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Proactive inventory policy intervention to mitigate risk within cooperative supply chains

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A B S T R A C T

This exploratory paper will investigate the concept of supply chain risk management involving supplier monitoring within a cooperative supply chain. Inventory levels and stockouts are the key metrics. Key to this concept is the assumptions that (1) out-of-control supplier situations are causal triggers for downstream supply chain disruptions, (2) these triggers can potentially be predicted using statistical process monitoring tools, and (3) carrying excess inventory only when needed is preferable as opposed to carrying excess inventory on a continual basis. Simulation experimentation will be used to explore several supplier monitoring strategies based on statistical runs tests, specifically "runs up and down" and/or "runs above and below" tests. The sensitivity of these tests in detecting non-random supplier behavior will be explored and their performance will be investigated relative to stock-outs and inventory levels. Finally, the effects of production capacity and yield rate will be examined. Results indicate out-of-control supplier signals can be detected beforehand and stock-outs can be significantly reduced by dynamically adjusting inventory levels. The largest benefit occurs when both runs tests are used together and when the supplier has sufficient production capacity to respond to downstream demand (i.e., safety stock) increases. When supplier capacity is limited, the highest benefit is achieved when yield rates are high and, thus, yield loss does not increase supplier production requirements beyond its available capacity.

1. Introduction

The recent economic crisis has forced many manufacturing firms to restructure their business models by reducing inventory levels, preventative maintenance and employing other cost cutting strategies. In turn, these practices have reduced the robustness of supply chains and, in turn, many customers find themselves increasing their own inventory levels to compensate or reacting just-in-time to impacts associated with supply chain disruptions (e.g., stock-outs). In lean production, recovering from such disruptions is a critical, yet difficult, task after the disruption has already occurred. It has been reported that firms suffering from supply chain disruptions experienced 33-40% lower stock returns relative to industry benchmarks, and that disruptions not only impact immediate performance but also long-term

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performance (Tang, 2006). Thus, when possible, it is crucial to prevent the impacts of disruptions proactively, as well as being adept at recovering from such impacts that have already occurred.

Supply chain risk management (SCRM) has been brought to the forefront in recent years and is reported to be the second largest concern to executives after supply chain visibility (Butner, 2010). SCRM is a broad area including topics such as material/information flows, financial arrangements, production methods and delivery models. Most literature focuses on conceptual frameworks and concepts. Discussion of mathematical models is limited (Giunipero, 2008).

A key aspect of supply chain risk management is inventory management (Caballini & Revetria, 2008). In the past, supply chain partners have been reluctant to share operational information and, thus, inventory risk mitigation has been done in isolation using practices such as safety stock. However, recently there are increasing cooperation and information sharing in supply chains (Albani & Dietz, 2009) and (Goswami et al., 2013). When operational information about key parameters (e.g., inventory level, yield rate) is shared with a partner, he can be more proactive in establishing his own inventory risk control policies in accordance with an acceptance risk level.

Accordingly, this exploratory paper will examine a proactive approach to supply chain risk management using a dynamic inventory policy based on cooperative supplier monitoring. The effectiveness of this policy will be studied in various cases. Research questions to be investigated include the following:

1. How effective is the supplier monitoring strategy at mitigating risk?
2. How do inventory levels change due to implementing the supplier monitoring strategy?
3. How well do the various statistical control tests investigated perform in mitigating risk?
4. What effect do operational factors such as supplier yield rate and production capacity have on the ability to successfully employ the supplier monitoring strategy?

2. Literature Review

This review focuses on key areas underlying the motivation and methodology used in this paper, namely supply chain risk management, inventory control in supply chains, supply chain modeling approaches, inventory monitoring using statistical methods, and the trend towards increased cooperation and information sharing among supply chain partners.

Supply chain networks are inherently vulnerable to disruptions, and failure in any network element can cause the entire supply chain to fail (Rice & Caniato, 2003). Although many firms have not been able to quantify the cost of supply chain disruptions (Blackhurst et al., 2005), a company surveyed by Rice & Caniato (2003) estimated a $50-100 million cost impact for each day that a disruption impacts its supply network. Other literature has studied the impact of supply chain disruptions (Hendricks & Sinfhal, 2003) and (Knight & Pretty, 1996), and the results indicate that disruptions will negatively affect the performance and business continuity of a firm. Also, current trends with global sourcing, increased responsiveness, higher agility levels and lower inventory levels will increase the potential for disruptions to occur (Blackhurst et al., 2005). These results demonstrate the perceived importance of supply chain risk management.

According to Tang (2006), supply chain risk management involves the risk event, the resultant impact and the risk mitigation approach utilized. Supply chain risk is defined as “variation in the distribution of possible supply chain outcomes, their likelihood and their subjective values” (March & Shapira, 1987). There are two types of supply chain risks: operational risk and disruption risk. Operational risk involves inherent uncertainties related to demand, supply and cost. Disruption risk involves events such as natural disasters, terrorist attack and economic crises (Tang, 2006). Although the business impact of disruption risk is often much greater than operational risk, operational risk is more predictable and, thus, easier to proactively manage.

A typical risk management process widely suggested consists of a four-stage process involving risk identification, risk assessment, implementation of risk management and risk monitoring (Blackhurst et al., 2008), (Halikas et al., 2004), (Juttner et al., 2003) and (Wagner & Bode, 2008). Examples of signals leading to risk identification include production interruptions, quality failures and delivery fluctuations. Once the risk is identified, suitable management approaches are developed and implemented in the next two stages. Consequently, ongoing monitoring is essential in order to identify and/or avoid similar risks in the future.

Inventory control is a key part of supply chain management (Caballini & Revetria, 2008). Demand fluctuations at a downstream customer are amplified as they move upstream throughout the supply chain. This phenomenon, called the "bullwhip effect," results in excessive inventory, revenue loss and inaccurate production planning (Lee & Wu, 2006). The bullwhip effect can be reduced by better sharing and coordinating demand information to upstream supply sites as well as improving operational efficiency (Fransoo & Wouters, 2000) and (Disney & Towill, 2003).

