JOURNAL OF BUSINESS LOGISTICS
STRATEGIC SUPPLY CHAIN RESEARCH

Journal of Business Logistics, 2013, 34(4): 253–269

Assessing the Efficiency of Risk Mitigation Strategies in Supply Chains

Srinivas (Sri) Talluri[1], Thomas J. Kull[2], Hakan Yildiz[1], and Jiho Yoon[1]

[1]*Michigan State University*
[2]*Arizona State University*

Mitigating supply chain risk is a critical component of a company's overall risk management strategy. Drawing upon Contingency Theory, we posit that the appropriateness and effectiveness of risk mitigation strategies are contingent on the internal and external environments and that there is no one-size-fits-all strategy. While literature on risk management has proposed a variety of tools and techniques for effectively evaluating and managing supply chain risks, comprehensive assessment of the efficiencies of alternative risk mitigation strategies has not been addressed in the literature. Such an assessment will help managers select the appropriate mitigation strategy for a given decision-making environment. To this end, this study is first of its kind in evaluating and proposing efficient supply chain risk mitigation strategies in the presence of a variety of risk categories, risk sources, and supply chain configurations. We combine an empirically grounded simulation methodology with data envelopment analysis and nonparametric statistical methods to analyze and rank alternative mitigation strategies. We find that the more efficient strategies focus on flexibility rather than on redundancy for supply chain failures. Our research presents several interesting and useful managerial insights for deciding what strategies are most capable of mitigating risks in a variety of contexts.

Keywords: supply chain risk; risk mitigation strategies; simulation; data envelopment analysis; nonparametric statistical methods

INTRODUCTION

Recent years have witnessed many disasters that have created numerous problems for the supply chains of global companies (Sodhi and Tang 2012), and these disasters and their aftermath have brought increased attention to the role of risk management in supply chains (Narasimhan and Talluri 2009). New information technologies make it possible to extend supply chains to global markets (Sahin and Robinson 2002). This increases the dependence on outside resources and makes firms vulnerable to failures affecting all partners within the supply chain (Craighead et al. 2007). Uncertainties in factors such as market conditions, supply availability, and transportation can interrupt operations, thereby causing adverse effects for the companies involved (Hendricks and Singhal 2003).

Traditional supply chain designs normally focus on cost efficiency, assuming that the elements in the supply chain will perform as expected (see Karabati and Kouvelis 2008). Sheffi (2005) provides examples of severe problems that illustrate the inability of traditionally designed supply chains to deal with unanticipated events. In denying the assumption that supply chain elements will perform flawlessly, the assessment and selection of risk mitigation strategies then become a crucial element in the process of risk management. Unexpected losses arise from a sequence of failures and/or causal events (Lewis 2003). Organizations must determine the potential for such a sequence by understanding the conditions that give rise to such problems, and, subsequently, they must assess the likelihood of problems occurring and any negative impact the problems may entail (Young and Tippins 2001).

Corresponding author:
Professor Srinivas (Sri) Talluri, Michigan State University, Supply Chain Management, N370 Business Complex, 632 Bouge Street, East Lansing, MI 48864, USA; E-mail: Talluri@bus.msu.edu

Firms use a number of strategies to manage supply chain risks (Hillman 2006). Mitigation strategies are those in which the firm takes some action in advance; therefore, the firm incurs the cost of the mitigating action whether or not an unanticipated event or outcome occurs (Kleindorfer and Saad 2005). Because a firm is liable for costs regardless of the situation's end results, the effectiveness of a strategy must be judged with respect to its cost and noncost factors. In this article, we consider the seven risk mitigation solutions described in Chopra and Sodhi (2004), which can be classified into either redundancy or flexibility approaches. These approaches are the two main risk mitigation strategies that are identified in the literature and utilized in practice (see Rice and Caniato 2003; Rice and Sheffi 2005; Tomlin 2006; Tang and Tomlin 2008; Park 2011). Multiple potential sources for risks produce varying effects on a supply chain and complicate the selection of a risk mitigation strategy. We base our theoretical framework on Contingency Theory (CT) 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. We seek to provide guidance to academics and managers on evaluating and selecting risk mitigation strategies by considering various risk categories, risk sources, and supply chain configurations. Our methodology focuses on an empirically grounded, discrete event simulation, coupled with data envelopment analysis (DEA) and nonparametric statistical analysis (Kruskal–Wallis test), to determine the most appropriate mitigation strategies across a variety of aforementioned conditions and configurations. To the best of our knowledge, such an analysis has never been undertaken before and will prove useful for companies designing supply chains that can better respond to unanticipated failures.

The rest of the article is organized as follows: The next section reviews relevant risk management in supply chains literature and addresses the related gaps. Following the literature review is a discussion of our theoretical framework. We then present our methodology, analyze the results of our study, and discuss the managerial implications. The final section focuses on conclusions and potential extensions of this research.

LITERATURE REVIEW

In this section, we review studies on supply chain risk management that are most relevant to the topic of this article and we highlight some of the key issues requiring further attention. We refer the interested reader to Tang (2006), Zsidisin and Ritchie (2008), Sodhi et al. (2012), and Tang and Musa (2011) for a thorough review on supply chain risk and disruption management literature.

There is a significant amount of work related to identifying the types of supply chain risks. Although most of this work does not explicitly differentiate between the sources and categories of risk, we find it very useful to look at risk types through these two dimensions. With respect to the sources of risk, several studies exclusively consider either supplier and supply risk (see, e.g., Craighead et al. 2007) or customer and demand risk (see, e.g., Federgruen 1993; Schwarz and Weng 2000; Qi et al. 2004). While these two approaches can be useful for addressing issues in isolation, they do not help form a holistic understanding on how a strategy performs across multiple sources and types of risk. Snyder et al. (2006) emphasize a holistic approach by arguing that decision makers should take supply uncertainty into account during all phases of supply chain planning, just as they account for demand uncertainty. Our work takes a similarly encompassing approach and explicitly examines risks emanating from both supply and demand sides, in addition to considering internal risks associated with the manufacturer. Our methodology follows a risk-source classification similar to those in Davis (1993) and Chopra and Sodhi (2004), but goes beyond these approaches by empirically testing the efficacy of alternative risk mitigation strategies under a variety of supply chain configurations.

In terms of risk categories, recurrent risks and disruptions are among the two most studied risk categories in the literature, and a vast majority of risk events fall into one of these two categories. Tomlin (2006) recognizes the features of disruptions by categorizing long-but-rare disruptions and short-but-frequent disruptions in planning mitigation strategies. Similarly, Chopra et al. (2007) show the importance of recognizing and decoupling disruptions and recurrent risks when planning mitigation strategies in a supply chain. We further disaggregate recurrent risks into delays and distortions following Gaonkar and Viswanadham (2004), as recurrent risks related to time and quantity of orders are naturally different. Thus, we focus on three broad risk categories: delays, disruptions, and distortions. A *delay* in material flow can be viewed as a recurrent risk and can occur because of many reasons, such as variations in transportation or production lead times. A *disruption* occurs when the supply chain is radically and unexpectedly transformed through nonavailability of certain production, warehousing, distribution, or transportation options, such as equipment failure. A *distortion*, also known as "forecast risk," occurs when one or more parameters within the supply chain system, such as order sizes, stray from their forecasted and expected values.

Extensive research has been performed to reveal approaches firms can use to mitigate certain supply chain risks. For instance, Sheffi et al. (2003) describe mechanisms that companies follow to assess terrorism-related risks, protect the supply chain from those types of risks, and attain resilience. They report case studies and interviews with companies' executives. Christopher and Lee (2004) suggest that a key element in any strategy to mitigate supply chain risks is improved visibility, and they argue that supply chain confidence will increase in proportion to the quality of supply chain information. Many proposed risk mitigation strategies focus on uncertainty of demand or lead-times through the use of decision models. For instance, Schmitt et al. (2011) deal with choosing between risk pooling and risk diversification strategies by considering contingency approaches subject to disruptions. Other risk mitigation strategy literature goes beyond inventory-based models with demand uncertainty and instead focuses on production or supply rate changes. For example, Wang et al. (2010) investigate process improvement and dual-sourcing strategies to handle supplier reliability, and they present whether and how characteristics of the supply base influence strategy preference. Demirel et al. (2012) also compare single- and dual-sourcing strategies in the face of production disruptions using a game theoretical model. These studies show that strategies should address supply variability across multiple tiers in the supply chain but generally do not take a more comprehensive view by also considering multiple channels. To overcome this issue, we focus on a dual-channel supply chain in this study.

In selecting a risk mitigation strategy to counter against a particular risk type, it is important to test and compare alternative risk mitigation strategies in a comprehensive manner. Tomlin (2009) evaluates 12 possible disruption management strategies in the context of a two-product newsvendor. His results show that contingent sourcing is preferred to supplier diversification as the supply risk increases, but diversification is preferred to contingent sourcing as the demand risk increases. With the exception of Tomlin's (2009) study, the majority of the work in this area tests and compares few strategies in isolation. This article fills this gap by testing several alternative risk mitigation strategies under various risk and source combinations.

As detailed above, scholars have utilized a variety of approaches to analyze supply chain risks under various conditions, but there are gaps in the extant literature that we address in this study. Much of the literature does not allow for the simultaneous incorporation of traditional cost and noncost factors in evaluating the effectiveness of strategies, which is one of the advantages of our approach in considering a more holistic evaluation process. In addition, we utilize industry-specific cost data and perform sensitivity analysis to demonstrate the impact of cost changes in the evaluation of the mitigation strategies. Moreover, the literature does not adequately cover the responsive element of supply chain risk (Sodhi and Tang 2012) and our work addresses this issue to a certain extent by providing guidelines for what specific strategies to utilize in response to a particular risk.

