	3,372	3,071	3,740
Sim 7		39,802	38,678	40,927	8,068	7,347	8,946
Diff (1-2)	Pooled	-14,174	-15,390	-12,959	6,183	5,782	6,645
Diff (1-2)	Satterthwaite	-14,174	-15,392	-12,957			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-22.9	<.0001			
Satterthwaite	Unequal	266.5	-22.9	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 35	200	34,632	6,287	445	21,094	58,173	
Sim 7	200	39,802	8,068	571	18,555	58,197	
Diff (1-2)		-5,170	7,232	723			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 35		34,632	33,756	35,509	6,287	5,726	6,972
Sim 7		39,802	38,678	40,927	8,068	7,347	8,946
Diff (1-2)	Pooled	-5,170	-6,592	-3,748	7,232	6,763	7,772
Diff (1-2)	Satterthwaite	-5,170	-6,592	-3,748			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-7.2	<.0001			
Satterthwaite	Unequal	375.6	-7.2	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 36	200	27,101	3,010	213	20,411	34,640	
Sim 7	200	39,802	8,068	571	18,555	58,197	
Diff (1-2)		-12,702	6,089	609			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 36		27,101	26,681	27,521	3,010	2,741	3,337
Sim 7		39,802	38,678	40,927	8,068	7,347	8,946
Diff (1-2)	Pooled	-12,702	-13,899	-11,505	6,089	5,693	6,543
Diff (1-2)	Satterthwaite	-12,702	-13,901	-11,502			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-20.9	<.0001			
Satterthwaite	Unequal	253.3	-20.9	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 37	200	29,336	10,544	746	-2,555	52,101	
Sim 8	200	17,357	11,309	800	-16,280	38,062	
Diff (1-2)		11,979	10,933	1,093			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 37		29,336	27,866	30,806	10,544	9,602	11,692
Sim 8		17,357	15,781	18,934	11,309	10,298	12,540
Diff (1-2)	Pooled	11,979	9,830	14,128	10,933	10,223	11,749
Diff (1-2)	Satterthwaite	11,979	9,830	14,128			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	11.0	<.0001			
Satterthwaite	Unequal	396.1	11.0	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 38	200	10,006	8,986	635	-26,215	25,230	
Sim 8	200	17,357	11,309	800	-16,280	38,062	
Diff (1-2)		-7,351	10,214	1,021			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 38		10,006	8,753	11,259	8,986	8,183	9,965
Sim 8		17,357	15,781	18,934	11,309	10,298	12,540
Diff (1-2)	Pooled	-7,351	-9,359	-5,343	10,214	9,551	10,976
Diff (1-2)	Satterthwaite	-7,351	-9,360	-5,343			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	-7.2	<.0001			
Satterthwaite	Unequal	378.7	-7.2	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 39	200	24,135	9,005	637	373	42,105	
Sim 8	200	17,357	11,309	800	-16,280	38,062	
Diff (1-2)		6,778	10,222	1,022			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 39		24,135	22,880	25,391	9,005	8,200	9,986
Sim 8		17,357	15,781	18,934	11,309	10,298	12,540
Diff (1-2)	Pooled	6,778	4,768	8,787	10,222	9,558	10,985
Diff (1-2)	Satterthwaite	6,778	4,768	8,788			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	6.6	<.0001			
Satterthwaite	Unequal	379.0	6.6	<.0001			

Mnemonic	N	Mean	Std Dev	Std Err	Minimum	Maximum	
Sim 40	200	22,842	6,122	433	4,060	30,986	
Sim 8	200	17,357	11,309	800	-16,280	38,062	
Diff (1-2)		5,485	9,093	909			
Mnemonic	**Method**	**Mean**	**95% CL Mean**		**Std Dev**	**95% CL Std Dev**	
Sim 40		22,842	21,989	23,696	6,122	5,575	6,789
Sim 8		17,357	15,781	18,934	11,309	10,298	12,540
Diff (1-2)	Pooled	5,485	3,697	7,272	9,093	8,503	9,772
Diff (1-2)	Satterthwaite	5,485	3,696	7,274			
Method	**Variances**	**DF**	**t Value**	**Pr > |t|**			
Pooled	Equal	398.0	6.0	<.0001			
Satterthwaite	Unequal	306.4	6.0	<.0001			

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