Giunipero (2008) stated that only 9% of supply chain management articles have used simulation or other modeling approaches. Most research has only provided general concepts or frameworks. Mathematical supply chain modeling has received little attention with the exception of research focusing on general inventory flows/costs and transportation logistics (Beamon, 1998) and (Croom et al., 2000). Due to the dynamic and inter-dependent nature of supply chains, a systems modeling approach is necessary (Perea et al., 2000). Examples of modeling approaches used to study supply chains in a systematic fashion include control theory (or system dynamics), multi-agent models and operations research approaches. There has been debate about which of these three methods is best at the operational level. Riddals et al. (2000) suggest none of the core OR methods are suitable at the operational level and provide better insights at the tactical level. Others suggest that a system dynamics or control theoretic approach is suitable. For example, it has been claimed that system dynamics may be the best way to study phenomena such as how a small fluctuation at one end of supply chain is amplified as it proceeds throughout the chain (Moraga et al., 2008). The importance of simulating supply chains using system dynamics has been emphasized in various studies (Lian & Jia, 2013), (Minegishi & Thiel, 2000), (Sterman, 2000) and (Towill, 1993).

Aelker et al. (2013) discuss how the trend towards globalization has increased the complexity involved in managing supply chains. New global markets, global sourcing and the need to reduce manufacturing costs have led to global dispersion of supply chains and increased complexity required to manage them. To assist supply chain managers in making complexity-optimized supply chain decisions, this paper examines a supply chain interpretation referred to as *Complex Adaptive System* (CAS) modeling for making complexity-optimized decisions within the semiconductor supply chain industry. CAS systems are non-equilibrium systems characterized by a large number of interacting and evolving agents which learn, adapt and, therefore, can be useful in solving the global supply chain complexity dilemma.

Hennies et al. (2013) conduct a comparative study of simulation-based supply chain modeling techniques while focusing on a fairly new simulation method called *mesoscopic supply chain simulation* (Reggelin & Tolujew, 2011). Mesoscopic simulation is alleged to combine the advantages of discrete event and continuous event simulation in the context of supply chains (e.g., continuous inventory reduction and discrete event-based inventory replenishment) while overcoming several limitations (e.g., permit modeling of supply chain material and information flows at the aggregate level instead of the individual level). The main benefit of the mesoscopic approach is that modeling efforts are balanced with the necessary level of detail which, in turn, facilitates quick and simple model creation and simulation.

Mobini et al. (2013) develop a simulation model to evaluate the performance of a wood pellet mill. Performance measures include energy consumption and CO_2 emissions as well as cost to deliver wood pellets to customers. The model is applied to an existing supply chain in British Columbia, Canada. Results suggest that cost can be reduced by 4.75% by blending 10% bark in the whitewood feedstock and by 1.5% by changing the drying fuel from sawdust to bark.

Smew et al. (2013) present a simulation study on supply chain-level production and inventory control. The potential impact of the hybrid Kanban-CONWIP production control strategy is examined relative to the competing tradeoff between maximizing customer service level and minimizing work-in-process inventory. Approaches involving simulation, Gaussian process modeling and optimization are investigated. An optimization framework is proposed that yields reasonably accurate solutions that are computationally less expensive than simulation methods.

Dominquez & Framinan (2013) introduce a multi-agent-based simulation platform (SCOPE) for simulating the order fulfillment process in a supply chain network. The framework is composed of reusable elements (agents, objects) to facilitate modeling of real-world-scale supply chains involving many different enterprises, products and structures. Each enterprise in the model can be customized with different policies and parameters for its various business functions.

Literature discussing concepts or methods for ongoing monitoring of supply chain performance and dynamic adjustments of policies and settings is very limited. Watts et al. (1994) suggest the use of statistical process control (SPC) methods to identify problems in reorder point systems using stock-outs as a trigger. Hill (1996) discusses the use of SPC to monitor customer demand using CUSUM charts. Pfohl et al. (1999) study demand and inventory control charts using four inventory rules and three demand rules to determine replenishment policy. Lee & Wu (2006) examine SPC-based inventory control techniques by modifying the approach of Pfohl et al. (1999) to include two common inventory replenishment policies, (s, Q) and (r, S).

Sambasivan et al. (2009) conduct a comprehensive survey of performance measures used in supply chain management based on industry practitioner input from the Malaysian electronics manufacturing industry. 838 performance measures are classified in terms of material flow, fund flow, internal process flow, sales and service flow, information flow and partner evaluation. Using confirmatory factor analysis, these metrics are further sub-classified into subgroups. Finally, 159 important measures are identified, along with 135 measures currently in use. Although the list of measures is extensive, none of them explicitly attempt to quantify inventory and stock-out effects related to dynamic supplier yield signals, as are considered in this research.

Recent literature has begun to study collaboration among supply chain partners. Albani & Dietz (2009) examine the increasing trend in inter-organizational cooperation and information sharing within modern supply chains. Strong economic pressures due to competitiveness, globalization of sales and sourcing, technological innovations and shorter product lead times and life cycles are changing the way companies are doing business. Business information related to production, product development, sales, delivery and services has been integrated in many cases, not only within a single company but also across its network of external partners. Sometimes these cooperative networks are permanent (e.g., health care), and other times they are temporary (e.g., engineering projects). In each case, the networks are dynamic due to new members joining and leaving. In short, companies are now recognizing that their competitive strengths lie not only in their core competencies, but also in their ability to cooperate effectively with business partners.

Goswami et al. (2013) also examine the need for collaborative information sharing among supply chain partners in terms of information visibility, namely the availability of relevant information for making supply chain decisions. Three dimensions of information visibility are considered - variety, quality and transfer - in a comparative analysis of two supply chain management information systems (SCIS).

Results show both systems perform well in supporting information visibility. However, they serve different and complementary purposes and, thus, supply chain characteristics need considered before choosing the most suitable SCIS.

