

The Human Factor in Supply Chain Risk Management

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ABSTRACT

In a three paper essay series we address the human impact in SCRM from the microeconomic and macroeconomic perspectives. First, using a positivist theory building approach, we synthesize behavioral risk management and supply chain risk management theory to propose behavioral supply chain risk management as a new topic area. This paper is microeconomic in nature and focuses mostly on individuals as the unit of analysis in a SCRM context. Second, we introduce cross-impact analysis as a scenario-based supplier selection methodology. We demonstrate how cross-impact analysis can be used to provide supply chain decision-makers with probability estimates of the future viability of the members of a given set of possible suppliers in a backdrop of macroeconomic risk.

The third and final paper in the series incorporates the probability estimates resulting from a cross-impact analysis exercise into a hybrid stochastic mixed-integer programming (SMIP) technique CIA-SMIP. We demonstrate how the CIA-SMIP approach can be utilized as a single-source supplier selection model.

In its totality, this dissertation represents a step towards the theoretical framing of the human impact on SCRM into two main distinguishable areas: microeconomic and macroeconomic.

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GENERAL AUDIENCE ABSTRACT

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Dedication

This dissertation is dedicated to my family:

My ever-loving ever-supportive wife, Erica Faye Cooper without whom none of this would have been possible. We started this together and we continue on this journey together.

And to the joy and light of my life, my daughter my “mini-me”, Natalya Ruvarashe Kwaramba who continues to inspire me to be better than I ever thought I could be.

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Finally, we raise a glass to my father PJ who was gone too soon, but I know is watching over me and is as proud as he could ever be.

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Introduction

Overview

As supply chains become more global and complex they are increasingly at risk of being adversely affected by random physical phenomena or events and/or human risk behavior (C. S. Tang 2006). The majority of supply chain risk management (SCRM) and operations management models are centered around protecting the supply chain from the negative effects of random physical phenomena or events that cause partial or complete interruptions of the flow of goods in the supply chains (Bendoly et al. 2006; Schorsch et al. 2017) . The impact of humans in the supply chain is a less studied area of supply chain management (Schorsch et al. 2017). Even less prevalent are studies that specifically address the impact of humans in a supply chain risk management context (see Ho, Zheng, Yildiz, & Talluri, (2015)).

Recently, there has been increased interest in the human impact on supply chains (Macdonald and Corsi 2013). A growing body of literature exists that addresses the human impact in SCRM from different perspectives. A significant portion of these studies is centered around risk taking behavior at the individual level (Ambulkar, Blackhurst, & Cantor, 2016; Cantor, Blackhurst, & Cortes, 2014; DuHadway, Carnovale, & Kannan, 2018) and at the firm level (Bode et al. 2011a; Chopra and Manmohan S Sodhi 2004; G. A. Zsidisin and Ellram 2003). A relatively small portion of SCRM studies focuses on the impact of human economic at the macroeconomic level (Anis et al. 2002; Cao et al. 2016; Erbahar and Zi 2017; Hammami et al. 2014; Hoekman and Leidy 1992) This dissertation, through a three paper series, extends prior research on the impact

of humans in SCRM by highlighting the differences between two main approaches to SCRM: 1) microeconomic and 2) macroeconomic (Ho et al. 2015).

SCRM through a microeconomic lens

In the first of three papers (Paper 1), we address the need for a unified approach to individual risk behavior in SCRM. Therein, we advocate for a bona fide behavioral supply chain risk management topic area. We propose that the field be named behavioral supply chain risk management (BSCRM). We contribute to the literature by conceptualizing BSCRM as a new topic through the synthesis of behavioral risk management and SCRM theory. This paper is microeconomic in nature and focuses mostly on individuals as the unit of analysis in a SCRM context. This is in contrast with the remaining two studies in the series which view the impact of humans through a macroeconomic lens.

SCRM through a macroeconomic lens

The second paper's (Paper 2) primary purpose is to introduce Cross-Impact Analysis (CIA) (Gordon and Hayward 1968) as a scenario-based methodology. In this study, CIA is used to predict ways in which a supply chain can be adversely affected by independent macroeconomic events that are external to it. CIA is well suited for the purposes of analyzing a set of interrelated events. Given a set of interdependent macroeconomic events, CIA provides practitioners with a way to systematically reduce the numbers of possible SCRM outcomes into a mathematically tractable and thus more manageable set of scenarios. We demonstrate how CIA can be used as a tool for supplier selection in a global environment faced with the risk of disruptions caused by macroeconomic events. CIA provides supply chain decision-makers with probability estimates of the future viability of the members of a given set of possible suppliers in a backdrop of macroeconomic risk.

The third and final paper in the series incorporates the probability estimates resulting from a CIA exercise like the one outlined in Paper 2, into a hybrid stochastic mixed-integer programming (SMIP) technique CIA-SMIP. We extend an SMIP model introduced in Sawik, (2018) and demonstrate how the CIA-SMIP approach can be utilized as a single-source supplier selection model.

Research agenda

The three studies, Papers 1, 2 and 3 aim to answer the following research questions respectively:

- 1) Should BSCRM be considered its own topic area?
- 2) How does human microeconomic activity impact supplier selection in global supply chains?
- 3) How can we incorporate the human impact into an extant quantitative supplier selection model?

In their totality, the three papers are a step towards the theoretical framing of the human impact on SCRM into two main distinguishable areas: microeconomic and macroeconomic. In general, we consider microeconomic activity to comprise the human impact that is internal to the supply chain. Whereas macroeconomic activity is considered as being external to the supply chain. Both microeconomic and macroeconomic events can expose the supply chain to operational and/or financial risks. The costly nature of the manifestation of supply chain risk has been confirmed in extant literature (Craighead et al. 2007). Thus, it is in the firms' interest to understand the various types of supply chain risks to which it is exposed, and also know how to mitigate against them. With the understanding that risk is unavoidable (Craighead et al. 2007; Sodhi, Son, & Tang, 2012), this dissertation paper series serves to add to the body of knowledge on possible ways of minimizing firms exposure to supply chain risks.

Chapter 1

Toward a Behavioral Theory in Supply Chain Risk Management

Abstract

We advance the topic area of supply chain risk management (SCRM) by addressing the lack of a clearly defined and unified approach to accounting for human risk behavior in supply chain studies. Using a positivist theory-building approach, we begin to develop a meta-theory and delineate behavioral supply chain risk management (BSCRM) from SCRM. We find that extant studies about behavior in SCRM mostly use the firm as the unit of analysis; even though it is individual decision-makers' risk behavior that is being realized in many SCRM outcomes.

Our main contributions to the literature are: 1) the conceptualization of BSCRM as a new topic and 2) the introduction of a BSCRM framework. We demonstrate how this framework synthesizes behavioral risk management with SCRM theory and paves the way for future theoretical contributions to this important field. As far as we can tell we are first to suggest the unifying term, 'behavioral supply chain risk management' (BSCRM).

1 Introduction

The role of human risk behavior in determining supply chain risk management (SCRM) outcomes is often overlooked. For example, few people recognize the 2007 global financial crisis as a SCRM problem (Shefrin, 2016). Aspiration and the exuberant prospect of personal gain drove individual decision-makers at Merrill Lynch and other similar investment banking firms to take inordinate amounts of risk leading up to the crisis (Shefrin, 2016). The result of these misguided behavioral choices was a concentration of high-risk strategy in the one part of the banking supply chain. Namely: the riskiest segment of the housing sector. This precarious concentration of risk ultimately proved to be unsustainable and was a direct cause of the 2007 global financial crisis (Shefrin, 2016).