Finally, early research in supply chain risk management has mostly been conceptual, case-based, or survey-based research. In recent years the focus has shifted toward quantitative models. As stated by Melnyk et al. (2009), case-based and empirical research is limited because it is difficult to evaluate how an event taking place at a supplier affects the performance of the firm and the overall supply chain, since we have to identify and account for the impact of any policies used and actions taken by the supplier. To develop a better understanding of supply chain disruptions—i.e., how to describe them, what factors influence them, and what policies/strategies can be used to deal with them—computer-based discrete event simulation is an approach that can add value. Moreover, simulation enables us to test the impact of internal and external environments on supply chain performance and the effectiveness of applying various risk mitigation strategies. In the context of supply chain risk, few studies utilize simulation. Levy (1995) presents a simulation model to examine the impact of demand uncertainty and supplier reliability on the performance of different supply chain network designs. Wilson (2007) developed a system dynamics simulation model to investigate the impact of a transportation disruption on supply chain performance by comparing a simple supply chain with a vendor-managed inventory system. Kull and Closs (2008) use discrete event simulation to show the effects of inventory and second-tier supplier disruptions on customer service. Munoz and Clements (2008) present a discrete event simulation of the Beer Distribution Game to quantify the potential lost sales revenue attributed to information and material delays in a supply chain. Dong et al. (2009) present a generalized simulation framework for tactical-level decision making for supply network analysis. Clearly, none of these studies are devoid of limitations. As some of the recent comprehensive reviews note (see Tang and Musa 2011 and Musa 2012), there is a dearth of in-depth simulation studies in the literature. Our study fills this gap and extends the supply chain risk simulation literature by using the simulation method that is grounded by secondary data and that is used in conjunction with DEA for efficiency evaluations.

THEORETICAL FRAMEWORK

Contingency Theory stems from behavioral theory and suggests that there is no universal set of choices that is optimal for all businesses (Gingsberg and Venkatraman 1985). The theory argues that optimal decisions within a firm are contingent on internal and external factors and the best way to organize depends on the nature of the firm's environment (Donaldson 2001). Performance, therefore, is affected by how well organizational resources match the corresponding business environment (Kim and Pae 2007). Several contributions have been made on this topic of the relationship between fit and performance in different fields of research, such as strategic management (Venkatraman 1989) and organization theory and design (Donaldson 2001). We base our theoretical framework on CT because firms that operate under risky conditions will implement mitigation strategies whose appropriateness and effectiveness are contingent on the internal and external environment.

This theoretical view is also utilized in other research studies on risk mitigation. Drawing upon CT, Park (2011) identifies internal risk, supply-related risk, customer-related risk, external risk, and risk taking propensity as antecedents that result in firms implementing flexibility- and redundancy-based supply chain risk mitigation strategies. Trkman and McCormack (2009) use CT to analyze the often conflicting findings on the role of environmental turbulence in supply chain risk management. They suggest a framework for the assessment of supplier risk of disruption based on a few factors that are modified by turbulence in their environment. Wagner and Bode (2008) apply CT and strategic choice theory to the relationship between supply chain risk and supply chain performance, and present hypotheses stating that the risk derived from various supply chain sources undermines supply chain performance. Given the applicability of CT in this context, we anchor our work in this domain and evaluate alternative mitigation strategies with the premise that utilization of a strategy is contingent on the internal and external environment to which the firm is exposed. Thus, we develop our article based on this theoretical lens.

METHODOLOGY

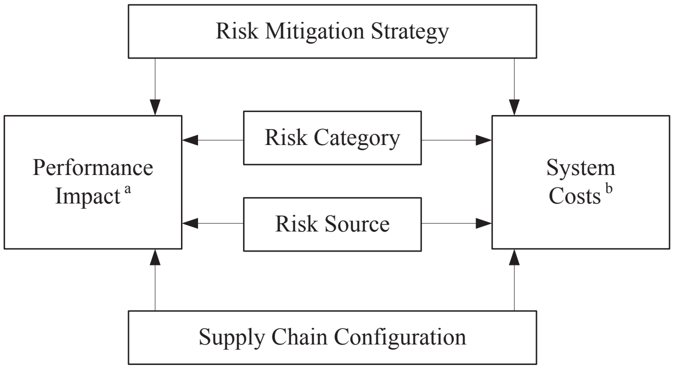
Simulation has long been used in operations management, logistics, and supply chain management (see Bowersox and Closs 1989; Chang and Makatsoris 2001; Holweg and Bicheno 2002; Shafer and Smunt 2004; Terzi and Cavalieri 2004; Kleijnen 2005; Evers and Wan 2012). Simulation experiments are effective and practical tools for analyzing supply chain phenomena (see Swaminathan et al. 1998 and Smaros et al. 2003). As discussed in the literature review section, few studies utilize simulation in the context of supply chain risk. This is likely because guidelines for supply chain risk simulations have only recently appeared (see Melnyk et al. 2009), and determining realistic parameters and settings can be challenging.

To compare alternative mitigation strategies, we conducted a simulation experiment, grounded in supply chain and simulation modeling theory (Swaminathan et al. 1998 and Law and Kelton 2000), to generate data on the effects of different strategies within different scenarios. Such an approach resembles the "what-if" supply chain risk analysis called for by Craighead et al. (2007). We used DEA to evaluate the resulting data from the simulation and generate the relative efficiency scores of alternative mitigation strategies under various supply chain structures. Since we were required to consider several factors in evaluating the effectiveness of alternative strategies, we selected DEA technique since it allows for the consideration of multiple factors in the form of inputs and outputs in the evaluation process. Subsequently, we utilized nonparametric statistical tests (Kruskal–Wallis) to identify the optimal mitigation strategies for a given supply chain structure. We employed this secondary method of testing to identify strategies that are not statistically different since it allows the decision maker to select the best strategy based on other factors, such as ease of implementation or resources available.

Simulation model

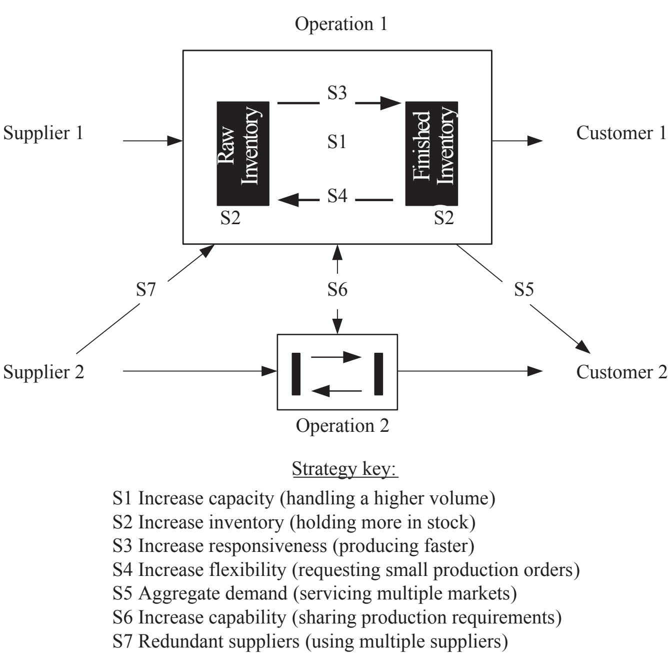
The influence diagram in Figure 1 depicts the processes that we incorporated into the simulation model. As shown, supply chain costs, such as transportation and inventory, and supply chain performance measures, such as service levels and cycle times, are impacted by supply chain configurations, such as ordering policies and demand variation. However, supply chain failures of different sources and categories negatively impact costs and performance, while mitigation strategies of different types lessen these negative impacts (Chopra and Sodhi 2004). Following this

Figure 1: Experimental framework.



[a]Operating performance (i.e., customer service level, inventory turns, etc.) of both manufacturing facilities. [b]Costs expected to vary with the strategy, risk type, and configurations.

Figure 2: Risk mitigation strategies mapped onto the supply chain structure.[a]



[a]Depiction of supply chain structure and location where risk mitigation strategy is in effect, noting that Operation 2 shares a similar mapping but is not shown for simplicity.

basic framework, we built a simulation model to accommodate the multitude of possibilities.

Simulation structure

To capture the essential features of each mitigation strategy while incorporating the increasingly common multichannel structure, we created a firm managing two parallel supply channels (Figure 2). Because supply chain phenomena are of interest, we assumed the focal firm performs light manufacturing to reduce internal manufacturing complexities. In the base case, we assumed both channels are supplied independently by a single supplier and serve independent customer markets that do not interact—a plausible condition if customer markets are heterogeneous or channel characteristics are diverse (Anderson et al. 1997). However, as described below, some mitigation strategies (designated by numbers in Figure 2) have these supply channels interacting in various ways. In Figure 2, we show a simple production cycle within each operation transforming raw material into finished goods. We constructed this simulation to model the flows within this supply chain structure.

The simulation is empirically grounded and approximates the operating levels found in top performing supply chains as reported in *Industry Week*'s value-chain survey.[1] Before introducing failures and strategies, manufacturing operations are configured to meet a 99% minimum service level, while optimizing[2] and minimizing excess manufacturing capacity and inventory levels. Suppliers are also configured to replicate the same *Industry Week* benchmarks. Basic model parameters and distribution assumptions are shown in Table 1 and are based on previous studies (Petrovic et al. 1998; Kull and Closs 2008). Thus, our model is grounded both in theory and in industrial practice.

When modeling supply chains, inventory control policies are a primary concern (Swaminathan et al. 1998). For the manufacturer's finished goods, we used a continuous review (s, S) ordering policy because of its popularity and efficiency in a light consumer goods industry (Scarf 1962; Ballou 2004). Our study assumed the following: a production order is issued when the *inventory position* (*IP*), which is calculated as *on-hand* + *in-process amount,* falls below s, with the order quantity determined by $S - IP$. To control the raw material, the manufacturer uses a periodic order-up-to policy in conjunction with a (s, S) policy (Petrovic et al. 1998; Gavirneni et al. 1999). Weekly replenishment orders are issued to the supplier to provide raw material levels up to a specified maximum quantity (M). With the parameters s, S, and M, the manufacturer controls the amount of finished and raw material inventory and the frequency of production orders.