Pezeshki et al. (2013) consider a divergent supply chain consisting of a supplier and several retailers who cooperate with the supplier as sales agents (i.e., revenue sharing contracts). Due to the retailers' proximity to customers, they can provide more accurate demand forecasts to the supplier. However, to ensure abundant supply and cope with demand variability, retailers have an incentive to exaggerate their private forecast information. To cope with this, a reward-punish coordination strategy based on trust is proposed with the ability to reward or punish agents. Results suggest the 'Trust' strategy outperformed the 'No Trust' strategy in all cases, thus suggesting that including trust in the design of supply chain coordination mechanisms may have a significant influence on the financial performance.

Ramanathan (2014) use a simulation approach in conjunction with industrial data to investigate the benefits of supply chain collaboration. Factors such as the number of collaborating partners, the level of investment in collaboration, and the duration of collaboration are studied in an attempt to quantify the optimal levels of collaboration at which maximum benefits are achieved.

Cigolini et al. (2014) study the relationship between supply chain performance and configuration. Performance factors such as stockouts and inventory levels are studied relative to configuration factors such as the number of sources, number of levels, number of nodes and distance between nodes. Results suggest lengthy supply chains do not affect retailer customer service level; however, they do require significant inventory stock. Moreover, increasing the number of suppliers can deteriorate distributor and manufacturer performance. Furthermore, collaboration (i.e., information sharing, reserved capacity) is useful to reduce supply chain variance. Finally, splitting capacity among many retailers can lead to high stockouts along the supply chain.

2.1 Research Synthesis and Problem Summary

Although the aforementioned literature has applied SPC methods to monitor the customer's own inventory behavior, none of this research has attempted to monitor supplier yield variability or other non-random performance patterns. In the existing literature, the key issue has been to adjust one firm's own inventory level for demand variability while ignoring the supplier's role. It is possible that monitoring and mitigating supply variability is just as critical as managing one's own demand variability and/or that it is a complementary topic. However, monitoring supplier variability requires collaborative information sharing between the supplier and downstream supply chain partner. Previous research papers discussed above have confirmed that such collaboration is an increasingly prevalent practice in modern supply chains.

In summary, the contribution of this paper is to explore supplier yield monitoring within the risk mitigation context of dynamic inventory control whenever collaborative information sharing exists within a supply chain. As will be discussed in the following sections, a sequential four-stage supply chain model will be examined using simulation to study the effect of employing two statistical runs tests, both individually and in conjunction, to monitor supplier yield rate behaviour in an attempt to predict when holding extra safety stock can be desirable. The subsequent impact on stockouts and inventory levels will be investigated in various cases and related to other factors such as production capacity.

3. Methodology

In a supply chain, a disruption, such as a stock-out, can be amplified throughout the chain as it moves downstream towards the customer. Avoiding such disruptions is a key goal in mitigating supply chain risk. Although an inventory policy change such as increasing safety stock can reduce the impact of an upstream supplier stock-out, it comes at a cost. The challenge is to know *when* to increase safety stock to mitigate risk. This paper will explore the use of a supplier performance monitoring to study how/when dynamic safety stock increases are cost-effective.

There is an increasing level of information sharing among supply chain partners (Albani & Dietz, 2009) and (Goswami et al., 2013). When operational information about key parameters (e.g., inventory level, yield rate) is shared, the customer can establish his own policies in accordance with an acceptance risk level. If he feels there is little risk, a low inventory level can be kept. If risk exists, the inventory level can be increased. This behavior was witnessed in McKay (1992) in which a scheduler, Ralph, monitored and regularly spoke to friends at key suppliers. Although it was not a formal sharing of operational data and was not officially recognized by management, Ralph would use this enriched information (e.g., inventory level, production yield, quality level, delivery time) to adjust his strategies at his own plant.

Although one could possibly rely on a human like Ralph to do the monitoring in an ongoing fashion, this paper will utilize methods from statistical process control, specifically run tests. When the supplier provides periodic operational data to the customer, the customer analyzes this data via the runs test methodology to check for non-random behavior. Such non-random patterns may signal that a supply disruption is imminent and, thus, prompt the customer to increase his safety stock. Similarly, when the non-random pattern (i.e., risk) subsides, inventory levels can return to normal. These run tests will be discussed further later in this section.

This paper will use simulation experimentation to study the aforementioned strategy using a four-stage sequential supply chain as shown in Fig. 1. We will focus on the dynamic behaviour of the middle two stages ("Factory 1" and "Factory 2") with the outer stages ("Supplier" and "Customer") modeled as a passive source and sink, respectively. Since the main purpose of this exploratory research is to study the dynamics of the strategy and to investigate possibilities for further research, this supply chain configuration is a logical starting point.

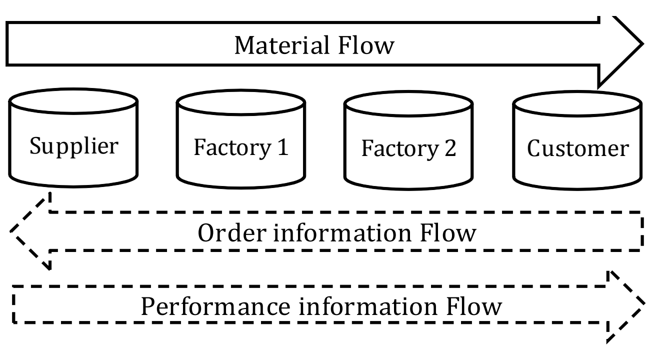

Fig. 1. Model Framework

As shown, the four stages consist of the supplier, Factory 1, Factory 2 and the customer. Orders are placed with upstream entities, product flows to downstream entities and key operational (performance) information flows to downstream entities. The supplier and customer entities, for purposes of this research, are viewed as a source and sink. The operation of Factory 1 and Factory 2 will be analyzed under the assumption that Factory 1 is the root cause of the supply disruptions. Thus, how Factory 2 can proactively manage these disruptions will be examined. Further discussion of system parameters and assumptions appears in Section 4.0.