Without even considering the human fallout and the long-lasting negative effects of the financial crisis, the US Treasury Department put the resultant total loss in household wealth in the US alone at \$19.2 billion (Childress, 2012). This realization that the global financial crisis could have been avoided through the appropriate management of behavioral risk in the banking supply chain, points to the relevance and importance of the human behavior in SCRM.

The area of SCRM, in general, is becoming increasingly popular and rich with innovative studies (Grötsch, Blome, & Schleper, 2013; Ho, Zheng, Yildiz, & Talluri, 2015; Hohenstein, Feisel, & Hartmann, 2015). However, the consideration of human or individual decision-makers' behavior in SCRM models and frameworks is in its nascent stages (Macdonald & Corsi, 2013)

In the past there has been an initial tendency for OM researchers to “assume away” the behavioral or human factor in their initial OM decision models (Bendoly, Donohue, & Schultz, 2006). In following the chronological evolution of other related topic areas in operations management (OM) such as product development, process improvement and design and, logistics and supply chain management (SCM), studies centered around the mechanistic operational aspect have generally preceded human behavior-based studies (Bendoly et al., 2006). For example, after a period characterized by an abundance of studies based on objective quantitative models, Boudreau et al. (2003) begin to address the behavioral gap in OM literature by identifying the common behavioral assumptions made in OM studies. They outline the criticality of human behavior when it comes to the success of OM tools and techniques. Bendoly et al. (2006) build upon Boudreau et al. (2003) and extol the unrealized potential for the explicit consideration of the human impact in OM. In a similar manner, as SCM has matured as a field, there has been increased interest in human behavior in the supply chain. For example, in logistics and distribution management, Tokar, (2010) highlights the significance of behavioral research as a way of building theory and improving the predictive accuracy of extant models. Later on, Schorsch et al. (2017) build upon this study and formally introduce a unified behavioral supply chain management (BSCM) framework which delineates BSCM as a separate topic area from SCM.

We predict that the same chronological turn of events is bound to occur in the SCRM. Our literature search reveals that the question of “*What* risks should be managed in the supply chain?” have thus far comprised the bulk of the literature but there is increasing interest in the questions of “Who manages supply chain risk?” and “How can they be managed?” However, this research direction is in its nascent stages and there is yet to be a unifying BSCRM framework and theory. We contend that applying Schorsch et al.'s (2017) BSCM theoretical framework as a way of closing the behavioral gap in SCRM research is insufficient because the risk management in a supply chain setting presents its own set of peculiar and distinct problems and challenges. The BSCM framework broadly defines the behavioral aspect of individuals while embedded in a SCM context (Schorsch et al., 2017). However, the BSCM framework makes no mention of human risk behavior in a SCRM context. The SCM context is clearly differentiated from the SCRM in the literature (Sodhi, Son, & Tang, 2012). Also, human beings have been shown to behave differently when faced with risk (Shefrin, 2016). Thus, it is not an inconceivable conceptual leap to assert that there should exist a theoretical delineation between human behavior in a SCM context and human behavior in a SCRM context. To that end, this study draws the line between the related fields of BSCM and behavioral supply chain risk management (BSCRM).

We argue that the proposed emergent topic area of behavioral SCRM (BSCRM) cannot be a simple add-behavior-to-SCRM-and-stir proposition. Managing people in the backdrop of risk calls for the specific application of risk behavior-based theoretical approaches. These differ from some of the popular normative behavioral theories prescribed in micro organizational behavior (OB) and management literature (Shefrin, 2016). Humans have been shown to display unexpected behavior when faced with risk (Shefrin, 2016). For example, the expected utility theory by Von Neumann & Morgenstern (1944) makes the normative assumption that *decision framing* affects actual choice. However, Tversky and Kahneman (1981) show, through the use of behavioral experiments, that the *loss or gains framing* elicits unexpected behavioral responses which were more adequately explained by their own prospect theory. There are relatively few studies that consider human behavior in a SCRM setting. Based on this, we make the case that BSCRM should be considered as a separate topic area from BSCM.

1.1 The scope of behavioral SCRM (BSCRM)

Drawing from Schorsch et al. (2017), we find defining BSCRM and its scope to be an appropriate starting point for theory building. SCRM is defined as a coordinated approach amongst supply chain members aimed at identifying and managing risks to the supply chain in order to decrease overall supply chain vulnerability (see Jüttner, 2004; Jüttner, Peck, & Christopher, 2003). We adapt this definition and define BSCRM as *the management of human behavior under uncertainty or risk in order to reduce supply chain vulnerability*. Pivotal to our BSCRM definition are the characteristics that set supply chains apart from simple traditional Business to Business (B2B) transactional arrangements. They include but are not limited to: approaches to inventory management; total cost control; increased visibility and information-sharing; deliberate joint planning amongst its members and interfirm coordination of risk (Cooper & Ellram, 1993). Supply chains are highly specialized and distinct entities that transcend firm boundaries. They are recognizable as a deliberate effort towards coordination (Arshinder et al. 2008) and collaboration (Wagner & Bode, 2008) amongst its firm members in all the important aspects of performance, including a common risk outlook (Li et al. 2015). This is in contrast to a collection of loosely connected businesses, each with its own different organizational culture and appetite for and approach to risk management.

1.2 Defining and identifying BSCRM studies

In order for any study to be relevant to BSCRM, it must be primarily considering risk management in a supply chain context. We posit that in order to satisfy this requirement, one or more of four widely accepted risk management constructs: 1) risk identification, 2) risk assessment, 3) risk mitigation, 4) risk response and risk performance measurement (Jüttner et al., 2003) have to represent the context of the basic argument or research question. Also necessary

would be at least one of two supply chain conditions: 1) at least two supply chain firms in an exchange relationship (Cooper, 1997) or 2) the individual risk behavior of a decision-maker under consideration having a direct and measurable effect on a supply chain risk. For example, a plant manager for a critical supplier may increase the whole supply chain's exposure to risk if she decides not to invest in costly plant robustness because doing so may result in a lower end-of-year bottom line and subsequently a lower annual personal bonus.

1 Literature review

Although scarce, the literature is not totally devoid of SCRM studies that take on a behavioral angle. Many, like Zsidisin (2003), use behavioral economic theory (Tarde 1902) to present the buyer and supplier as being part of a principle and agent arrangement in which the negotiation of interfirm contracts between a principle (the more powerful firm; usually the buyer) and an agent (the subordinate or less powerful firm; usually the supplier) is studied. The firm is the unit of analysis in this case. Others that adopt the same firm level approach include Celly & Frazier (1996), Eisenhardt (1989), Lassar & Kerr (1996), Payan & Nevin (2006), Zeng et al. (2015). The firm level approach to BSCRM is rooted in the idea of a uniform organizational approach to SCM. We conjecture that this approach is appropriate and adequate for the study of firm behavior in SCM. However, in a SCRM context and when human risk behavior is a consideration, the abstraction of BSCRM should be studied at the individual level. This is because risk behavior is rooted in psychology (Shefrin 2016) and is thus directly attributable to the individual. The unit of analysis should thus be the individual. Studies like Parker & Russell (2004) identify behavioral issues such as psychological contracts within inter/intra work groups, power and trust as being highly significant managerial issues at the individual level. In another study, Thornton et al. (2016) use a broad managerial survey

conducted within the U.S. retail industry to suggest that the relationship between organizational politics and supply chain orientation is impacted when the top supply chain executive is perceived to be politically skilled. Villena et al. (2009) show how employment and compensation systems that increase supply chain executives' risk bearing reduce their willingness to make risky decisions thus disincentivizing supply chain integration. The focus of these preceding studies is on individuals' human behavior within supply chains. Thus, they serve as excellent reference points because they begin to inform how a BSCRM theoretical framework could begin to take shape. Even though they allude to risk taking contexts, the distinction between these studies and BSCRM studies is that SCM outcomes like performance or quality, rather than supply chain continuity, are what is emphasized. An explicit SCRM orientation is a necessity for BSCRM. Specifically, we contend that the management of individual risk behavior in a SCRM context has to result in outcomes that are in line with organizational goals.