Supply chain failures

Chopra and Sodhi (2004) describe how three types of supply chain failures—disruption, delays, and distortion[3]—can occur from three different sources—supplier, manufacturer, and customer. Together, these failures form the nine failure types shown in Table 2. Disruptions relate to an unexpected drop in supply or spike in demand and we modeled disruptions either as a decrease in capacity or an increase to the order volume. Delays pertaining to individual orders delivered later than expected are modeled as increases in mean cycle time. Distortions related to unforeseen changes in order size, a key feature of the bullwhip effect (Lee et al. 1997), are modeled as larger but less frequent order quantities. When a particular risk is instigated in this study, it is applied to both channels simultaneously yet independently.

We would like to note that, as illustrated in Table 2, the supply chain risks are considered only in one direction. For exam-

[1]http://www.industryweek.com/benchmarking

[2]Using ARENA's Optquest feature (Kelton et al. 2004).

[3]Chopra and Sodhi (2004) referred to this as information processing and forecast risk.

Table 1: Supply chain model assumptions

Parameter assumptions*	**Mean (days)**	**Distribution**
Supplier processing time	1.0	Normal (SD = 0.3)
Transit time to manufacturer	5.0	Lognormal
Manufacturer purchase order time	0.3	Triangular (min = 0.1, max = 1.0)
Manufacturer sales order time	0.5	Triangular (min = 0.2, max = 2.0)

Customer demand assumptions
Interarrival times are daily, constant, and for a single product;
Demand distribution is uniform with mean 100 and range ±20% or ±40%.
Model operations assumptions
All facilities operate 24 hr per day, 7 days per week;
Finished goods and raw material stock levels preloaded with typical days-on-hand (DOH) inventory;
Order policies are determined based upon strategic goals and no supply chain failures;
Order policy parameters are constant throughout simulation run;
Simulation run is 4,000 days after a 100-day warm-up; 10 replications, 252 scenarios;
Finished goods follow an (*s, S*) policy for production orders;
Raw material follows a 5-day periodic review, order-up-to policy (M = max qty) for purchase orders;
Cost assumptions[†]
\$40 processing cost per order;
\$450 logistics cost per shipment;
\$2.4 per finished good DOH for each day;
\$1.1 per work-in-process and raw material DOH for each day.[‡]

Notes: *Closs et al. (1998).
[†]Derived from CAPS Benchmarking Report (2007) assuming \$100 per unit sales price.
[‡]Cost of capital from the Value Line database of 7,364 firms. http://pages.stern.nyu.edu/~adamodar/New_Home_Page/

ple, for customer-related distortion risk, we only considered the case where the customer orders in larger batches. However, if a customer orders in smaller batches, the case would be considered a distortion risk as well. In some of the other cases, but not all, a deviation from status quo in either direction could result in supply chain issues. Since our paper is the first to broadly examine the various risk category–risk source combinations, we took a parsimonious approach and chose only one direction of change.

Mitigation strategies

This study utilized two main risk mitigation strategy types that are identified in the literature and used in practice: redundancy and flexibility. Rice and Caniato (2003) and Rice and Sheffi (2005) claim that firms can strengthen their resilience by either building in redundancy or by building in flexibility. Rice and Sheffi (2005) also emphasize that flexibility brings in benefits in the normal course of business, even if there are no risk realizations. According to Christopher and Peck (2004), resilient processes are both flexible and agile. Furthermore, Christopher and Peck (2004) also state that supply chains should reexamine the efficiency versus redundancy trade off. Taleb et al. (2009) state that lack of redundancy makes companies vulnerable to changes in the environment, and they posit redundancy as a good risk management strategy. We considered the seven risk mitigation strategies that Chopra and Sodhi (2004) proposed, which can be classified into either redundancy or flexibility strategies. Specifically, increasing capacity, redundant suppliers, and increasing inventory are redundancy strategies. Increasing responsiveness, increasing flexibility, aggregating demand, and increasing capability are flexibility strategies. We introduced each strategy independently and tested across all nine possible failure types. We chose to follow the advice of Chopra and Sodhi (2004) in selecting the parameters for mitigation strategies so that these values are large enough to reveal effects, but small enough to represent what is realistic.

Before introducing failures and strategies, we configured manufacturing operations in accordance with approaches by Gavirneni et al. (1999) and Kull and Closs (2008) to meet at least a 99% service level. That is, a search procedure within the simulation software is utilized with multiple iterations across varying levels of capacity and inventory in a step-wise fashion to find the lowest value to meet the service level threshold. Thus, we created a base case that removes potential confounds to performance when supply chain failures scenarios are examined.

Mitigation Strategies 1 through 4 are intra-operational. The first strategy relates to *capacity*, which places limits on when an operation can produce orders (Slack and Lewis 2008), and is

Table 2: Types of supply chain risks

	Risk source		
Risk category*	**1. Supplier-related**	**2. Internal**	**3. Customer-related**
1. Disruptions	Supplier capacity drops by 20%–r_{11}	Operational capacity drops by 20%–r_{12}	Demand goes up by 20%–r_{13}
2. Delays	Deliveries delayed by 4 MCT[†]–r_{21}	Production orders delayed by 4 MCT–r_{22}	Customer orders delayed by 4 MCT–r_{23}
3. Distortion	Supplier increases minimum order size by 20%–r_{31}	Production orders must increase size by 20%–r_{32}	Customers order in 20% larger batches–r_{33}

Notes: *Selected based upon nature of failure and possibility of emanating from each of three risk sources.
[†]Manufacturing cycle time (MCT) = Average order processing + Manufacturing processing time.

simulated as how often the schedule is open for new orders. When a capacity strategy was used, capacity increased by 20%. The second strategy involves increasing *inventory*, both raw material and finished goods, and is controlled by the policy parameters M and s, respectively. When an inventory strategy was used, these increased by 20%, which resulted in an increase of both cycle and safety stock levels. The third strategy increases *responsiveness*, which is related to faster deliveries, and is also simulated as a 20% increase in production rates. The fourth intra-operational strategy increases *flexibility*, which can be achieved with changing batch sizes because production volume will closely match demand, queue sizes will be reduced, and customers wait less for large batch completion (see Buzacott and Yao 1986; Agus and Mohd Shukri 2012). Thus, we simulated flexibility by reducing production order quantities by 20%. While we utilized 20% as the standard percentage change in all of the cases, the model can easily be modified to consider other levels.

Our research also simulated mitigation strategies 5, 6, and 7 as inter-operational, relating to activities between operational channels. As such, Strategy 5 involves *aggregating demand* and is simulated following the work of Ballou and Burnetas (2003), where customer orders are allowed to be serviced by the alternate supply channel if finished goods inventory is available. Similarly, Strategy 6, increases *capability*; that is, it allows production orders to be completed by the operation in the other supply channel if raw material is unavailable at the current channel. Finally, Strategy 7 involves using *redundant suppliers*. This strategy is simulated using purchase order splitting between the two suppliers (Thomas and Tyworth 2006). In addition, different supply chain conditions impact the usefulness of mitigation strategies; in particular, demand variability and supply uncertainty are two critical factors. These two dimensions are varied from low to high as shown in Table 3.

Simulation formulation and validation

To simulate the supply chain structure and experiment with the various risk elements, we utilized ARENA V4.01 simulation by Rockwell Software (Kelton et al. 2004). ARENA is a discrete event simulator, combining the SIMAN simulation language with a graphical interface, which aids the visual tracing of orders and material, and allows for operational and conceptual model validity (Sargent 2000). The logical flow of orders, production, and transportation is assured through use of standard simulation flow charts (Banks and Gibson 2001). Following Law and Kelton's (2000) techniques for simulation model development, and consistent with previous studies (Wan and Evers 2011), we programmed submodels and verified them individually before inclusion into the larger model so as to simplify debugging. In addition, supply chain performance graphs showed expected results during model test-runs under extreme settings (e.g., excessive production or transportation times).

Important to the simulation experiment were initial conditions, warm-up length, run length, factorial design, and replications (Law and Kelton 2000). We set initial inventories at the expected average. Given that preliminary observations found orders to propagate rapidly and that the system reached steady state quickly, we utilized a 100-day warm-up length, followed by a 4,000-day run length. We chose 10 replications with unique random number seeds based on Law and Kelton's (2000) procedure.[4] Since the seven mitigation strategies were compared across the nine risk types under four supply chain conditions, shown in Table 3, we utilized a 7 × 9 × 4 full factorial design with 10 replications, producing 2,520 samples.

Table 3: Experimental design

Factor type	Factor name	Settings
Risk types	Risk categories	Disruption/Delays/Forecasts
	Risk sources	Supplier/Internal/Customer
Supply chain configurations	Demand variation	Low/High*
	Risk likelihood	Low (0.2)/High (0.4)
Mitigation strategies	1. Increase capacity	+20% capacity
	2. Increase inventory†	+20% cycle and safety stock
	3. Increase responsiveness	−20% cycle time§
	4. Increase flexibility	−20% production quantity¶
	5. Aggregate demand	+cross filling**
	6. Increase capability	+transshipment††
	7. Redundant suppliers‡	+supplier

Notes: *Standard deviation from an expected constant demand rate.
†Increase parameters for ordering policies for both finished goods and raw material.
‡Uses supplier splitting (Thomas and Tyworth 2006).
§Decrease ordering and manufacturing processing times.
¶Accompanied by an increase in frequency.
**Send order to other manufacturing facility if finished goods are unavailable (Ballou and Burnetas 2003).
††Allow manufacturing facilities to produce products for each other if raw material unavailable.