Fig. 2 displays the causal loop diagram used to implement the simulation logic. Positive feedback, shown with a '+' arrow, implies the variables change in the same direction. Negative feedback, shown with a '−' arrow, implies the variables change in the opposite direction. The mathematical equations used to describe the inventory system are as follows:

Raw material inventory = initial raw inventory + (qty arrived–production qty) (1)
Finished goods inventory = initial f.g. inventory + (production qty–qty shipped) (2)

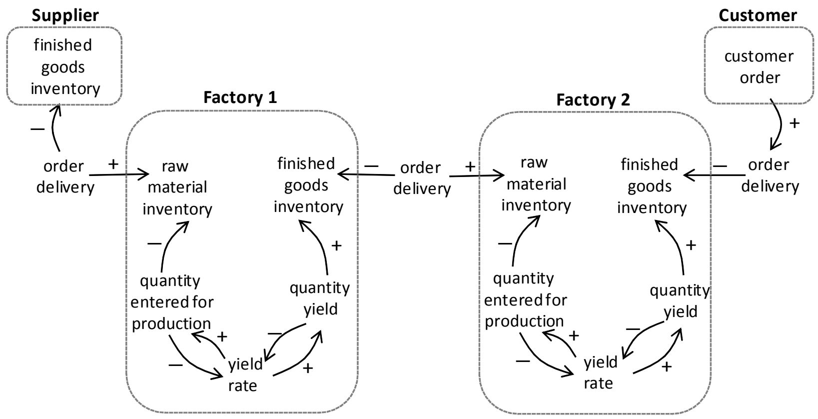

Fig. 2. Casual Loop Diagram for Simulation Variable Relationships

The production quantity is based on the production schedule, which is specified when the order arrives. The daily production quantity in effect during the next order cycle is then given by:

Production qty = min[(*order qty + safety stock shortage)/cycle time, production capacity*] (3)

For example, suppose the target production quantity for the next 5-day order cycle is 220 units. However, production capacity is limited to 40 units per day. In this case, the daily production schedule is 40 units on Day 1 through Day 5 and 20 units on Day 6.

A shortage in safety stock may arise whenever safety stock is used to meet demand. It can be computed as follows:

Safety stock shortage = max[*0,safety stock – (current inventory – order qty)*] (4)

For example, suppose current raw material inventory is 170 units including safety stock of 30 units. Order quantity is fixed at 150 units for each 5-day order cycle. When the order arrives, 150 out of 170 units will be shipped, thus leaving 20 units in inventory. Since safety stock is supposed to be 30 units, a safety stock shortage of 10 units exists. Thus, a total of 150 + 10 = 160 units must be produced by the time the next order arrives. Since the expected order cycle time is 5 days, the daily production schedule for each of the next 5 days will be 160 / 5 = 32 units per day (assuming sufficient production capacity exists).

As stated, statistical runs tests will be used to monitor supplier performance. Specifically, two types of runs tests will be used: "runs up and down" and "runs above and below" tests. In the "runs up and down" test, the magnitude of consecutive observations is compared. If the latter is larger, + is assigned; otherwise, – is assigned. A "run" consists of a series of +'s or –'s. The "runs above and below" test is similar; however, each observation is compared to the sample mean rather than an adjacent value. If the value exceeds the mean, + is assigned; otherwise, – is assigned. In each test, the total number of runs in the sequence is counted and compared to upper and lower critical values at a desired level of significance (α). If the total number of runs exceeds the upper critical value or falls below the lower critical value, then it is inferred that non-random variability exists and, thus, a potential supply chain disruption is likely. In this case, proactive risk mitigation should be undertaken by increasing safety stock level.

In conclusion, the proactive supplier monitoring strategy will be explored by the examining the following research questions, described in slightly more detail than stated in Section 1.0:

1. How effective is the supplier monitoring strategy at reducing stock-outs?
2. How much will average inventory levels increase when applying the strategy? Since applying the strategy will dynamically increase safety stock when non-random supplier patterns are detected, it is expected to increase inventory levels to some extent.
3. How do the different types of runs tests utilized affect the performance of the strategy?
4. How do operating conditions, namely yield and capacity, affect the performance of the strategy? Increasing safety stock will trigger earlier order placement which, in turn, places an unexpected demand increase on the supplier. If the supplier is operating close to its maximum capacity, it may not always be able to meet this demand increase.

4. Experimental Design

Simulation experimentation using *Simul8* software was used to generate the data. The experimentation was conducted in two stages. The first stage comparatively explored the performance of the various supplier monitoring strategies (i.e., run tests) under three yield rates. Consequently, the second stage further studied the sensitivity of the chosen strategy to yield rate. Performance measures include number of stock-outs and average inventory level.

The first stage explored the following four cases, corresponding to possible combinations of usage of the “runs up and down” and “runs above and below” supplier monitoring strategies.

Case 1: Strategy is not applied
Case 2: Strategy is applied using runs up and down test
Case 3: Strategy is applied using runs above and below test
Case 4: Strategy is applied using both types of runs tests

Each case was examined under three different yield rates: 95%, 90% and 85%. 50 simulation replications were run for each sub-case. Table 1 shows the experimental parameter settings at Factory 1 and Factory 2 which were selected based on preliminary experimentation.

The supplier monitoring strategy will use yield rate as the monitored variable. Thus, when the supplier’s yield rate shows variability in excess of what can be attributed to random fluctuations (i.e., runs test upper and lower critical values), the supplier will be deemed “out of control.” In this case, safety stock will be increased by 30 units (i.e., one day’s expected demand). To illustrate the logic, Fig. 3 and Fig. 4 display inventory levels with and without strategy employed. In this example, a non-random yield pattern at Factory 1 was detected by Factory 2 at Day 58. Thus, Factory 2 increased its raw material safety stock by 30. Accordingly, as shown in Fig. 3, the raw material inventory level at Factory 2 increased slightly after Day 58 in comparison to the case when the inventory policy was not applied. Fig. 4 displays a corresponding example where the finished goods inventory level at Factory 1 has shifted ahead in time after Day 51 under the supplier monitoring strategy since Factory 2’s increased order quantity (i.e., safety stock) has necessitated placing the order at Factory 1 earlier than usual. Utilizing the strategy from Stage 1 which best mitigated stock-outs (i.e., Case 2, 3 or 4), the second stage of the experimentation further studied the sensitivity of the strategy to yield. Yield rates between 80% and 100% (99% in some cases) were examined in increments of 1%. Results were compared to the baseline Case 1 (no strategy). Again, 50 simulation replications were run in each experimental sub-case.