A prominent study that adopts a BSCRM stance (and is closest to this research) is Ellis et al. (2010). This survey-based study examines the risk perceptions of purchasing managers and buyer of direct materials. It draws from exchange theory to show how the individual decisions of these frontline individuals can impact supply chain risk. From this study's results we deduce that individual risk decisions are expressed as firm level outcomes. Therefore, the risk behavior of even a single employee can expose the supply chain to the risk or disruption or even total failure. This is why we assert that there is a need for a theoretical BSCRM framework that can be used to derive models that predict the risk behavior of individuals in a SCRM setting.

To begin construction of this framework, we make a few key assumptions: 1) we assume that at the institutional level there is a uniform SCRM orientation; and 2) based on the characteristics of a true supply chain (see Cooper (1997) and Cooper & Ellram (1993)), we

assume that one of main goals of member firms in a supply chain is a mutual desire for minimization of overall supply chain risk through the inter-firm coordination of their risk management efforts across the whole supply chain.

As our primary contribution to the literature, we introduce BSCRM as a new topic area comprising the study of individuals and individual risk-taking on the organizational production frontlines in a SCRM context. On a secondary level, we propose the synthesis of two behavioral risk approaches psychological (Kahneman and Tversky 1979) and cognitive (Lopes 1987) with SCRM concepts to create a novel BSCRM framework. We hope that our framework will become a logical marker or reference point for future researchers as we strive towards a unified BSCRM theory.

In order to arrive at our contribution, we made some conceptual leaps. Conceptual leaps are often a necessary process in the building of nascent theory (Klag and Langley 2013). In particular, we used abductive reasoning to derive new insights (Klag and Langley 2013). We argue that the unit of analysis in behavioral SCRM should not be the supply chain or even the firm behavior because: 1) it is individuals that make SCRM decisions; neither supply chains nor their member firms, as entities, can make decisions that affect supply chain risk, and 2) the theoretical concepts of behavioral risk and behavioral risk management are linked to individual psychology and individual bias (Kahneman and Tversky 1979; Lopes 1987). Thus, we specify the individual as the unit of analysis. We believe that the idea of the individual operating in and affecting change in a vast SCRM backdrop rises to the level of an interesting and significant contribution. This behavioral approach to theory- building in SCRM will open the door for much needed empirical studies (experimental or survey-based) grounded in both behavioral risk management theory and the supply chain context.

In the ensuing sections we present our theoretical foundation and framework. First, we deduce from contingency theory (Fiedler 1972) and also prospect theory (Kahneman and Tversky 1979) that human behavior is shaped by managerial and risk contexts. We then assert that individual decision-makers will not necessarily be rational in uncertain environments where the prospect of gain or loss plays a key role (Kahneman and Tversky 1979). Ultimately, we argue that SCRM decisions that require direct human input are, reflect in part, driven by the risk orientation and appetite of the individual decision-maker. We adopt a positivist approach and use our SRCM and behavioral risk management theoretical building blocks to construct some preliminary propositions based on evidence from the literature. We follow this with a general discussion of our findings and an overview of the managerial implications of our study. We conclude the paper with a study on limitations and suggestions for future research.

2 Theoretical foundation

Researchers in the past have studied behavior in SCRM through a variety of theoretical lenses. For example, agency theory (Mitnick 1975; Ross 1973) has been used to form hypotheses about inter-firm relationships. The basic argument is that a focal powerful buying firm can play the role of the principal and the supplier plays the role of the subordinate agent (Zsidisin & Ellram, 2003). The underlying hypothesis is that purchasing firms are likely to use their power and/or trust in this context to encourage or coerce an alignment of their suppliers' risk appetites with that of their own as risk options become more prevalent (Li et al., 2015; Zsidisin & Ellram, 2003). Other theories have also been used in behavioral SCRM studies. For example, contingency theory has been used to demonstrate that supplier insolvency risk can be reduced through the implementation of mechanistic management control systems, a rational cognitive approach and the deliberate maintenance of buyer supplier relationships (Grötsch et al. 2013).

Resource dependency theory (RDT) has been applied in strategic purchasing (Paulraj and Chen 2007) and in sustainability and SCRM (Bode et al. 2011) to explain relationships between institutional risk and supplier management. In another example, Hult et al. (2010) extend real options theory to assert that managerial decisions are based on creating and then exercising or not exercising certain opportunities in an inter-firm setting.

Overall, in most SCRM related studies the unit of analysis is the aggregate behavior supply chain or the firm. However, few studies like Grötsch et al., (2013) consider individual behavior along with overall firm behavior as units of analysis. We are specific about the unit of analysis because it is important in that it is inextricably tied to our definition of BSCRM which proposes a micro OB approach. While there are many excellent extant studies that allude to behavior in SCRM, and even propose associative theories, the vast majority examine the issue from a macro OB B2B perspective. The gap we identify is that individual actions, which are the bedrock of behavioral economic theory, are rarely considered (Tokar 2010). As pointed out by Bendoly et al. (2006), when quoting Croson & Donohue (2002), aggregated assumptions made about behavior within supply chains may end up being too simplistic and too grounded in rationality. These generalizations may fail to account for the intent, action and responses (IAR) of individual decision-makers who are the actual difference-makers in OM (Bendoly et al., 2006). The IAR classification system (Bendoly et al., 2006) provides a useful framework for the categorization and subsequent retesting of behavioral assumptions of extant SCM models. Bendoly et al. (2006) and Tokar (2010) argue that the accuracy of many extant OM models can be improved by the incorporation of behavioral economics theory. Using this logic, behavioral risk theory should be used to inform and improve the predictive efficacy of extant SCRM models.

3 The ‘risk’ in Supply chain risk

Note that the word ‘risk’ in our definition of BSCRM has a dual purpose in that it pertains to both behavioral risk and supply chain risk which are two different concepts with two different meanings. When we consider risk in SCRM, we will be referring to risk in an objective operational and strictly classical Bayesian statistics sense (i.e. the probability of risk manifestation is event-driven). The realization of supply chain risk is usually operational and is marked by the occurrence of an event that is unfavorable to supply chain functionality. The event set is theoretically finite and quantifiable with some type of probability distribution rooted in both the present the prior (Flam 2014). Thus, in this instance the spurious likelihood (Flam 2014) of quantifiable risk events will more aptly be calculated using standard Bayesian statistical techniques. The risk in supply chain is often portrayed through the SCRM theoretical framework outlined below.