For each sample, we provided five performance outcome averages over the entire simulation run. We computed average total cycle time by summing the average cycle time for sales orders, production orders, and purchase orders, and we calculated the average customer service level using percentage of nonbacklog orders. We used average days-on-hand inventory instead of actual amounts to improve generalizability. Our methodology generated utilization rates based on how often resources are busy producing orders. Finally, we calculated variable costs using published cost values (see Table 1) that pertain to those variables affected by the factors in the model: inventory holding costs, ordering costs, and transportation costs. Values for both supply

[4]To compute the number of replications, the largest relative variance [Var(x)/Avg(x)] among the outcome variables was determined for 10 replications. Then using formula 9.3 from Law and Kelton (2000, 512), $n^*(\gamma) = \min\{i \geq n : t_{i-1,1-\alpha/2}\sqrt{S^2(n)/i}/|\bar{X}(n)| \leq \gamma\}$, where gamma is the relative error, it was determined that 10 replications were appropriate for at most a 1% relative error among all the outcome variables. Law and Kelton (2000) recommend at least a gamma of .15 and an n of 10 or more.

channels were computed and combined where applicable for overall averages. These values were then analyzed using the DEA model, which also incorporates fixed costs as detailed in the results section later.

Data envelopment analysis

DEA is a linear programming-based technique that evaluates the relative efficiencies of a homogenous set of decision-making units (DMUs) in the presence of multiple input and output factors. Efficiency is defined as the ratio of weighted outputs to weighted inputs. In this study, we used DEA to identify the efficiency of the seven risk mitigation strategies, which correspond to DMUs in the context of this method. The only output considered in our evaluations is the *cycle service level* (CSL), whereas the inputs are *total costs (fixed and variable)*, *total average cycle time,* and *total inventory days on hand*. Note that we utilized factors where low is better as inputs and high is better as outputs, which is consistent with one of the ways by which inputs and outputs are categorized in DEA (see Khouja 1995).

The strengths of DEA are that it does not require limiting assumptions of many parametric methods, such as normality and equal variance; it does not need a priori factor weights to be specified in the evaluation process; and it is based on best practice, not average (mean) practice. DEA has extensively been utilized in the efficiency evaluation of various DMUs, such as schools, bank branches, hospitals, and manufacturing plants (Charnes et al. 1994). The DEA model as first introduced by Charnes et al. (1978), referred to as the CCR model, is shown below as problem (1):

Problem (1):

$$
\begin{aligned}
\max \quad & \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}} \\
s.t \quad & \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \leq 1, \quad \forall i \\
& v_k, u_j \geq 0 \quad \forall k, j
\end{aligned}
$$

where x_{ji} and y_{ki} indicate the jth input and kth output of the ith DMU (i.e., risk mitigation strategy in this study), respectively; x_{jp} and y_{kp} indicate the jth input and kth output of the pth DMU that is being evaluated, respectively; u_j and v_k are the weights assigned to jth input and kth output, respectively.

In the above model, each DMU "selects" input and output weights that maximize its efficiency score subject to constraints that prevent the efficiency scores of all the DMUs when evaluated with these weights from exceeding a value of 1. Thus, the input and output weights selected by a DMU are the decision variables in the model. A DMU is considered to be efficient if it achieves a relative efficiency score of 1 and is deemed inefficient with a score of less than 1. Problem (1) is a nonlinear model and can easily be converted to a linear programming model as shown in problem (2):

Problem (2):

$$
\begin{aligned}
\max \quad & \sum_{k=1}^{s} v_k y_{kp} \\
s.t \quad & \sum_{j=1}^{m} u_j x_{jp} = 1 \\
& \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0, \quad \forall i \\
& v_k, u_j \geq 0 \quad \forall k, j
\end{aligned}
$$

Problem (2) is solved once for each DMU in determining the relative efficiency scores. The dual problem of the above linear program is shown as problem (3) below:

Problem (3):

$$
\begin{aligned}
\min \quad & \theta \\
s.t \quad & \sum_{i} \lambda_i x_{ji} \leq \theta x_{jp} \quad \forall j \\
& \sum_{i} \lambda_i y_{ki} \geq y_{kp} \quad \forall k \\
& \lambda_i \geq 0 \quad \forall i
\end{aligned}
$$

where θ represents the efficiency score of DMU p and λ_i are the dual variables.

Because problem (3) is the dual problem, the objective function minimizes the efficiency score of unit p. The first two constraint sets in the model try to identify a composite unit, constructed from DMUs in the set, which utilizes less input than DMU p while generating at least the same output levels. If such a composite unit is identified, then DMU p that is being evaluated achieves a score of less than 1 and is considered to be inefficient. While the above problem works under the assumptions of constant returns to scale, Banker et al. (1984) extend problem (3) to consider variable returns to scale by including a convexity constraint that limits the summation of the λ values to 1, as shown in problem (4) below, and referred to as the BCC (Banker et al. 1984) model:

Problem (4):

$$
\begin{aligned}
\min \quad & \theta \\
s.t \quad & \sum_{i} \lambda_i x_{ji} \leq \theta x_{jp} \quad \forall j \\
& \sum_{i} \lambda_i y_{ki} \geq y_{kp} \quad \forall k \\
& \sum_{i} \lambda_i = 1 \\
& \lambda_i \geq 0 \quad \forall i
\end{aligned}
$$

Readers are encouraged to review the DEA references provided for more detailed information on model development.

Using the output from the simulation analysis, our methodology utilized the variable returns to scale structure of problem (4) to conduct DEA efficiency evaluations based on a variety of factors. In most production settings, the use of the BCC model works under the logical assumption that outputs cannot increase proportionally to increases in inputs.

In a traditional DEA application, it is critical to categorize inputs and outputs in a manner such that inputs are generally resources utilized and outputs involve a variety of performance and activity measures, such as flow times, quantity and quality of products produced, work-in-process levels, utilization rates, etc. This is because in a traditional DEA application, we generally investigate how the inefficient DMUs either reduce their inputs for the same level of outputs, or increase outputs for the same level of inputs in order to become efficient, that is, input-oriented and output-oriented DEA methods. Such an analysis provides managers with information regarding how to adjust the input/output factors of inefficient DMUs to make them efficient. However, in the context of our study, we were merely trying to differentiate between strategies that are efficient and strategies that are inefficient. Since we were not focusing on specific improvements associated with DMUs, it is reasonable to consider factors where "low" is better as inputs and factors where "high" is better as outputs. Our approach is similar to what Khouja (1995) utilizes in his study. DEA in our analysis defines an efficient mitigation strategy as having: high levels of output (high CSLs); and low levels of inputs (low *total costs* [variable costs + fixed costs = total transportation costs + inventory costs + fixed costs], low *total average cycle time* [average sales order cycle time + average manufacturing order cycle time + average purchase order cycle time], and low *total inventory days on hand* [finished goods + work-in-process + raw materials]). Thus, we can view this as a score that is being maximized based on variety of factors.

Kruskal–Wallis test

The DEA efficiency scores in our research were generated based on the three inputs and one output by considering all the 2,520 samples from the simulation analysis. Homogenous groups of mitigation strategies were subsequently obtained by investigating significant differences in efficiency scores among alternative strategies under a specific scenario combination; this investigation was conducted through the Kruskal–Wallis test (Conover 1999). The Kruskal–Wallis test is a nonparametric version of the standard *F*-test that is utilized under conditions of nonnormality. Since the efficiency scores do not lend themselves to assumptions of normality, we have considered the test for evaluating efficiency differences. The null and alternative hypotheses for the test in the context of our analysis are shown below:

H_0: The k population (mitigation strategies) distribution functions are identical.

H_a: At least one of the populations (mitigation strategy) yields larger observations than one of the other populations.

Test statistic is shown as expression (5) below:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{5}$$

where: k, the number of samples; n_i, the number of observations in the ith sample, where $i = 1$ through k; $N = \Sigma n_i$, the number of observations in all samples combined; R_i, the sum of the ranks in the ith sample.

Decision Rule: if $H > X^2$ $(k - 1,\ 1 - \alpha)$, then reject H_0; otherwise, fail to reject H_0, where α is the probability of making a type I error.

Once we rejected the null hypothesis, we evaluated the best strategies based on the pair-wise (strategy i vs. strategy j) differences of efficiency scores associated with the test. We made multiple comparisons using a one-way ANOVA to determine which samples are different. The samples i and j are different when the inequality shown as expression (6) is satisfied:

$$\left|\frac{R_i}{n_i} - \frac{R_j}{n_j}\right| > t_{1-\left(\frac{\alpha}{2}\right)} \left(S^2 \frac{N-1-T}{N-k}\right)^{\frac{1}{2}} \left(\frac{1}{n_i} + \frac{1}{n_j}\right)^{\frac{1}{2}} \tag{6}$$

where:

$$S^2 = \frac{1}{N-1}\left(\sum_{allranks} R\left(X_{ij}\right)^2 - N\frac{(N+1)^2}{4}\right) \tag{7}$$

$R(X_{ij})$, the rank assigned to observation j in ith group; t, the $(1 - \alpha/2)$ quantile of t distribution with $r - k$ df; α, the same as in the Kruskal–Wallis test.

DATA, RESULTS, AND DISCUSSION

The efficiencies of the seven mitigation strategies depend, in part, on the fixed costs associated with using each strategy. In order to ground the model in actual industrial costs, we used data from the U.S. Census Bureau[5] and from CAPS Research (a global research center for strategic supply management). Data were summarized by NAICS code to provide a range of typical cost values relative to the value of total capacity. We derived a low and high estimate to test the sensitivity of our results to the changes in fixed costs. Table 1A in the Appendix summarizes the operationalization of fixed costs, the formulas utilized, and the values used for each mitigation strategy. Strategies 2 and 4 do not have fixed costs, as these strategies increase only the variable cost and do not require up-front investments. Strategy 5 is actualized by closing down one facility and pooling machinery into one large facility, which reduces fixed costs, much like savings derived from consolidation and economies of scale. The other remaining four strategies—1, 3, 6, and 7—have traditional fixed costs associated with them. The procedure utilized for calculating these costs is explained in detail in the Appendix.

All data used for these estimations are available for 21 industry categories (see Tables 2A and 3A). This granularity allowed us to choose a specific industry and use the fixed cost estimates for that industry. To test the impact of the increase in fixed cost estimates on the efficiencies of mitigation strategies, we calculated efficiencies for the lowest and highest values of fixed costs. For instance, the fixed cost for Strategy 1 is the lowest for the furniture and related product industry ($263,069) and the highest for the computer and electronic industry ($710,287).