Table 1
Experimental Parameter Settings at Factory 1 and Factory 2

	Factory 1	Factory 2
Max production capacity (units/day)	39	42
Production lines	3	3
Initial finished goods inventory level (units)	170	60
Safety stock of finished goods inventory (units)	20	30
Initial raw material inventory level (units)	180	170
Safety stock of raw material inventory (units)	60	20
Reorder point of raw material inventory (units)	90	110
Raw material order quantity (units)	150	150
Delivery lead time of raw material supply (days)	1	3
Simulation time period	100 days	
Order and shipment frequency	Daily	
Order quantity	30 units/day	
Expected daily demand	30 units/day	
Safety stock increase when inventory policy changes	30 units	
Significance level for runs tests	$\alpha = 0.1$	

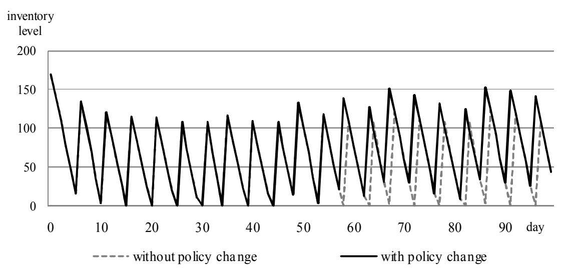

Fig. 3. Raw Material Inventory at Factory 2 With/Without Inventory Policy Change

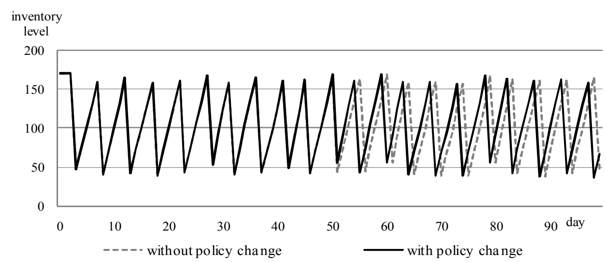

Fig. 4. Finished Goods Inventory at Factory 1 With/Without Inventory Policy Change

5. Experimental Results and Discussion

As discussed in Section 4.0, Stage 1 of the experimentation examined four potential strategy cases under three different yield rates. Table 2 shows the mean and standard deviation of the number of stock-outs at each inventory phase (Factory 1 raw material, Factory 1 finished goods, Factory 2 raw material and Factory 2 finished goods) for each of the four experimental strategy cases. Since the simulation is set to provide sufficient raw materials for Factory 1, no stock-outs occurred in raw material inventory at Factory 1. Table 3 shows the corresponding percentage *decrease* in stock-outs for Cases 2, 3 and 4 in relation to Case 1 (no supplier monitoring). Thus, a negative number actually represents an *increase* in stock-outs.

Table 2
Mean and Standard Deviation of Number of Stock-outs

		95% yield				90% yield				85% yield			
		Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4
F1	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RAW	St Dev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1	Mean	4.44	5.00	5.34	5.34	9.52	10.76	11.60	11.80	16.70	16.78	16.74	16.72
FG	St Dev	0.50	0.67	0.56	0.52	1.50	1.70	1.44	1.26	1.49	1.34	1.45	1.44
F2	Mean	13.34	9.30	5.48	4.88	19.70	17.92	17.50	17.04	28.56	28.50	28.38	28.38
RAW	St Dev	1.44	4.78	3.90	3.72	1.82	3.43	2.66	3.24	2.15	1.53	1.66	1.66
F2	Mean	0.10	0.08	0.06	0.04	5.08	4.28	3.66	3.46	13.34	13.20	13.02	12.98
FG	St Dev	0.30	0.27	0.24	0.20	1.08	1.33	1.24	1.18	0.87	0.83	0.87	0.84

Table 3
Percentage Reduction in Stock-outs

	95% yield			90% yield			85% yield		
	Case2	Case3	Case4	Case2	Case3	Case4	Case2	Case3	Case4
F1 FG	-12.6%	-20.3%	-20.3%	-13.0%	-21.8%	-23.9%	-0.5%	-0.2%	-0.1%
F2 RAW	30.3.%	58.9%	63.4%	9.0%	11.2%	13.5%	0.2%	0.6%	0.6%
F2 FG	20.0%	40.0%	60.0%	15.7%	28.0%	31.9%	1.0%	2.4%	2.7%

As shown in Table 2, stock-outs at both factories tend to increase as yield rate decreases which is intuitive based on the effect scrap has on production capacity. From Table 3, we see that applying both runs tests in conjunction (Case 4) results in the largest reduction relative to Case 1 in stock-outs at Factory 2. Thus, Case 4 appears to be most sensitive in detecting non-random supplier behavior. Finished goods stock-outs have increased at Factory 1due to the demand that Factory 2's increased order quantity (i.e., safety stock) places upon Factory 1's capacity. Moreover, the "runs above and below" test (Case 3) does a better job overall at decreasing stock-outs at Factory 2 than the "runs up and down" test (Case 2). Lastly, the relative advantage of applying supplier monitoring strategies tends to decrease as yield rate decreases. This phenomenon will be discussed in more detail later in relation to production capacity.

As stated before, average inventory level is the second performance measure considered. Table 4 shows the mean and standard deviation of inventory level for each case. Table 5 shows the corresponding percentage *increase* in average inventory level for Cases 2, 3 and 4 in relation to Case 1. In this case, a negative number represents a *decrease* in average inventory level.