SCRM frameworks, in general, address the following risk management constructs: 1) *risk identification* (Christopher and Peck 2004; Jüttner et al. 2003; S. M. Wagner and Bode 2008; Wu et al. 2006); 2) *risk assessment* (Blackhurst et al. 2008; Gaudenzi et al. 2011; Harland et al. 2003; Samvedi et al. 2013); 3) *risk mitigation* (Chang et al. 2015; Craighead et al. 2007; C. Tang 2006); 4) *risk response* (Fisher 1996; Ponomarov and Holcomb 2009; Su et al. 2014) and *risk performance outcomes and measurement* (Hendricks and Singhal 2014, 2005; Sheffi and Rice 2005; Zobel 2014). We use these constructs as specific contexts in which individuals make decisions that affect the risk level of supply chain.

3.1.1 The ‘risk’ in behavioral risk

Behavioral risk, in contrast to operational risk, is subjective and rooted in psychological theory because it is based on human biases and centered around the probability of negative outcomes

that can precipitate from them (Shefrin 2016). On the surface, the probability distribution functions in behavioral risk management can be considered binomial in nature. That is, from a management perspective there are basically two possible outcomes: 1) an individual will either conform to organizational protocols and behave in a manner that is acceptable risk-wise or 2) go rogue and assume a level of risk that is misaligned with organizational mandate. The problem is human risk behavior is highly dependent on context and situation along with the subject's unique perceptions and attitudes towards risk. Thus, simply scaling up or aggregating human risk behavior to arrive at a discrete probability value of errant SCRM behavior in a Bayesian sense is impractical because the Bayesian approach does not allow for probabilities to be associated with unknown parameters. (Everitt and Skron dal 2010). The frequentist approach to inference, for which the result is either a "true or false" conclusion from a significance test, may yield better results. Therefore, experimental methods for testing will be more appropriate (Everitt and Skron dal 2010).

3.1.2 Behavioral Risk Management

Behavioral risk management is defined as the process of institutionalizing and mitigating the subjective bias and judgmental risk of decision makers at the firm or institutional level (Goto 2007). The study of behavioral risk management is divided into two general camps, psychological and cognitive (Shefrin 2016). These two schools of thought are not necessarily mutually exclusive. In fact, they are complimentary in many ways (Shefrin 2016). However, they still remain distinct from each other.

3.1.3 Psychological view

The psychological context presents peoples' risk behavior as being the result of balancing three psychological needs based on fear, hope and aspiration (Lopes 1987). Lopes (1987) states

that, individual risk behavior is governed by: “1) the need to assuage fear by providing security 2) The need to offer hope by providing upside potential and 3) the need to succeed by achieving a predefined aspiration or goal.”. Lopes named the framework SP/A (for security, potential and aspiration) theory and we refer to the psychological school of behavioral risk management thought as SP/A.

3.1.4 Cognitive view

The cognitive viewpoint is based on prospect theory (Kahneman and Tversky 1979). Prospect theory is centered around individual’s subjective and often erroneous perceptions of gain and losses in risky situations (Kahneman and Tversky 1979). It asserts that : “1) people interpret risk through the lenses of gains and losses relative to some reference point and 2) people tend to replace subjective possibilities with uncertainty weights which are reflective of their attitudes towards uncertainty and just degrees of belief“ (Kahneman and Tversky 1979). The replacement of uncertainty weights with subjectivity and also the misspecification of an appropriate reference point by individuals often results in errors in judgment and subsequently, negative SCRM outcomes. It is these individual deviations from supply chain overall risk management objectives and goal that supply chain risk managers at the strategic or firm level should aim to maintain a handle on.

4 Integrating the theoretical risk behavior approaches and the SCRM framework

The link between the two types of risk, and the key to this study, is that risk behavior lies at the core of operational risk (Shefrin 2016). This means that negative SCRM outcomes can usually be traced back to human risk behavior. For example, in a well-documented example, a fire in a Philips plant in 2000 interrupted the operations of two major customers: Ericsson and Nokia. Nokia decisions-makers chose to quickly find an alternative source and was up and running in

three days. On the other hand, Ericsson lost about a month's worth of production and extensive market share while waiting for Philips to recover (Chopra and Sodhi 2014). The difference in the actions, or lack thereof of decision-makers in this example resulted in two opposing outcomes. Thus, we hypothesize a causal relationship between risk behavior and some SCRM outcomes. We believe that the case can be made that individual risk behavior can result from misappropriation, by the individual, of a supply chain's desired appetite for risk as it relates to one of the four aforementioned SCRM constructs (identification, assessment, mitigation and response). An individual may deliberately or subconsciously act in a specific errant manner when it comes to: 1) accurately identifying supply chain risk, 2) correctly assessing the risk 3) mitigating the risk in the most efficient manner and 4) appropriately responding to supply chain risk. Through a reconciliation of these two definitions of risk we assert that risk behavior is an antecedent to the SCRM constructs. In so-doing we arrive at a basic but coherent framework for the elaboration of BSCRM theory.

For the remainder of the paper, we will use extant literature to formulate theoretical arguments and propositions that will serve to reconcile the two behavioral risk theoretical viewpoints in a SCRM context. We consider some (not all) behavioral realities in the backdrop of each of the individual commonly accepted SCRM framework constructs using a series of propositions. We regard our arguments and propositions not as replacements, but as qualitative complements to extant SCRM models. Our ultimate aim is to contribute towards significantly increasing their robustness, predictive accuracy and overall usefulness (Tokar 2010).

4.1 Risk identification, assessment and supply chain risk behavior

The risk identification and assessment stages are often presented together in the literature. They are both critical to SCRM success (Neiger et al. 2009). Most SCRM approaches use

organizational level objectives to identify and assess risk. Some approaches solve the problem of visibility or risk by establishing a clear link between risk minimization and increased firm performance (Gaudenzi and Borghesi 2006; Ritchie and Brindley 2007). Yet others are aimed at providing mechanisms for real-time risk identification (Carbonara and Pellegrino 2017). Other risk identification studies use mathematical models to quantify risk (Ambulkar, Blackhurst, & Grawe, 2015; Hendricks & Singhal, 2005). Increasing supply chain visibility has been suggested as a way to improve managers' ability to identify and assess risks. The literature on supply chain risk behavior in a risk identification context is sparse. A notable example is the investigation by Zsidisin & Wagner, (2010) into the relationship between managers' risk perceptions and supply chain disruption occurrence. (DuHadway et al. 2018) also discuss the relationship between organizational communication and supply chain risk perception. They concluded that managers ability to acknowledge risk is positively related to the levels of communicated risks.

Risk identification and assessment are extremely vulnerable to judgement bias (Shefrin 2016) . From a psychological or SP/A perspective, the individual's ability to accurately identify and assess supply chain risk will be correlated to an individual's 'risk style' (Ingram and Bush 2013). Ingram and Bush hypothesize that there are four distinct risk styles: 1) conservators for whom fear is a dominant emotion and set their aspiration level to a point of zero loss. 2) maximizers whose focus is on accepting more risk to achieve gains 3) managers who use cost benefit analyses to balance cost and rewards 4) pragmatists are different from the other three in that they adopt an uncertainty perspective (Shefrin 2016). Pragmatists are most comfortable in situations which afford them the greatest flexibility (Shefrin 2016). From a prospect theory perspective, supply chain risks will have low risk aversion coefficients (Shefrin 2016). They are governed by hope and will more likely quickly forget instances of unfavorable events (Shefrin 2016).

To tie the concepts of risk behavior and supply chain risk identification and assessment together, we assert that conservators are the most compatible risk type to the dominant organizational approach to risk identification and assessment. However, because conservators are prone to the hot hand fallacy (Shefrin 2016), we propose that they may tend towards being maximizers when placed in settings where there are long periods devoid of negative supply chain events.