As discussed earlier, we evaluated a total of 2,520 scenarios with respect to the three inputs and one output in evaluating the relative efficiency scores. We obtained variance within a specific configuration with the 10 replicates generated for each case. Table 4 depicts the results of our analysis based on statistical comparisons of efficiencies (based on the Kruskal–Wallis test), and demonstrates the best (most efficient) strategies for each risk

[5] http://www2.census.gov/econ2010/AM/sector31/AM1031GS101.zip

Table 4: Best Supply Chain Risk Mitigation Strategies for a Given Configuration and Scenario*

Risk Scenario			**Configuration with respect to demand variability (DV) and risk likelihood (RL)**				
Risk category	**Risk source**	**Fixed costs**	**Low DV & Low RL**	**Low DV & High RL**	**High DV & Low RL**	**High DV & High RL**	**Robust for given scenario**†
Disruption	Supplier-related	Low	1,3,4,5	3,5,7	1,3,4,5	3,4,5,7	3,5
		High	1,4,5	5	1,4,5	4,5	4,5
	Internal	Low	1,3,4,5,7	3,7	3,5	3,7	3,7
		High	5	5	5	5	5
	Customer-related	Low	1,3,4,5	1,3,5,6	1,3,4,5	3,5	1,3,5
		High	1,4,5	1,5,6	1,4,5	5	1,5
	Robust for given configuration†		1,4,5	5	1,4,5	5	5
Delay	Supplier-related	Low	3,6	3,6	3,6	3,6	3,6
		High	5,6	5,6	3,5,6	5,6	5,6
	Internal	Low	3,7	3,6,7	3,7	3,6,7	3,7
		High	5	5	5,6	5	5
	Customer-related	Low	3,7	3,7	3,7	3,7	3,7
		High	5	5,7	5	5,7	5
	Robust for given configuration†		n/a	n/a	3	n/a	n/a
Distortion	Supplier-related	Low	1,4,5	4	1,4,5	1,4,5	4
		High	1,4,5	1,4,5	1,4,5	1,4,5	1,4,5
	Internal	Low	3,5	3,5	3,5	3,5	3,5
		High	5	5	5	5	5
	Customer-related	Low	4,5	3,5,6,7	1,4,5	3,5,6,7	5
		High	4,5	5	1,4,5	5	5
	Robust for given configuration†		4,5	5	1,4,5	5	5

Notes: *Strategies are numbered as follows: (1) Increase capacity, (2) Increase inventory, (3) Increase responsiveness, (4) Increase flexibility, (5) Aggregate demand, (6) Increase capability, and (7) Redundant suppliers.
†Strategy is considered robust if it appears in the majority of cells in a row or a column.

category and supply chain configuration combination. For example, if the type of risk category is disruption and it is supplier-related and occurs in a situation where the demand variability and risk likelihood is low, then the most efficient mitigation strategies are 1 (increase capacity), 3 (increase responsiveness), 4 (increase flexibility), and 5 (aggregate demand) when fixed cost is low, and 1, 4, and 5 when fixed cost is high. This type of analysis provides an excellent roadmap for the decision maker by outlining which mitigation strategies to focus on for a specific risk and supply chain configuration. An interesting finding reveals that decision makers have a set of strategies that are equally effective; that is, the efficiency differences between them are not statistically significant. This analysis provides the decision maker with alternative choices, and the decision can be based on ease of implementation of a particular strategy.

Table 4 reveals the importance of taking a CT perspective and sheds light on what strategies are robust across risk scenarios and supply chain configurations. For example, if the type of risk category is disruption and it is internal, then Strategy 3 (increase responsiveness) and Strategy 7 (redundant suppliers) work best across all supply chain configurations when the environmental condition is of low fixed cost. By contrast, Strategy 5 (aggregate demand) is best when the environmental condition is high fixed cost. These results reveal the importance in building environmental-contingent types of capabilities that lead to short- and long-term mitigation strategies as the supply chain transforms. Decision makers can use this information to plan for contingent capabilities to better fit their environmental realities in order to manage risks without increasing redundancy in the supply chain.

In addition, Table 4 points to which strategies are robust for a given internal environment supply chain configuration. For example, if the demand variability is high and risk likelihood is low, then, in general, the best set of strategies across all risk types are 1 (increase capacity), 4 (increase flexibility), and 5 (aggregate demand). If decision makers have clear knowledge of what specific supply chain contingencies they exist in, then this analysis assists them in building situational-specific capabilities that mitigate various risks in an effective manner. The row and column analysis for Table 4 provides important information for decision makers to manage and appease related risks in their supply chains.

Beyond the CT perspective, at a high level, the results we obtained in this study mostly align with the recommendations provided by Chopra and Sodhi (2004), although not all of their recommendations are proved to be efficient. The two best strategies across all risk types appear to be the same in our analysis and in Chopra and Sodhi (2004): Strategies 5 (aggregating demand) and 3 (increasing responsiveness). Thus, our article validates the theoretical framework provided by Chopra and Sodhi (2004) for risk mitigation. As for the least efficient strategies, both studies identified Strategy 6 (increasing capability) as one of the cases. Our results indicate Strategy 2 (increasing inventory) as a second inferior case, which is not highlighted in Chopra and Sodhi (2004). We see this finding as further validating our efficiency perspective: holding just-in-case inventory is a costly strategy that serves only to shield risks and does not aid in risk recovery. In general, we find that the more efficient strategies focus on flexibility rather than on redundancy for supply chain failures. In the next section, we discuss specific managerial implications associated with our results and expand on the recommendations for strategy selection.

MANAGERIAL IMPLICATIONS

Managers face the problem of designing their supply chains for risk events that cannot be precisely predicted. Since supply chain failures can occur in a multitude of forms, choosing a mitigation strategy that protects the supply chain from many types of risks simultaneously is more desirable than strategies applicable only for a specific type of risk. To this end, we propose efficient strategies that span across a variety of risks and supply chain configurations. This approach has important benefits for companies wanting to mitigate risks both from effectiveness and resource allocation standpoints. If a particular mitigation strategy works well in appeasing multiple types of risks, management can allocate scarce resources in developing that specific strategy instead of designing multiple strategies that might not be cost effective.

In this study, we addressed concerns managers face in risk management approaches. We find that the most efficient strategies across many risks are not designed to shield firms from effects (i.e., redundancy), but rather are designed to improve the recovery process (i.e., flexibility). These results seem to be the overarching reasoning for the best strategies we have identified. In particular, the demand aggregation strategy—typically meant to reduce demand variation so that inventories are lower (Eppen 1979)—is robust in allowing the supply system to divert orders to other supply channels and prevent disruptions for customers. Even though this strategy strains the alternate supply channel, the effect is temporary and allows the failed channel time to recover. Our results follow the theme of other research by recommending the resilience of a supply chain as a critical design feature (see Christopher and Peck 2004; Sheffi 2005).

While certain mitigation strategies are dominant, we find evidence for contingent efficiencies depending on the risk category, risk source, and supply chain configuration. In other words, managers must consider that some unique strategies are better suited than others for given circumstances. For instance, while increasing capacity and flexibility (Strategies 1 and 4) efficiently mitigates disruption risks in many of our scenarios, such strategies are not as efficient for delay-type risks. Similarly, having supplier redundancy (Strategy 7) is primarily seen as being efficient for nonsupplier delay-type risks. One of the reasons for these variations is that the type of risk often has a bearing on the mechanism that makes a strategy useful. For example, Strategies 1 and 4 are useful because they allow quick recovery from failure, but a delay specifically diminishes this ability to recover quickly. Similarly, supplier-related delays directly prevent supplier redundancy (Strategy 7) from being beneficial. These results show that managers who foresee specific types of risk as becoming more probable can consider our study in developing a contingency-based risk mitigation response.

Contingent effects of fixed costs and supply chain configurations are also observed. Specifically, as an industry's fixed cost increases, strategies such as increasing capacity (Strategy 1) and increasing responsiveness (Strategy 3) tend to diminish in efficiency. This decline in efficiency is expected because such strategies consume excessive resources in anticipation of an event. Companies in the computer/electronics and chemical industries that have higher fixed costs (as shown in Table 2A) should be particularly sensitive to such information. As risks become more probable, fewer efficient strategy options are available and demand aggregation (Strategy 5) tends to dominate. This conclusion indicates that as the prevalence of failures increases, the ability to alternate how customers are served becomes highly critical.

Finally, managers must build into their contingency plans ways to respond when competitive and supply environment changes as risks become more or less likely. Knowing if transitions will be needed from one strategy to another is important for supply chain design choices and resource deployment. For example, if a company predicts that distortion risks will decrease and delay risks will increase, it might need to reconfigure supply chain designs from a reliance on excess capacity (Strategy 1) to a focus on increasing responsiveness (Strategy 3). Thus, by having knowledge regarding the relationships between risks and strategies, forward-thinking supply chain managers and decision makers can build strategy transitions into their long-range planning and supply chain designs. Moreover, certain strategies have path dependencies (e.g., building cross-filling capabilities to create transshipment capabilities). This somewhat restricts how easy future strategies are to implement. We show how strategies group by statistical equivalence (i.e., differences are statistically insignificant). This points decision makers toward options as they map out mitigation strategies that are not only efficient, but are also easier to implement and better aligned with their firms' capabilities.

CONCLUSIONS AND EXTENSIONS

This study evaluates and compares the efficiency of alternative risk mitigation strategies under a variety of risk categories, risk sources, and supply chain configurations. We base our theoretical framework on CT because the appropriateness and effectiveness of risk mitigation strategies are contingent on the internal and external environment, and because a blanket strategy does not prove effective under all conditions. The article builds on the initial conceptual work of Chopra and Sodhi (2004) relating to risk mitigation and optimal strategy selection in supply chains. In the area of risk mitigation, to the best of our knowledge, this is the first paper that looks at comprehensive evaluation of mitigation strategies. Thus, our work has important implications for academics and managers and sets the stage for future developments.