Table 4
Mean and Standard Deviation of Average Inventory Level

		95% yield				90% yield				85% yield			
		Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4
F1	Mean	113.40	113.16	112.79	112.78	111.18	110.76	110.53	110.42	109.92	109.68	109.69	109.66
RAW	St Dev	1.31	1.16	1.21	1.16	1.59	1.70	1.72	1.62	1.88	1.88	1.74	1.76
F1	Mean	92.18	92.22	92.23	92.22	89.65	90.14	90.17	90.20	97.85	97.75	97.58	97.52
FG	St Dev	0.82	0.80	0.85	0.85	2.02	1.80	1.67	1.66	2.18	2.16	2.43	2.36
F2	Mean	65.98	73.06	79.24	80.43	62.29	64.08	64.43	64.92	55.86	55.94	56.16	56.16
RAW	St Dev	1.32	7.83	6.79	6.36	1.48	3.18	2.69	3.13	0.98	1.02	1.24	1.24
F2	Mean	45.48	46.34	47.08	47.22	41.15	41.74	41.89	42.06	35.96	35.98	36.03	36.03
FG	St Dev	0.65	1.12	0.90	0.84	0.97	1.35	1.15	1.29	1.28	1.26	1.27	1.26

Table 5
Percentage Increase in Average Inventory Level

	95% yield			90% yield			85% yield		
	Case2	Case3	Case4	Case2	Case3	Case4	Case2	Case3	Case4
F1 RAW	-0.21%	-0.54%	-0.55%	-0.38%	-0.58%	-0.68%	-0.22%	-0.21%	-0.24%
F1 FG	0.04%	0.05%	0.04%	0.55%	0.58%	0.61%	-0.10%	-0.28%	-0.34%
F2 RAW	10.73%	20.10%	21.90%	2.87%	3.44%	4.22%	0.14%	0.54%	0.54%
F2 FG	1.89%	3.52%	3.83%	1.43%	1.80%	2.21%	0.06%	0.19%	0.19%

From Table 4, we see that raw material and finished goods inventory levels at Factory 2 increase when the supplier monitoring strategies are used, which is intuitive since the additional safety stock carried whenever non-random supplier patterns are detected will lead to higher inventory levels. Average inventory levels are highest under Case 4 when both runs tests are used in conjunction. This finding also is intuitive, since two tests used in conjunction will be more sensitive than only one test. Overall, raw material and finished goods inventory levels at Factory 2 decline as yield rate declines. Finished goods inventory at Factory 1 varies by a much smaller proportion under supplier monitoring and can even decrease slightly at low yield rates (85%) due to the effect that yield loss and production capacity have on inventory. Changes in Factory 1 raw material levels are not particularly noteworthy due to the experimental parameter settings used and, in fact, are not of significance in this research since Factory 1's upstream suppliers are not modeled (i.e., only Factory 2's upstream supplier is considered).

In summary, Table 5 indicates that Case 4 (i.e., both runs tests used together) resulted in the highest overall increase in Factory 2 raw material and finished goods inventory levels (relative to Case 1). Furthermore, Factory 2 inventory levels decreased (relative to Case 1) as yield rate decreased due to the effect that yield loss has on inventory levels. In addition to stock-outs across the entire simulation timeframe, stock-outs after the inventory policy change point were examined as well. As Fig. 5 shows, the policy change point is the time at which a non-random supplier pattern is detected for the first time.

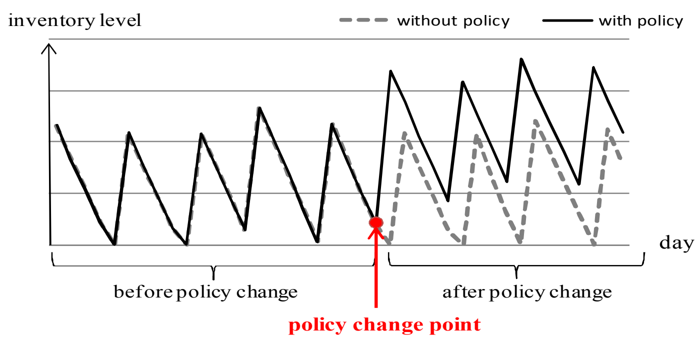

Fig. 5. Illustration of inventory policy change point

Table 6 indicates that inventory policy changes occur more frequently when Case 4 is utilized. Again, this indicates that Case 4 is a more sensitive strategy than either Case 2 or 3.

Table 6
Number of Times Inventory Policy Change Occurred in 50 Replications

	Case 2	Case 3	Case 4
95% yield	31	46	48
90% yield	34	46	48
85% yield	27	45	46

In summary, since the primary experimental objective for Factory 2 is to reduce stock-outs by implementing supplier monitoring, the Case 4 strategy (both runs tests) will be selected to proceed to Stage 2 of the experimentation. In Stage 2, Case 4 will be compared to the baseline Case 1 strategy (no supplier monitoring) to further examine the sensitivity of the strategy to yield rate. As with Stage 1, 50 simulation replications will be run in each experimental sub-case. Results will be reported as averages across those 50 replications.

Table 7 shows the number of stock-outs in Factory 2 raw material and finished goods, as well as the percent reduction, at yield rates between 80% and 99%. Several observations are noteworthy. First, no finished good stock-outs occur at yield rates 96% or above. Second, the number of stock-outs in both Cases 1 and 4 has a strong inverse relationship with yield rate. Specifically, they increase as yield rate decreases. Third, the percent reduction in stock-outs (Case 4 vs. Case 1) has a strong direct relationship with yield rate. Specifically, the stock-out reduction benefit by using the Case 4 supplier monitoring strategy increases as yield rate increases and decreases as yield rate decreases. Although two percent reduction values (59.31% and 4.76%) may appear to be "outliers" relative to the overall trend, the low stock-out values achieved at those high yield rates can easily generate such results. Lastly, the benefit achieved using the Case 4 supplier monitoring strategy becomes insignificant at yield rates at/below 85%.