According to risk compensation theory, humans tend to become complacent over time in the absence of adverse consequences for their action (Hedlund 2000). Furthermore, the overall attitude towards risk of the manager is guided by company communicated goals (DuHadway et al. 2018; Macdonald and Corsi 2013). In light of this we come up with the following propositions.

P1. Managers' propensity to fail to identify supply chain risk will increase over time in the absence of unfavorable supply chain events.

P2. Managers are more likely to be conservators in settings where organizational level objectives are used as a basis for identifying and assessing supply chain risk.

The propositions are an important preliminary step toward theory-building and will later be used as a basis for constructing hypotheses in future studies.

4.2 Risk mitigation, response and supply chain risk behavior

Much of the behavioral research in this context is centered around a buyer/suppliers relationship context with trust and dependence being two prominent factors that govern risk behavior (see Bode, Wagner, Petersen, & Ellram, 2011). The firm is the unit of analysis and it can either adopt a bridging or buffering strategy to mitigate risk (Bode et al., 2011; Mishra et al., 2016). While this dyadic firm-level approach has resulted in some excellent research studies, it assumes that

the firm is an entity that is capable of making decisions. This is contrary to the assertion made by Bendoly et al. 2006 that it is individuals, not firms, who ultimately make decisions in OM settings. Our viewpoint is more aligned with Bendoly et al.'s proposition.

Prominent studies like Bode et al, (2011) observe and measure supply chain risk mitigation behavior at the firm level. However, it is clear in this study that it is the process by which individual decision-makers arrive at these decisions on behalf of the firm that is pertinent.

Establishing the unit of measurement is key. By identifying the individual as the unit of analysis, SP/A and prospect theory can be applied to propose a relationship between human risk behavior and supply chain risk management. Risk mitigation can be costly to a firm. Therefore, it is not surprising that, in praxis, many decision-makers' compensations are tied to their firm's bottom line. According to Lopes (1987) most individuals will be governed by aspiration in situations where there is a high probability for payoff. If the risk of high impact supply chain disruption is low, then supply chain managers will be drawn to the prospect of high personal compensation if revenues that could be used for mitigation is preserved and shown as a positive on the bottom line. According to prospect theory, individuals will be more likely risk seekers even if the probability of a high payoff is marginally increased (Kahneman and Tversky 1979). This means that managers will again more likely pick the alternative that is likely to line their own pockets. Considering that high impact and cost supply chain disruptions are often of the low probability variety, we would expect managers to be risk-seeking and less likely to invest in supply chain risk mitigation. In light of this we formulate the following proposition:

P3. Managers faced with low probability high impact supply chain disruption risk are less likely to invest in supply chain risk mitigation than managers faced with high probability low impact disruption risk even if the expected cost of both scenarios is the same over a set period of time.

4.3 Risk performance outcomes, their measurement and risk behavior

With regards to risk performance outcomes and risk behavior, there appears to be a significant gap in SCRM literature. Extant research focuses on SCM and uses the firm as the unit of analysis (Wagner & Bode, 2008). However, we contend that manager's behavior is driven not only by the risk management structures (see Shefrin (2016)) of the firm but also by two other factors: namely, their individual biases and the firm's internal risk management orientation. We assert that that if a firm incentivizes a SCRM orientation, then it may be more likely that its decision makers will adopt the same outlook; especially if their compensation is tied into their adherence to firm-backed risk management strategy and performance. Using SP/A, we posit that fear of loss or no gain will drive managers to seek the security that comes from adhering to firm risk management outlook. Thus, we propose:

P4 Managers in companies with strong risk management orientations will more likely be pragmatists whose risk appetite will, on average, align with that of the firm's or supply chain's objectives.

5 Discussion

The purpose of this study was to address the behavioral gap in SCRM literature by advancing the study of human risk behavior in a supply chain setting. The delineation and classification of any new field of research from an extant one is not a trivial matter (Sodhi & Tang, 2012) because classification is a necessary step in understanding a research area (Lambert 2015). Defining and unifying the topic area of SCRM will open the door to a consistent approach to managing risk in supply chains (Sodhi & Tang, 2012). In that spirit, we originate the term Behavioral SCRM (BSCRM) with the aim of delineating a new behavioral risk management-focused sub-area of SCRM.

The aim of this paper was to provide a foundational framework upon which to organize, categorize, and originate future behavior-based SCRM literature at the micro OB level. BSCRM studies are scattered across different areas such as Corporate Social Responsibility (CSR) (Gallear et al. 2014), Sustainability (Busse et al. 2016) Strategy (Ireland and Webb 2007) and even Marketing/Operations (Aust and Buscher 2012). Even the small number of behavioral studies in SCRM seldom explicitly identify risk behavior as a key term. We delineate BSCRM from SCRM and provide a theoretical foundation upon which future behavior based SCRM studies can be originated. Our main contribution to the literature is the BSCRM theoretical framework which synthesizes aspects of behavioral risk management theory with SCRM theory. We identify the individual decision-maker as the unit of analysis and deliberately advance the notion that it is individual, not firms, that make supply chain decisions. However we concede that firms may be able to influence or ‘debias’ (Lopes 1987; Shefrin 2016) individual decision makers’ risk perceptions. This could be achieved through well-thought out institutional risk management structures that reward them for being in line with the firm’s risk management strategy and goals.

The argument can be made that ERP system decision models and parameters can also influence SCRM outcomes. However, it is still human beings who are ultimately responsible for setting and adjusting the decision models and algorithms therein. ERP systems are just as good as the decision makers who operate and program them. This line of reasoning is based on the well-known computer science concept of garbage in, garbage out (GIGO). While these decisions could be somewhat regulated based on decision models and algorithms within ERP systems, the uniqueness of some disruption scenarios could make it difficult for programmers and analysts to preemptively account for every possible scenario and contingency. The exact time and nature of

disruption event is extremely difficult to predict (Cantor et al. 2014). When the ERP system decision models are poised to contribute towards an undesirable but unavoidable outcome, the onus would be on humans to make the decision to override them before the negative occurrence. The reluctance of managers to override ERP systems in the face of risk is an expression of risk behavior in its own right. In the end, blame cannot be placed on ERP systems when SCRM outcomes negatively affect a firm in a major way.

6 Managerial Implications

As supply chains have become central to their member firms' competitive advantage strategies, there has been an increasingly urgent need for more studies that help companies achieve even greater supply chain efficiency (Marley et al. 2014). Much of the literature in SCRM has focused on how to decrease risk in the supply chain through increased efficiency and supply chain optimization. The majority of the literature is centered on production-based deterministic approaches to supplier risk management. However, there is growing interest in the human behavior aspect of SCRM (Macdonald and Corsi 2013). What is missing is a theoretical framework upon which to develop future studies.

One of the peculiarities of human risk behavior in SCRM that may set it apart and make it interesting and worthy of study, is that individual behavior and attitude towards supply chain risk may not be necessarily predictable and consistent. The supply chain presents yet another level of abstraction which further complicates decision-making. In some instances, supply chain goals may often appear to be in conflict with firm objectives and individual goals. For example, certain individual managers at the firm level may be less likely to invest in programs to reduce supply chain risk because SCRM programs are often cost centers whose programs may never be used (Sodhi & Tang, 2012). Since "nobody gets credit for fixing problems that never happened"

the prospect of monetary gain for individuals responsible for managing risk in the supply chain is generally cost-based (Repenning & Sterman, 2002; Sodhi & Tang, 2012). Lack of individual incentive for investment in SCRM programs is probably why many firms are caught flat-footed when disaster strikes. Similarly, when we consider the irrational exuberance displayed by bankers in the banking supply chain example given at the beginning of this article, individuals were not just indifferent to supply chain risk, they sought it! It is reasonable to conclude that the sales professionals' behavior was almost certainly purely driven by the prospect of monetary gain. It is unlikely that SCRM and its associated cost was an important consideration for them. However, their behavior still negatively impacted supply chain viability and functionality.