Our work effectively validates the suggestions developed by Chopra and Sodhi (2004) for risk mitigation by using a well-designed simulation study combined with DEA efficiency analysis and nonparametric statistical methods. The article presents robust results based on a scientific methodology from which managers can benefit.

Our study also directs managers to robust and effective mitigation strategies under a variety of contingencies. This is important in resource allocation decisions because managers can focus on building and investing in competencies that can appease a variety of risks. We find evidence that comports with other literature extolling the benefits of supply chain resiliency through flexibility as an efficient risk mitigation strategy, while showing costly redundancy strategies, like inventory buffering, to be less preferred options. Our results provide a useful roadmap for managers challenged by the task of using limited resources to manage risks.

While this study makes significant advances in the research of supply chain risk, it is not devoid of limitations. First, our simulation experiment was designed around multichannel supply chain arrangement. While many firms use such arrangements, particularly with the advent of direct and brick-and-mortar supply chain channels (Metters and Walton 2007), some managers may not face such a scenario. However, our research can easily be extended to a single channel arrangement that models a more traditional one manufacturing plant scenario. Applying this study to single channel supply chain risk involves more complicating factors within production, but such research would further enrich our framework.

While identifying the key parameters for the simulation and some of the risk mitigation strategies, we chose mitigation strategy values that are large enough to reveal effects, but small enough to represent what is realistic. An alternative and more realistic approach may be to include costs associated with risk events (including demand variations, supply variations, and the revenue impact of service levels) when calculating those key parameters. This alternative model can be a very useful extension to our study, where readers who become aware of our findings will be able to select a specific strategy–risk combination and find the optimal policy parameters.

Regarding the types of risks, Chopra and Sodhi (2004) note numerous other events that we do not examine that can also result in supply chain issues. These events deserve further study by taking a narrower but deeper look into each risk type. We also studied risks and strategies in isolation. That is, we did not allow for multiple risks or strategies to be interacting simultaneously. While this approach was necessary in order to gain relational insights, further research should consider how such interactions create complementary or counteracting effects. In addition, greater cost variations can be introduced to further approach industry actualities. Finally, we see the need for empirical validations by querying managers as to what has worked in the past and why. These are some potential extensions that can be considered to gain additional insights into this important and practical area.

APPENDIX A

Fixed costs are calculated by using industrial annual cost estimates. These figures are then scaled to the size of our simulated company. For Strategies 1, 3, 5, 6, and 7, this calculation is performed by using the proportion of the capacity of the simulated company for the duration of the simulation run (FCAP) to the annual industrial capacity (ICAP). Both capacities are expressed in USD. The annual industrial capacity is calculated by dividing the annual industrial value of shipments (TVS) by the industry capacity utilization rate (IU). TVS is defined as the received or receivable net selling values of all products shipped. IU is obtained from the Quarterly Survey of Plant Capacity Utilization (QPC),[6] which provides quarterly statistics on the rates of capacity use for the U.S. manufacturing sector. The QPC is conducted across ~7,500 manufacturing establishments selected from the Economic Census.

The capacity of the simulated company is calculated in a similar way by dividing the value of shipments by the capacity utilization ratio obtained from the simulation results. Below we explain the various industry costs used for the affected mitigation strategy. The formulas used for each strategy and the value range obtained are given in Table 1A.

Strategy 1 (increasing capacity) fixed cost is assessed as the capital expenditures required for higher throughput. This cost is estimated using the annual capital expenditures (ITCX) from the U.S. Census, which represents total new and used capital expenditures reported by establishments in operation and under construction. These data include expenditures for permanent additions, major building alterations, new and used machinery, equipment used for replacement, and additions to plant capacity, including transportation and information processing equipment.

Strategy 3 (increasing responsiveness) fixed cost is evaluated as the expenditures for enhanced information processing. This cost is estimated by using the expenditures for enhanced information processing capabilities (ITE) from the U.S. Census.

Strategy 5 (aggregating demand) fixed cost is computed as the savings from consolidating to a single facility. This cost is estimated by using total annual building/structure expenditures (IBE) from the U.S. Census with a typical depreciation used for buildings after average use (20% of original).

Strategy 6 (increasing capability) fixed cost is appraised as the expenditures for enhanced machine processing. This cost is estimated by using the total annual machinery and equipment expenditures (IME) from the U.S. Census. Since Strategy 6 refers to upgrading rather than purchasing new machinery, we multiply this cost by a discount factor of 10%.

Strategy 7 (redundant suppliers) fixed cost is assessed as the coordination costs for adding an additional supplier. This cost is estimated by using the average supply management operating expenses per shipment value (ES) from the CAPS Research Data, which includes all the supply management group's salary- and payroll-related expenses (e.g., FICA, benefits); allocated expenses (e.g., space, facilities, equipment, utilities, telecommunications, information technology, etc.); and unallocated expenses (controllable expenses incurred such as travel, training, materials, and supplies). This cost is then multiplied by the simulated company's baseline value of shipments for full simulation run (FVS).

[6] http://www.census.gov/manufacturing/capacity/

Table A1: Estimation of fixed costs by mitigation strategy

Mitigation strategy	Associated fixed cost	Estimation equation*,†,‡	Value range (low-high) over simulation run
1. Increase capacity	Capital expenditures required for higher throughput	$\frac{ITCX}{ICAP} \times FCAP \times 20\%$	\$263,069 to \$710,287
2. Increase inventory	Not applicable—variable cost only		
3. Increase responsiveness	Expenditures for enhanced information processing	$\frac{ITE}{ICAP} \times FCAP \times 20\%$	\$2,631 to \$76,290
4. Increase flexibility	Not applicable—variable cost only		
5. Aggregate demand	*Savings* from consolidating to a single facility	$\frac{IBE}{ICAP} \times FCAP \times DEP$	(\$42,091) to (\$139,427)
6. Increase capability	Expenditures for enhanced machine processing	$\frac{IMR}{ICAP} \times FCAP$	\$85,497 to \$290,691
7. Redundant suppliers	Coordination costs for adding a supplier	$\frac{ES}{SS} \times FVS$	\$157 to \$4,235

Abbreviations from US Census Data: ITCX = Industry total annual capital expenditures (average for 2009 and 2010)—CEXTOT in census data; ITE = Industry total annual information technology expenditures (average for 2009 and 2010)—CEXMCHC in census data; IBE = Industry total annual building/structure expenditures (average for 2009 and 2010)—CEXBLD in census data; IMR = IMER = Estimate of upgrade/retro-fit costs—note that IME is too high as this may include additional equipment, not just retrofitting; R = some fraction of machinery costs to represent a retro-fit—currently given at 10%; IME = Industry total annual other machinery and equipment expenditures (average for 2009 and 2010)—CEXMCHO in census data; ICAP = Estimate of industrial output capacity = TVS/IU; TVS = Industry average total annual value of shipments (average for 2009 and 2010); IU = Industry capacity utilization rate (average for 2009 and 2010); DEP = Typical depreciated, used value for buildings after average use (20% of original).

†Abbreviations CAPS Research Procurement Characteristics: ES = Average percent supply management operating expenses per shipment value = OE × SP; SP = Average spend percent of shipment value; OE = Average supply management operating expense (SMOE) percent of spend; SS = Average number of strategic suppliers.

‡Abbreviations Simulated Firm Characteristics: FCAP = Firm baseline capacity for simulation run = FVS/FU; FVS = Firm baseline value of shipments for full simulation run = avg. daily shipment value (\$100/unit × 100 units × 2 facilities) × 3900; FU = Firm baseline utilization rate (computed without risks or strategies included).

Table A2: Generalizable industrial ratios for use in estimating fixed costs

Manufacturing industry	Utilization	Capital expenditures (CX)	Value of shipments (VS)	Total capacity (CAP) in value of shipments (VS/U)	Material cost per value of shipments	Cost of capacity (CX/CAP)	Information processing (CEXMCHC) per CAP	Building & structure (CEXBLD) per CAP	Machinery and equipment (CEXMCHO) per CAP
Food	69.6%	13,823,388	613,247,694	880,835,221	56%	1.6%	0.05%	0.29%	1.18%
Beverage & tobacco products	68.0%	3,165,082	123,544,822	181,803,313	37%	1.7%	0.05%	0.34%	1.30%
Textile mills	65.0%	814,253	28,010,491	40,943,508	51%	1.6%	0.07%	0.20%	1.35%
Textile product mills	59.0%	437,695	20,384,591	34,580,255	51%	1.3%	0.10%	0.16%	0.95%
Apparel	67.9%	174,149	10,205,938	15,034,123	35%	1.2%	0.17%	0.30%	0.65%
Leather & allied products	55.7%	99,547	4,514,331	8,374,988	48%	1.2%	0.09%	0.31%	0.79%
Wood product	51.9%	1,633,234	64,233,921	123,958,103	55%	1.3%	0.06%	0.20%	0.97%
Paper	80.9%	5,083,977	161,367,849	199,368,625	47%	2.5%	0.08%	0.23%	2.21%
Printing & related support activities	56.9%	2,238,557	79,240,559	139,636,458	35%	1.6%	0.16%	0.17%	1.24%
Petroleum & coal products	67.4%	14,946,592	530,456,114	784,317,249	84%	1.9%	0.01%	0.21%	1.71%
Chemical	68.8%	19,546,166	606,956,659	881,707,127	44%	2.2%	0.09%	0.45%	1.66%
Plastics & rubber products	64.8%	5,780,644	171,860,222	267,266,418	48%	2.2%	0.07%	0.22%	1.85%
Nonmetallic mineral product	51.9%	3,613,488	86,254,732	166,410,667	37%	2.2%	0.05%	0.23%	1.76%
Primary metal	61.1%	7,406,963	194,491,863	316,586,072	61%	2.4%	0.04%	0.31%	1.98%
Fabricated metal product	59.8%	7,534,003	270,597,571	452,969,953	42%	1.7%	0.10%	0.22%	1.29%
Machinery	59.5%	7,639,218	282,092,601	474,236,081	49%	1.6%	0.11%	0.27%	1.20%
Computer & electronic products	64.5%	12,781,392	307,454,580	478,797,825	36%	2.7%	0.29%	0.53%	1.83%
Electrical equipment & component	58.7%	2,469,539	101,766,309	173,226,319	48%	1.4%	0.10%	0.27%	1.04%
Transportation equipment	51.8%	14,613,018	570,135,962	1,099,766,910	56%	1.3%	0.06%	0.24%	1.00%
Furniture & related products	62.2%	916,969	54,584,530	87,805,180	43%	1.0%	0.11%	0.17%	0.72%
Miscellaneous	64.8%	3,875,872	136,008,270	210,522,711	31%	1.8%	0.21%	0.35%	1.25%
Average	62.4%	6,123,512	210,352,838	334,197,481	47%	1.7%	0.10%	0.27%	1.33%
Minimum	51.8%	99,547	4,514,331	8,374,988	31%	1.0%	0.01%	0.16%	0.65%
Maximum	80.9%	19,546,166	613,247,694	1,099,766,910	84%	2.7%	0.29%	0.53%	2.21%