Table 7
Number of Stock-outs and Percent Stock-out Reduction at Factory 2 vs. Yield Rate

	Factory 2 Raw Material			Factory 2 Finished Goods		
Yield Rate	Case1	Case4	Percent Reduction	Case1	Case4	Percent Reduction
99%	4.70	0.00	100.00	0.00	0.00	n/a
98%	8.06	3.28	59.31	0.00	0.00	n/a
97%	11.84	3.46	70.78	0.00	0.00	n/a
96%	13.34	4.88	63.42	0.00	0.00	n/a
95%	14.82	6.02	59.38	0.30	0.12	60.00
94%	16.02	7.56	52.81	0.84	0.80	4.76
93%	16.64	11.32	31.97	2.18	0.90	58.72
92%	17.16	13.62	20.63	3.60	1.86	48.33
91%	19.70	17.04	13.50	3.60	1.86	48.33
90%	19.70	17.04	13.50	5.80	3.46	40.34
89%	21.28	19.92	6.39	8.54	7.62	10.77
88%	23.74	22.62	4.72	8.54	7.62	10.77
87%	25.70	25.02	2.65	10.42	9.72	6.72
86%	27.44	27.02	1.53	12.00	11.42	4.83
85%	28.56	28.38	0.63	13.34	12.98	2.70
84%	30.22	30.20	0.07	14.54	14.46	0.55
83%	30.20	30.14	0.20	15.60	15.56	0.26
82%	31.86	31.86	0.00	16.64	16.62	0.12
81%	32.46	32.46	0.00	17.68	17.68	0.00
80%	33.74	33.74	0.00	18.84	18.84	0.00

A major reason for Case 4's decline in performance as measured by stock-out reduction as a function of yield rate relates to production capacity and the inability to replenish yield loss. To further study this issue, Table 8 shows the effective capacities of Factories 1 and 2 based on the 39 unit/day and 42 unit/day maximum production capacities, respectively, given in Table 1.

Table 8
Effective Capacities at Factories 1 and 2 (Units/Day) as Function of Yield Rate

	Factory 1 (max capacity = 39 units/day)	Factory 2 (max capacity = 42 units/day)
95% yield rate	$39 \times 0.95 = 37.05$	$42 \times 0.95 = 39.90$
90% yield rate	$39 \times 0.90 = 35.10$	$42 \times 0.90 = 37.80$
85% yield rate	$39 \times 0.85 = 33.15$	$42 \times 0.85 = 35.70$
80% yield rate	$39 \times 0.80 = 31.20$	$42 \times 0.80 = 33.60$

Recalling the 30 unit/day expected daily demand (ref. Table 1), the reason the performance benefit drops significantly as yield rate declines is obvious. For example, when yield rate is 80%, a maximum of 31.2 units/day and 33.6 units/day can be produced at Factories 1 and 2, respectively. These values are close to the 30 unit/day expected daily demand and, thus, it is difficult to recover from any extra demand imposed by supplier monitoring. Thus, Factory 1 will not have the capacity to successfully increase its production rate whenever an order arrives earlier, as will happen when Factory 2 carries extra safety stock in response to an out-of-control condition signaled during supplier monitoring. In turn, Factory 2 cannot successfully increase its inventory (safety stock) level, even when a non-random condition is detected. *Therefore, it is important that Factory 1 has sufficient capacity to increase its production in order to effectively employ the supplier monitoring strategy.* In the case when Factory 1 is out of control much of the time and/or generally has low yields, it must carry greater levels of safety stock in finished goods inventory to allow Factory 2 to increase its safety stock, thereby permitting the strategy to work as planned.

Switching the focus from stock-outs to inventory levels, Table 9 shows the average inventory levels of raw material and finished goods at Factory 2. Since employing the supplier monitoring strategy requires temporarily increasing inventory levels when an out-of-control situation is detected, it is expected that average inventory levels will increase under the Case 4 strategy. Based on the data, this assumption is *mostly* true. At the highest yield rate (100%) and lowest yield rates (82% and below), average raw materials inventory levels at Factory 2 are actually the same in Cases 1 and 4. At 100% yield, an out-of-control situation at Factory 1 is never detected and, thus, Factory 2 will never increase its safety stock. At 80%-82% yield, Factory 1's production capacity in relation to its yield loss renders it unable to successfully respond to Factory 2's demand increase, thus "locking up" the system. Consequently, Factory 2 raw material inventory levels are the same for Cases 1 and 4 at these extreme yield rates. At yield rates between 83% and 99%, the differential between Factory 2 raw material inventory levels is much greater at higher yield rates. For example, at 97% yield, Case 4 results in 14.94 units of additional raw materials inventory (85.75 – 70.81) on average than does Case 1. Conversely, at 85% yield, Case 4 only results in 0.3 units of additional raw materials inventory (56.16 – 55.86) on average than does Case 1. As previously discussed, Factory 1's production capacity limits its ability to respond to Factory 2's increased safety stock demand whenever yield rates are low. To a lesser extent, Factory 2's finished goods inventory follows the same general pattern with a peak in differential occurring at yield rates between 92%-95%.

In summary, this experimentation has shown that out-of-control supplier situations can be detected using runs tests and that stock-outs can be significantly reduced by dynamically using safety stock. When both runs tests are used together, Factory 2 raw material stock-outs declined on average 25.07% across all yield levels (Table 7), while average inventory levels increased on average 8.45% (Table 9). Similarly, Factory 2 finished goods stock-outs declined on average 18.58% (Table 7) across all yield levels, while average inventory levels increased only 1.51% (Table 9).