Despite the highly individualized nature of human risk behavior, adopting a behavioral risk management approach as a supplement to classical SCRM models, which tend to be at the inter-firm level, could improve their efficacy. In order to facilitate this, we assume that those responsible for overall institutional risk management in each organization will have a SCRM orientation and know their decision-makers on the supply chain frontlines well enough to know their general individual dispositions towards organizational and personal risk. Those employees whose risk appetites and agendas are deemed, over time or through psychoanalytical testing, to be more malleable and aligned with the organization's SCRM strategy and orientation could be identified and groomed for positions that would require them to make SCRM-related decisions on a regular basis. To elaborate even further, using agency theory and bridging (Bode et al., 2011), buyer firms could create SCM structures that incentivize the same approach to the selection of supply chain decision-makers at the first or even second tier of the supply chain.

Another application of BSCRM in praxis could be based on risk management structures and their use towards ensuring alignment of organizational supply chain risk appetite with

individual perceptions and attitudes. Both prospect theory and SP/A imply that an individual must perceive some appreciable measure of intrinsic value or gain from adopting a certain stance towards risk. We postulate that if an employees' personal compensation is correctly aligned with their firms' SCRM strategy it means that their individual biases, as it pertains to risk taking, will more than likely coincide with organizational goals. Thus, we would advise companies to consider more than just the bottom line when it comes to compensation for such individuals.

The banking industry example illustrates how human risk behavior in one part of a supply chain can result in negative outcomes that cascade or "ripple" across the whole supply chain (Ivanov et al. 2014). Despite the differences in the performance measures, i.e., cost-based vs revenue-based, personal gain seems to be a common theme. What is undeniable, and the point of this article, is that unbridled human risk behavior at different levels of the organization can result in supply chain risk outcomes for better or for worse.

7 Study Limitations and Future Research

We are aware that our study has some limitations. For example, we realize and acknowledge that our overview of the literature was by no means exhaustive. No study of this nature can never be truly complete because there is always more related research that can be included (Boell and Cecez-Kecmanovic 2010). Our approach is meant to serve as a generalized overview of the BSCRM concept and to, hopefully, serve as a useful springboard for future researchers. We believe our study adequately achieves this goal. The framework we propose allows for the elaboration of theory in BSCRM because researchers could use it as a foundation for testing other relevant behavioral risk theories. We are not suggesting that future researchers limit their focus to SP/A and prospect theory alone. However, we do prescribe the use of the risk management framework and its constructs to provide SCRM context. In the same vein, we

acknowledge that the examples of the behavioral realities we provided in conjunction with our propositions are by no means exhaustive. This, of course, also applies to the propositions themselves. Our examples were perfunctory demonstrations of our theory building approach/technique. We are certain that numerous future different, more sophisticated and innovative hypotheses exist and will in future result from our suggested basic framework.

The other limitations of this study are based on the characteristic of supply chains. For example, we assume that those responsible for risk management strategy and the appointment of personnel to key SCRM-related positions have perfect knowledge regarding how to identify optimum levels of supply chain risk at any given time supply chain risk at the institutional and inter-firm level. This was a necessary assumption to make in order to illustrate our point. The silver lining is that we recognize that this assumption opens up the door for even more future research in which we may examine the factors that may influence SCRM strategies at the corporate level. For example, we could examine factors that lead this particular set of decision-makers to behave in ways that increase supply chain risk. We could also do away with the assumption of perfect knowledge and examine whether factor such as increased visibility or maybe executive compensation structures may have a debiasing effect. We also assumed perfect supply chain visibility and that supply chain actors were always in synch with their external counterparts when it came to supply chain strategy at the inter-organizational level. We did not consider the psychological effect of disruption events on individuals nor did we consider the frequency of such events. Our aim was to isolate the behavioral or human factor in a SCRM environment.

For future research, we will develop the propositions in this study into testable hypotheses. We will also use behavioral experiments to empirically test or retest behavioral

theories in conjunction with the SCRM framework to provide new insights or confirm previous assumptions and conclusions. For example, through a theory elaboration approach (Fisher and Aguinis 2017), agency theory could be paired with prospect theory (see (Kahneman and Tversky 1979)) to describe the risk behavior of supply chain agents in uncertain environments. Or conversely, resource dependency theory (Pfeffer and Salancik 1978) and behavioral economic theory (Tarde 1902) could be applied to describe how principals can better manage individuals' risk appetite and avoid the theoretical pitfalls associated with rent-seeking behavior (Buchanan et al. 1983). The actor-network theory (Latour, 1996, 2005) could be used explain the applicability, and also the limitations, of prospect theory in a supply chain network setting with multiple echelons.

In the end, we see this study as an incremental step towards a more practical approach to the management of risk in supply chain that involves elements of diverse areas such as psychology, organizational behavior, behavioral risk management and operations research. We believe our approach will result in new and novel solutions that will help to complement and increase the accuracy of SCRM models and the efficiency of supply chains in general.

Chapter 2

Supplier Selection: A Futures Approach Using Cross-Impact Analysis

Abstract

Global supply chains are under increasing threat from economic disturbances such as sudden increases in tariffs, unexpected interest hikes from government or the world bank, or increases in oil prices, to name a few. This enhanced threat has implications for a global firm's selection of future suppliers. This study introduces Cross-Impact Analysis (CIA) as a way to analyze and quantify supplier risk. In scenario prediction, the analysis of all the possible scenarios that could be generated from a given cascading event set often becomes mathematically intractable due to the large number of possible event combinations. We demonstrate how CIA's scenario-building approach can be used to reduce the number of possible future scenarios in order to provide practitioners with an easier-to-understand predictive tool. Using CIA, we show how the number of plausible economic disruption risk scenarios is systematically reduced from a possible 2^N distinct outcomes and $N2^{N-1}$ pathways that span the range of none of the events occurring to all of them occurring in a given time frame to just N outcomes and N^2 pathways. This gives practitioners an additional analytical method to inform selection decisions in the face of future disruption risk.

1 Introduction

Choosing the right supplier can be a critical decision for many global supply chain executives. One CEO of a large supplier to Ford Motor Company whom we interviewed said, "once some of our supplier-buyer relationships are established, they are more or less set in stone. Neither

inventory storage or switching suppliers is an option. When disruptions occur, we just roll with the punches! Choosing the right supplier at the beginning is very important for us". The problem is that in general, supplier selection models offer two basic methods of alleviating the risk of supplier outage: (1) Supplier redundancy, and/or (2) inventory buffering (Hult et al. 2010). Supplier redundancy or multi-sourcing allows a firm to source the same product from multiple suppliers and shift flow of product from one supplier to another in the event of a supplier becoming incapacitated (Chopra and ManMohan S. Sodhi 2004). Inventory buffering dampens the effect of supplier disruption through the accumulation of inventory at the buyer site (Bode et al., 2011). This strategy can help maintain the normal delivery of service to the end customer while giving the supplier time to recover.