Table A3: Generalizable industry estimates for supply management operating expenses per supplier*

Industry	Strategic suppliers (SS)	Averages and estimates: SM operating expense as percent of spend (OE)	Spend as percent of sales (SP)	SM operating expense as percent sales (ES = OE x SP)	ES per strategic supplier (SME=ES/SS)
Aerospace	214	2.52%	46.11%	1.16%	0.00543%
Automotive & transport	432	1.04%	56.75%	0.59%	0.00137%
Chemical	338	0.90%	52.52%	0.47%	0.00140%
Computer software	706	0.47%	30.30%	0.14%	0.00020%
Consumer products	1,631	0.63%	52.67%	0.33%	0.00020%
Diversified food & beverage	539	0.33%	57.09%	0.19%	0.00035%
Defense contractors	427	1.94%	41.74%	0.81%	0.00190%
Electronics	2,471	1.14%	49.00%	0.56%	0.00023%
Industrial manufacturing	1,272	0.76%	47.94%	0.36%	0.00029%
Metals & mining	589	0.54%	51.35%	0.28%	0.00047%
Petroleum	494	0.60%	28.65%	0.17%	0.00035%
Pharmaceutical	637	0.63%	48.80%	0.31%	0.00048%
Semiconductor	188	0.64%	55.73%	0.36%	0.00190%
Average	707	0.93%	47.59%	0.44%	0.0011%
Minimum	188	0.33%	28.65%	0.14%	0.0002%
Maximum	2,471	2.52%	57.09%	1.16%	0.0054%

*Based on data from the most recent CAP Research Cross-Industry Benchmark Data (2009).

REFERENCES

Agus, A., and Mohd Shukri, H. 2012. "Lean Production Supply Chain Management as Driver Towards Enhancing Product Quality and Business Performance." *The International Journal of Quality and Reliability Management* 29(1):92–121.

Anderson, E., Day, G.S., and Rangan, V.K. 1997. "Strategic Channel Design." *Sloan Management Review* 38(4):59–69.

Ballou, R.H. 2004. "Inventory Policy Decisions: Reasons for Inventory." In *Business Logistics Management*, edited by R.H. Ballou, 328–30. Englewood Cliffs, NJ: Prentice Hall.

Ballou, R.H., and Burnetas, A. 2003. "Planning Multiple Location Inventories." *Journal of Business Logistics* 24(2): 65–89.

Banker, R.D., Charnes, A., and Cooper, W. 1984. "Models for the Estimation of Technical and Scale Inefficiencies in Data Envelopment Analysis." *Management Science* 30:1078–92.

Banks, J., and Gibson, R. 2001. "Simulating in the Real World." *IIE Solutions* 33:38–40.

Bowersox, D.J., and Closs, D.J. 1989. "Simulation in Logistics: A Review of Present Practice and a Look to the Future." *Journal of Business Logistics* 10(1):133–48.

Buzacott, J.A., and Yao, D.D. 1986. "Flexible Manufacturing Systems—A Review of Analytical Models." *Management Science* 32(7):890–905.

Chang, Y., and Makatsoris, H. 2001. "Supply Chain Modeling Using Simulation." *International Journal of Simulation* 2 (1):24–30.

Charnes, A., Cooper, W., Lewin, A.Y., and Seiford, L.M., eds. 1994. *Data Envelopment Analysis: Theory, Methodology, and Application*. Boston: Kluwer.

Charnes, A., Cooper, W., and Rhodes, E. 1978. "Measuring the Efficiency of Decision Making Units." *European Journal of Operations Research* 2(6):429–44.

Chopra, S., Reinhardt, G., and Mohan, U. 2007. "The Importance of Decoupling Recurrent and Disruption Risks in a Supply Chain." *Naval Research Logistics* 54(5):544–55.

Chopra, S., and Sodhi, M.S. 2004. "Managing Risk to Avoid Supply-Chain Breakdown." *MIT Sloan Management Review* 46(1):53.

Christopher, M., and Lee, H. 2004. "Mitigating Supply Chain Risk Through Improved Confidence." *International Journal of Physical Distribution and Logistics Management* 34(5):388–96.

Christopher, M., and Peck, H. 2004. "Building the Resilient Supply Chain." *International Journal of Logistics Management* 15(2):1–14.

Closs, D.J., Roath, A.S., Goldsby, T.J., Eckert, J.A., and Swartz, S.M. 1998. "An Empirical Comparison of Anticipatory and Response-Based Supply Chain Strategies." *International Journal of Logistics Management* 9(2):21–34.

Conover, W.J. 1999. *Practical Nonparametric Statistics*. 3rd ed. New York, NY: Wiley Publishers.

Craighead, C.W., Blackhurst, J., Rungtusanatham, M.J., and Handfield, R.B. 2007. "The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities." *Decision Sciences* 38(1):131–56.

Davis, T. 1993. "Effective Supply Chain Management." *Sloan Management Review* 34(4):35–46.

Demirel, S., Kapuscinski, R., and Chen-Ritzo, C. 2012. "Strategic Behavior of Suppliers in the Face of Production Disruptions." Doctoral Dissertation, University of Michigan, Ann Arbor, MI. http://deepblue.lib.umich.edu/bitstream/handle/2027.42/93917/sdemirel_1.pdf?sequence=1

Donaldson, L. 2001. *The Contingency Theory of Organizations*. Thousand Oaks, CA: SAGE Publications, Incorporated.

Dong, J., Wang, W., and Wu, T. 2009. "A Generalized Simulation Framework for Responsive Supply Network Management." In *Managing Supply Chain Risk and Vulnerability*, edited by T. Wu and J. Blackhurst, 67–88. London: Springer.

Eppen, G. 1979. "Effects of Centralization on Expected Costs in a Multi-Location Newsboy Problem." *Management Science* 25:498–501.

Evers, P.T., and Wan, X. 2012. "Systems Analysis Using Simulation." *Journal of Business Logistics* 33(2):80–99.

Federgruen, A. 1993. "Centralized Planning Models for Multi-echelon Inventory Systems Under Uncertainty." In *Logistics of Production and Inventory*, edited by S.C. Graves, A.H. Rinnooy Kan, and P.H. Zipkin, 133–73. Amsterdam: North-Holland Publishing Company.

Gaonkar, R., and Viswanadham, N. 2004. "*A Conceptual and Analytical Framework for the Management of Risk in Supply Chains*." Proceedings of the 2004 IEEE International Conference on Robotics and Automation, New Orleans, LA, 2699–704.

Gavirneni, S., Kapuscinski, R., and Tayur, S. 1999. "Value of Information of Capacitated Supply Chains." *Management Science* 45(1):16.

Gingsberg, A., and Venkatraman, N. 1985. "Contingency Perspectives of Organizational Strategy: A Critical Review of the Empirical Research." *Academy of Management Review* 10 (3):421–34.

Hendricks, K.B., and Singhal, V.R. 2003. "The Effect of Supply Chain Glitches on Shareholder Wealth." *Journal of Operations Management* 21(5):501–22.

Hillman, M. 2006. "Strategies for Managing Supply Chain Risk." *Supply Chain Management Review* 10(5):11–13.

Holweg, M., and Bicheno, J. 2002. "Supply Chain Simulation a Tool for Education, Enhancement and Endeavor." *International Journal of Production Economics* 78(2): 163–75.

Karabati, S., and Kouvelis, P. 2008. "Optimal Quantity Discount Design With Limited Information Sharing." *Decision Sciences* 39(4):791–819.

Kelton, D.W., Sadowski, R.P., and Sturrock, D.T. 2004. *Simulation With Arena*. 3rd ed. New York: McGraw-Hill.

Khouja, M. 1995. "The Use of Data Envelopment Analysis for Technology Selection." *Computers and Industrial Engineering* 28(1):123–32.

Kim, N., and Pae, J. 2007. "Utilization of New Technologies: Organizational Adaptation to Business Environments." *Journal of the Academy of Marketing Science* 35(2):259–69.

Kleijnen, J.P.C. 2005. "Supply Chain Simulation Tools and Techniques: A Survey." *International Journal of Simulation and Process Modeling* 1(1):82–89.

Kleindorfer, P.R., and Saad, G.H. 2005. "Managing Disruption Risks in Supply Chains." *Production and Operations Management* 14(1):53–68.

Kull, T., and Closs, D. 2008. "The Risk of Second-Tier Supplier Failures in Serial Supply Chains: Implications for Order Policies and Distributor Autonomy." *European Journal of Operational Research* 186(3):1158–74.

Law, A.M., and Kelton, W.D. 2000. *Simulation Modelling and Analysis*. 3rd ed. New York, NY: McGraw Hill Higher Education.

Lee, H.L., Padmanabhan, V., and Whang, S. 1997. "Information Distortion in a Supply Chain: The Bullwhip Effect." *Management Science* 43(4):546.