Table 9
Average Inventory Levels at Factory 2

	Factory 2 Raw Materials			Factory 2 Finished Goods		
Yield Rate	Case1	Case4	Percent Increase	Case1	Case4	Percent Increase
100%	88.10	88.10	0.00	50.10	50.10	0.00
99%	75.02	95.34	27.09	49.41	49.70	0.59
98%	72.56	85.36	17.64	48.57	49.02	0.93
97%	70.81	85.75	21.10	47.74	48.50	1.59
96%	68.22	84.42	23.75	46.66	48.02	2.91
95%	65.98	80.43	21.90	45.48	47.22	3.83
94%	64.70	78.49	21.31	44.42	46.60	4.91
93%	64.35	76.27	18.52	43.40	45.74	5.39
92%	64.53	71.00	10.03	42.99	44.55	3.63
91%	64.07	68.12	6.32	42.36	43.47	2.62
90%	62.29	64.92	4.22	41.15	42.06	2.21
89%	61.10	61.93	1.36	40.26	40.62	0.89
88%	59.55	60.31	1.28	38.91	39.28	0.95
87%	58.15	58.74	1.01	37.76	37.96	0.53
86%	56.76	57.37	1.07	36.80	36.97	0.46
85%	55.86	56.16	0.54	35.96	36.03	0.19
84%	54.78	54.85	0.13	34.58	34.60	0.06
83%	54.78	54.90	0.22	34.44	34.47	0.09
82%	54.32	54.32	0.00	33.83	33.83	0.00
81%	54.12	54.12	0.00	33.15	33.15	0.00
80%	53.69	53.69	0.00	31.79	31.79	0.00

6. Conclusion, Limitations and Future Directions

This paper has conducted an exploratory analysis of a supplier monitoring and inventory policy change strategy. By "exploratory," we do not claim that the model and parameters studied are "optimal" and/or all inclusive in any sense. We simply wish to "lay the foundation" by conducting, to the best of our knowledge, the first quantitative assessment of a dynamic supplier monitoring and inventory change strategy in the context of supply chain risk mitigation. Key to the concept studied is the assumption that out-of-control situations at a supplier can be causal triggers for stock-outs, and that these triggers can be predicted by using statistical monitoring tools. It is also assumed that a dynamic policy is better than simply setting an artificially high safety stock level and maintaining it *ad infinitum*. Another objective of this study is to understand the conditions under which it such a policy performs the best.

In summary, the key findings of this exploratory research are stated below:

- The supplier monitoring strategy may be able to significantly reduce raw material and finished goods stock-outs at Factory 2, albeit at slightly increased inventory levels.
- The monitoring strategy (Case 4) consisting of both runs tests performed the best at reducing Factory 2 stock-outs.
- Overall, the number of stock-outs at Factory 2 increased as yield rate decreased.
- Overall, the average inventory levels at Factory 2 decreased as yield rate decreased.
- Due to Factory 1 capacity limitations, the relative benefit achieved using the Case 4 monitoring strategy can decline as yield rate decreases.

The experimentation has suggested that out-of-control situations can be detected using runs tests before a disruption actually occurs, and that stock-outs can be significantly reduced by temporarily adjusting inventory levels (i.e., adding safety stock). For example, when both runs tests are used in conjunction, Factory 2 raw material stock-outs declined on average 25.07% across all yield levels while average inventory levels increased on average 8.45%. Similarly, Factory 2 finished goods stock-outs declined on average 18.58% across all yield levels while average inventory levels increased only 1.51%. Although the cost of the inventory increase should be computed by a firm prior to utilizing the supplier monitoring strategy, the overall cost savings due to reduced supply chain disruptions may render the strategy worthwhile to pursue, especially in supply chain environments with a high cost and/or high risk of disruptions. Moreover, it was found that the possible benefit achieved by using the supplier monitoring and inventory change strategy is highest when both runs tests are used in conjunction and when the supplier has sufficient production capacity to respond to unexpected customer demand (safety stock) increases. When supplier production capacity is limited, the highest benefit is achieved when yield rates are relatively high and, thus, yield loss does not increase the supplier's production requirements in excess of its capacity. A major challenge faced by customers in applying such a strategy in a real world situation will be obtaining actual data from its supplier(s). In certain hostile supply chains, it is unlikely that suppliers would provide such operational information to their customers. However, there are supply chains in which the relationships are not hostile and are long term in nature (e.g., the Japanese model for key supplier relationships). In such friendly contexts, information sharing is more forthcoming and, thus, application of the proposed strategy may be feasible. Further examples of inter-organizational information sharing in modern supply chains have been presented as well (Albani & Dietz, 2009) and (Goswami et al., 2013).

There are certain assumptions and limitations used in this exploratory study which, if relaxed or approached differently, may provide different results. In turn, they serve as logical extensions and directions for future research. These items include, but are not limited to, the following:

1. Only yield rate is considered to model operational behavior at both factories. Factors such as production breakdowns or processing time variability are not addressed. Future research could study other such operational factors to assess their impact.
2. The same yield rate is used at both Factory 1 (i.e., supplier) and Factory 2 (i.e., customer). Future research could study the effect of differing yield rates at each supply chain entity.
3. Factory 1 is assumed to have a sufficient supply of raw material. Thus, no raw material shortages occurred at the supplier level. This assumption is largely the result of considering only one supplier and one customer in the supply chain. Future research could extend the supply chain model to include multiple suppliers at each stage and/or multiple levels of suppliers, thus explicitly addressing upstream raw material shortages at suppliers.
4. Two types of run tests are considered in this study, "runs up and down" and "runs above and below" tests. Future research could examine other types of statistical monitoring methods and/or control chart variations, either in isolation or in combination, to detect the existence of non-random supplier patterns.

5. Only a safety stock increase of 30 is considered when a non-random pattern is detected. Future research could examine various safety stock increases and relate those values to the resultant stock-out decrease, inventory increase and/or other performance measures.

In summary, although limited in scope, this paper has shown that if operational information can be shared between the supplier and customer, the customer can use relatively simple logic to dynamically respond to casual triggers which represent leading indicators for disruptive events that can impact a supply chain. In such cases, it is possible to reduce the downstream impacts (e.g., raw material shortages) associated with these events which, in turn, can stabilize those downstream entities. The sharing and use of such information does not currently exist in the supply chain management literature. Hopefully, this exploratory research will provide some insights and inspiration for further research into proactive supply chain risk management.

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