Both multi-sourcing and inventory buffering, either singularly or in conjunction with each other, represent the basic prescription for the amelioration of supplier risk across the breadth of SCRM literature (Sodhi and Tang 2012). However, there are cases when neither of the two methods is economically feasible leaving the firm fundamentally unprotected for supply chain disruptions.:

1.1 Cases when multi-sourcing is infeasible

In large scale manufacturing, an extremely high cost of assets to total cost (COA/TC) ratio of establishing a supplier site can make it next to impossible to achieve economies of scale with a multi-sourcing strategy. In some cases, strict governmental regulation concerning product safety and quality may call for a very high level of production precision and coordination. Such sustained precision can only be attained through a very close, exclusive, long-term relationship between buyer and supplier (Maruchek et al., 2011). Also, these types of relationships require heavy time and financial investment. Simultaneously, inventory may be extremely expensive to

both buy and store. Establishing more than one supplier site may result in an intolerably high amortized cost of production (Wilson 2007).

1.2 Cases when inventory buffering is infeasible

A finite demand horizon may obviate the option of inventory buffering when per-unit inventory cost is so high that it is highly uneconomical to have any leftover inventory at the end of a planning period (Schwarz 1972). Some of the main modular components of automobiles such as engines are good examples of this. Thus, the scenario described above is very common in the automobile industry.

A requisite single-sourcing strategy leaves a firm faced with a choice of only one from a set of possible suppliers. Despite the possible devastating consequences of choosing the wrong supplier, the literature offers little in the form of supplier risk assessment for the initial stages of supply chain construction and configuration.

The problem with determining the probability of risk of disruptions at a new supplier site is often two-fold. First, the buyer may not have enough information on the supplier to gauge its ability to consistently satisfy demand. Secondly, there may be limited knowledge regarding the supplier's exposure to exogenous disruptive events. We assume that the supplier will, for the most part, be reliable and consistently satisfy demand. Thus, we are only interested in quantifying the supplier's exposure to exogenous events. Many exogenous events do not happen in a vacuum but are interrelated. The problem is that disruptions and their triggering events can be notoriously difficult to forecast and quantify (Simchi-Levi et al. 2014). Many have no known probability distribution; rendering statistical methods used for forecasting ineffective (Sawik 2018).

The ripple or cascading effect of supply chain disruption events due to the interrelatedness of endogenous supply chain risks has received attention in recent times (see (Ivanov et al. 2014; Samvedi et al. 2013; Simchi-levi et al. 2015)). Many exogenous factors are not directly related to the supply chain's functionality. However, they can be part of a set of interrelated events that culminate in the manifestation of a supply chain disruption risk in a domino-like fashion. An example of this would be a major natural disaster like hurricane Katrina. The storm interrupted between 10 and 15% of US gasoline production and subsequently raised both domestic and international oil price (Ivanov et al. 2013), which in turn resulted in increases in transportation costs, increasing many global supply chains' variable costs.

The threat of disruption to supply chains is real and managers would be well served to prepare for plausible disruptions scenarios. However, it is almost impossible to predict supply chain disruption outcomes because the number of possible events that could negatively affect a supply chain is infinite. Furthermore, if we consider that these events are interrelated and can cascade in different sequential combinations, the sheer number of possibilities makes attempts to optimize supplier selection using the normal linear model mathematically intractable. This is why there is a general absence of models that attempt to accomplish this. To address this gap in the literature, we introduce Cross-Impact Analysis (CIA) as a new way for supply chain practitioners to systematically generate and analyze a set of plausible post-disruption scenarios *before* committing to investment in expensive supply chain configurations.

CIA is a powerful tool that takes a set of future events and calculates the causal impact that any given event may have on others in the set while simultaneously considering the relative probabilities of such events (Bañuls and Turoff 2011). The power of CIA is that it allows practitioners to systematically reduce a set of possible interrelated disruption events into a

mathematically manageable number without sacrificing functionality and efficacy. CIA has been widely-used in other fields such as Political Science and Economics for generating and analyzing scenarios (Bañuls and Turoff 2011). However, our exhaustive literature search reveals that it has received very limited attention in Operations Management (OM) and SCRM. The only instance of CIA use in OM we found was (Menck et al. 2014) who use CIA in production system planning. Their focus is on the internal operations of factories and the future impact of decisions made in the present on production systems and the employees involved in the planning process. They do not consider, as we do, the inter-organizational SCRM context.

In this paper, we show how CIA can be used to forge the missing link between the probability of exogenous disruptive events *and* their cascading nature. CIA has been used in conjunction with other techniques such as Interpretive Structural Modeling (ISM) and Analytical Hierarchy Process (AHP) to improve its functionality (see Bañuls and Turoff, 2011 and Lee and Geum, 2017). However, it has not yet been used in a SCRM setting. Thus, we present this study as an introduction to one potential use of CIA in SCRM. We answer the following pressing research question: *Can a futures approach be used to model supplier failure in global supply chains faced with various and unpredictable exogenous risks?*

The rest of the paper is as follows: Section 2 comprises the literature review. Section 3 describes the methodology and presents some numerical results from a realistic SCRM scenario. Section 4 contains a discussion of our findings, practical applicability and limitations of the methodology, and a brief which proposes future derivative research questions and studies.

2 Literature Review

Supplier selection solutions in the literature can generally be divided into three main categories: (1) multi-criteria decision-making techniques like analytical hierarchy process

(AHP), analytical network process (ANP), technique of order performance by similarity ideal solution (TOPSIS), etc. (Samvedi et al. 2013). (2) Mathematical programming techniques such as Linear programming (Chopra and Sodhi 2014; Ravindran et al. 2010) and (3) more recently artificial intelligence and machine learning techniques such as neural networks (Kim et al. 2014; Kuo et al. 2010; Zhang et al. 2016) and decision trees (Ruiz-Torres et al. 2013; Ruiz-Torres and Mahmoodi 2007) have started to become more prevalent in the literature.

Mathematical multi-objective programming (MMOP) techniques represent the majority of supplier selection multi-criteria models in the literature between 2008 and 2012 (Chai et al. 2013; Chopra and Sodhi 2014). MMOP techniques are well suited for supplier selection because the objectives of supply chain effectiveness and efficiency often contradict one another (Heckmann et al. 2014). For example, the simultaneous objectives of reducing costs *and* increasing supply chain responsiveness after disruption are in contradiction with each other because the latter may require extensive investment in additional or redundant infrastructure (Sawik 2018).

Mathematical models, such as MMOP, optimize some unexpressed utility function over a feasible region (Olson 1988). The problem is that using mathematical models in this way can result in an impractically large number (sometimes infinite) of feasible solutions (Olson 1988). Also, MMOPs are, by nature, quantitative and cannot account for qualitative factors except maybe through the expression of arbitrary aspiration levels which cannot accommodate subjective attributes. The advent of analytical techniques such as the widely-used AHP overcome some of this deficiency. These techniques are decision-maker driven and allow for subjective risk quantification (Olson 1988). They also can expedite the decision-making process by producing an initial linear approximation of the MMOP analysis (Olson 1988). They provide

decision makers with a smaller and more manageable set of alternatives from which to choose (Samvedi et al. 2013).