Levy, D. 1995. "International Sourcing and Supply Chain Stability." *Journal of International Business Studies* 26 (2):343–60.

Lewis, M.A. 2003. "Cause, Consequence and Control: Towards a Theoretical and Practical Model of Operational Risk." *Journal of Operations Management* 21(2):205–24.

Melnyk, S.A., Rodrigues, A., and Ragatz, G.L. 2009. "Using Simulation to Investigate Supply Chain Disruptions." In *Supply Chain Risk: A Handbook of Assessment, Management, and Performance*, edited by G.A. Zsidisin, and R. Ritchie, 103–22. New York: Springer.

Metters, R., and Walton, S. 2007. "Strategic Supply Chain Choices for Multi-Channel Internet Retailers." *Service Business* 1:317–31.

Munoz, A., and Clements, M.D. 2008. "Disruptions in Information Flow. A Revenue Costing Supply Chain Dilemma." *Journal of Theoretical and Applied Electronic Commerce Research* 3(1):30–40.

Musa, S.N. 2012. "Supply Chain Risk Management: Identification, Evaluation and Mitigation Techniques." PhD Thesis, Linköping University, Sweden.

Narasimhan, R., and Talluri, S. 2009. "Perspectives on Risk Management in Supply Chains." *Journal of Operations Management* 27(2):114–18.

Park, K. 2011. "Flexible and Redundant Supply Chain Practices to Build Strategic Supply Chain Resilience: Contingent and Resource-Based Perspectives." Doctoral Dissertation, University of Toledo, Toledo, OH.

Petrovic, D., Roy, R., and Petrovic, R. 1998. "Modelling and Simulation of a Supply Chain in an Uncertain Environment." *European Journal of Operational Research* 109(2):299–309.

Qi, X., Bard, J.B., and Yu, G. 2004. "Supply Chain Coordination With Demand Disruptions." *Omega* 32(4):301–12.

Rice, J.B., and Caniato, F. 2003. "Building a Secure and Resilient Supply Network." *Supply Chain Management Review* 7(5):22–30.

Rice, J.B. Jr., and Sheffi, Y. 2005. "A Supply Chain View of the Resilient Enterprise." *MIT Sloan Management Review* 47 (1):41–48.

Sahin, F., and Robinson, E.P. 2002. "Flow Coordination and Information Sharing in Supply Chains: Review, Implications, and Directions for Future Research." *Decision Sciences* 33 (4):505–36.

Sargent, R. G. 2000. "*Verification, Validation, and Accreditation of Simulation Models*." In Proceedings of the 2000 Winter Simulation Conference, 50–59.

Scarf, H. 1962. "The Optimality of (s, S) Policies in the Dynamic Inventory Problem." In *Mathematical Methods in Social Sciences*, edited by S. Arrow, S. Karlin, and P. Suppes, 196–202. Stanford, CA: Stanford University Press.

Schmitt, A.J., Snyder, L.V., and Shen, Z.M. 2011. "*Centralization and Decentralization: Risk Pooling, Risk*

Diversification, and Supply Uncertainty in a One-Warehouse Multiple Retailer System." Working Paper. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1115392

Schwarz, L.B., and Weng, Z.K. 2000. "The Design of a JIT Supply Chain: The Effect of Lead-Time Uncertainty on Safety Stock." *Journal of Business Logistics* 21(2):231–53.

Shafer, S.M., and Smunt, T.L. 2004. "Empirical Simulation Studies in Operations Management: Context, Trends, and Research Opportunities." *Journal of Operations Management* 22(4):345–54.

Sheffi, Y. 2005. *The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage*. Cambridge: The MIT Press.

Sheffi, Y., Rice, J.B., Jr, Fleck, J.M., and Caniato, F. 2003. *Supply Chain Response to Global Terrorism: A Situation Scan*. Center for Transportation and Logistics, MIT, Department of Management, Economics and Industrial Engineering, Politecnico di Milano: European OMA-POMS Conference.

Slack, N., and Lewis, M. 2008. *Operations Strategy*. 2nd ed. Harlow: Prentice Hall.

Smaros, J., Lehtonen, J.-M., Appelqvist, P., and Holmstrom, J. 2003. "The Impact of Increasing Demand Visibility on Production and Inventory Control Efficiency." *International Journal of Physical Distribution and Logistics Management* 33(4):336–54.

Snyder, L.V., Scaparra, M.P., Daskin, M.S., and Church, R.L. 2006. "Planning for Disruptions in Supply Chain Networks." Tutorials in Operations Research: Models, Methods and Applications for Innovative Decision Making, INFORMS.

Sodhi, M.S., Son, B.G., and Tang, C.S. 2012. "Researchers' Perspectives on Supply Chain Risk Management." *Production and Operations Management* 21(1):1–13.

Sodhi, M.S., and Tang, C.S. 2012. *Managing Supply Chain Risk*. New York: Springer Verlag.

Swaminathan, J.M., Smith, S.F., and Sadeh, N.M. 1998. "Modeling Supply Chain Dynamics: A Multiagent Approach." *Decision Sciences* 29(3):607–32.

Taleb, N.N., Goldstein, D.G., and Spitznagel, M.W. 2009. "The Six Mistakes Executives Make in Risk Management." *Harvard Business Review* 87(10):78–81.

Tang, C.S. 2006. "Perspectives in Supply Chain Risk Management." *International Journal of Production Economics* 103(2):451–88.

Tang, C.S., and Tomlin, B. 2008. "The Power of Flexibility for Mitigating Supply Chain Risks." *International Journal of Production Economics* 116(1):12–27.

Tang, O., and Musa, S.N. 2011. "Identifying Risk Issues and Research Advancements in Supply Chain Risk Management." *International Journal of Production Economics* 133:25–34.

Terzi, S., and Cavalieri, S. 2004. "Simulation in the Supply Chain Context: A Survey." *Computers in Industry* 53(1):3–16.

Thomas, D.J., and Tyworth, J.E. 2006. "Pooling Lead-Time Risk by Order Splitting: A Critical Review." *Transportation Research Part E: Logistics and Transportation Review* 42(4):245–57.

Tomlin, B. 2006. "On the Value of Mitigation and Contingency Strategies for Managing Supply Chain Disruption Risks." *Management Science* 52(5):639–57.

Tomlin, B. 2009. "Disruption-Management Strategies for Short Life-Cycle Products." *Naval Research Logistics* 56:318–47.

Trkman, P., and McCormack, K. 2009. "Supply Chain Risk in Turbulent Environments—A Conceptual Model for Managing Supply Chain Network Risk." *International Journal of Production Economics* 119(2):247–58.

Venkatraman, N. 1989. "The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence." *Academy of Management Review* 14(3):423–44.

Wagner, S.M., and Bode, C. 2008. "An Empirical Examination of Supply Chain Performance Along Several Dimensions of Risk." *Journal of Business Logistics* 29(1):307–25.

Wan, X.A., and Evers, P.T. 2011. "Supply Chain Networks With Multiple Retailers: A Test of the Emerging Theory on Inventories, Stockouts, and Bullwhips." *Journal of Business Logistics* 32(1):27–39.

Wang, Y., Gilland, W., and Tomlin, B. 2010. "Mitigating Supply Risk: Dual Sourcing or Process Improvement." *Manufacturing and Service Operations Management* 12(3):489–510.

Wilson, M.C. 2007. "The Impact of Transportation Disruptions on Supply Chain Performance." *Transportation Research – Part E* 43(4):295–320.

Young, P.C., and Tippins, S.C. 2001. *Managing Business Risk: An Organization-Wide Approach to Risk Management*. New York: AMACOM.

Zsidisin, G.A., and Ritchie, R., eds. 2008. *Supply Chain Risk: A Handbook of Assessment, Management, & Performance*. New York: Springer International.

SHORT BIOGRAPHIES

Srinivas Talluri (PhD University of Texas at Arlington) is a Professor of Operations and Supply Chain Management at the Eli Broad College of Business at Michigan State University. His research interests are in the areas of purchasing and supply chain management, technology evaluation and justification, and performance evaluation. He has more than 60 journal publications in journals such as *IIE Transactions, Decision Sciences, Production and Operations Management Journal, International Journal of Production Research, European Journal of Operational Research, Journal of Operations Management, Journal of Business Logistics,* and *IEEE Transactions on Engineering Management*. Sri serves as a Department Editor for IEEE *Transactions on Engineering Management*, Associate Editor for *Decision Sciences Journal* and the *Journal of Business Logistics*, and editorial board member for *Production and Operations Management Journal* and the *International Journal of Production Research*. He is a member of DSI, POMS, and INFORMS.

Thomas J. Kull (PhD Michigan State University) is an Associate Professor of Supply Chain Management at the W. P. Carey School of Business, Arizona State University. He researches behavioral issues in operations and supply chain management, as well as supply chain risk issues. He has published a book based on his research (*People, Process, & Culture: Lean Manufacturing in the Real World*, CRC Press) and his research has appeared in the *Journal of Operations Management, Journal of Business*

Logistics, Journal of Supply Chain Management, European Journal of Operational Research, and other supply chain related journals. He serves on numerous editorial review boards including the *Journal of Operations Management*, *Decision Sciences*, and *Journal of Supply Chain Management*.

Hakan Yildiz (PhD Carnegie Mellon University) is an Assistant Professor in the Department of Supply Chain Management at Michigan State University. His research interests include supply chain risk management, logistics optimization, and resource management in service operations. Current projects include reliable supply chain network design, planning for equipment rentals, and talent supply chain management. His research has appeared in *Naval Research Logistics, European Journal of Operational Research*, *Journal of the Operational Research Society,* and *Interfaces*.

Jiho Yoon (MS University of Michigan) is a PhD candidate in the Department of Supply Chain Management at Michigan State University. He received his MS degree in industrial and operations engineering in 2010. His current research interests include developing mathematical optimization models and determining design principles for supply chain networks. His work focuses on supply chain risk management in the context of risk mitigation strategy evaluation and selection, and reliable supply chain network design.