More recently, artificial intelligence (AI) techniques such as neural networks and decision trees have gained prominence. They also boast the ability to provide the user with a smaller set of alternatives. AI decision models are advantageous because they can be easily “trained” by front line practitioners using historical data (Guo et al. 2009). AI models are particularly helpful in the ranking of suppliers and supplier portfolios (see Guo et al. 2009 and Zhang et al. 2016). Both AI and analytical techniques such as AHP have proved useful for quantifying the weight, or relative importance, of risks in a supply chain. Their main shortfall is that they assume independence of supply chain disruption risks. They would be inadequate for situations in which disruption risks are dependent on one another (see Samvedi et al. 2013) and thereby have a propensity to cascade in a domino-like manner across a supply chain network (Ivanov et al. 2014).

ANP is an improvement upon AHP. ANP accounts for interdependencies and provides a systematic way to deal with all kinds of feedback and interactions. Another similar analytical technique that has been used in SCRM to address the assumption of independence, is interpretive structural modeling (ISM) which provides support for risk managers in identifying supply chain risks and their interdependencies (Pfohl et al. 2013). However, while ISM and ANP have proven useful for risk identification in terms of consequences, they do not account for the respective probabilities of dependent events in a dynamic or temporal model (Pfohl et al. 2013). Event dependency is an important consideration that should not be ignored when considering the potential effect of supply chain disruption events which are stochastic in nature.

The complexity and diversity of the real world exposes the shortfalls of the aforementioned methods in this condensed literature review (Chai et al. 2013). The quest for an all-encompassing method for dealing with various supplier selection issues such as group aggregation, uncertain information fusion, classification, prediction, and clustering has resulted in the advent of more complete and comprehensive solutions that integrate multiple techniques (Chai et al. 2013). For example, Samvedi et al. 2013 combine the AHP and TOPSIS to quantify and consolidate supply chain risk values into a comprehensive risk index.

In general, maximizing efficiency has long been the most addressed objective of supplier selection models. The problem is that pure cost- and/or waste-based objectives are only tactical and retroactive in nature (Heckmann et al. 2014). Forward-looking methods that are temporal or predictive in nature (especially models that may be capable of predicting supplier failure over multiple future periods) have received very little attention in the literature (Heckmann et al. 2014). We respond to this by proposing the use of futures-oriented techniques such as CIA to help model more realistic dynamic supply chain models. The aim and the scope of this study is to provide an introduction to the use of CIA in SCRM. We demonstrate how CIA can be used to assist in the design of capital-intensive global supply chains so as to minimize the probability of supply chain disruption. In so doing, we address the following research gaps in the literature as identified by Heckmann et al., (2014):

1. The lack of techniques addressing effectiveness-driven objectives
2. The need for complex context sensitive approaches that incorporate qualitative and subjective decision-making.
3. Integration of time-aspects and their potential impact on qualitative models

3 Methodology

3.1 Problem description

To provide context, and for illustrative purposes, we briefly describe a typical supplier selection problem: A focal firm (a major supplier to the automotive manufacturing industry) with many suppliers of its own wins a bid to become the sole provider of an important assembled part such as an automobile engine. The engine is supplied to the automobile manufacturer under a strict Make-To-Order (MTO) agreement. The focal firm is required to fully satisfy the demands of its important customer through a just-in-time (JIT) delivery of customer orders over the next decade or face sanctions in the form of fines or even the eventual loss of business. The focal firm can choose to source a critical component needed to assemble the engine from a set of 10 potential suppliers each located in a geographical region across the globe. We assume that once the focal firm settles on a supplier to fulfill all the demand for this particular critical component, the supplier-buyer arrangement cannot be revoked or replaced until the end of time T ; the entire time horizon under consideration.

Following the structure of general supplier selection models, let \mathbf{I} be a set of potential suppliers each located in one of the sets of different geographical regions \mathbf{R} across the globe. We then let \mathbf{K} be the set of components needed in the assembly of the focal firms' product to be delivered to its customer based on prevailing demand.

Each supplier would be responsible for the production and delivery of a single component $k \in \mathbf{K}$. The focal firm will need to select a subset of suppliers from \mathbf{I} and allocate to each a percentage of the total demand for k of its customer to minimize the probability of disruption over time T . We propose three supply chain disruption categories depicted in Table 1 low-impact (L), high-impact (H), and total-impact (X). We assume that the product being delivered to the

end customer: 1) is substitutable and 2) that successive quarters of delayed delivery of the final product will cause the end customer to balk and purchase a competitor's product. We also assume a very long product life cycle and tendency towards brand loyalty such that this nature of customer substitution results in practically a permanent loss of market share.

Note that suppliers can easily overcome low-impact disruptions (L) with the production deficit made up immediately in the next period. However, there is a per-period penalty cost, C_t from the customer which is associated with the delay that the focal firm incurs. Additionally, we assume that for any supplier, more than one low impact disruption in a period will result in a delay of product flow of one period for which the supplier cannot make up.

Table 1 Disruption intensity categories

Disruption Category	Expected Effect on Supply Chain Functionality
Low-Impact (L)	Flow of goods is briefly disrupted but the supplier can make up the slack.
High-Impact (H)	Flow of goods is disrupted for a period of more than six weeks resulting in some loss of market share
Total-Impact (X)	Supplier is insolvent as a result of a disruption and goes out of business for good

The estimated probability of supplier i experiencing a low-impact disruption is denoted by p_i^L and p_i^H is the estimated probability of supplier i experiencing a high-impact disruption. The objective for the focal firm is to satisfy demand D_t for each period t while minimizing $E(X) = \sum_{t \in T} C_t$, the expected value of the losses incurred over total period T . The expected value can also be represented by

$E(X) = \sum p_i^L C_t + \sum p_i^H C_t + \sum p_i^X C_t$ which is the expected penalty cost with respect to p_i^L, p_i^H and p_i^X .

A high-impact disruption, H, may result in a loss of market share commensurate to the proportion of components that the affected supplier is responsible for delivering. For example, if

supplier i is responsible for delivering half the required quantity of component k during each production period, then the ability of the firm to deliver to the customer is degraded by 50% assuming the final assembly of the part only requires one of k . In this case we assume that the supplier is responsible for satisfying 100% of the demand for k . This presents a problem for both the final manufacturer and the focal firm. Let p_i^X be the estimated probability of the total elimination of a supplier as node in the supply chain network. Total loss could be due to a particularly devastating disruption event. Examples of this include permanent supplier insolvency due to a class action lawsuit or a freak environmental disaster event like radioactive fallout that renders the region uninhabitable and permanently unproductive. We assume that the probability of a total loss of supplier due to insolvency is so minute that it set a zero.

Note that solving a mathematical optimization model based on C_t . will be the subject of future studies. Our focus in this paper is to provide a new methodology for systematically calculating the probabilities of disruption. Many supplier selection models assume that the decision maker has some knowledge about the probability of disruption. The problem is that in praxis there is often no known probability distribution for many disruptive events; rendering their approximation normal statistical inference techniques mathematically intractable. To tackle this deficiency, we propose the use of CIA to determine the values of p_i^L , p_i^H and p_i^X for any given supplier i . Having a more robust measure for p_i^L , p_i^H and p_i^X is, obviously, a critical step towards equipping practitioners with the ability to build more realistic scenarios that could be used to determine the vulnerability of different proposed supply chain configurations. Thus, singular purpose and scope of this study is to introduce CIA as an analytical methodology for estimating the values of p_i^L , p_i^H and p_i^X .

1.3 Determining probabilities using Cross-impact Analysis

CIA is a futures-oriented scenario-building technique introduced by Gordon Hayward in the late 1960s. Before CIA, the Delphi method of collating expert judgment was an overwhelming favorite for scenario building. A drawback of the Delphi method is that it offers no way of obtaining meaningful quantitative subjective measures of the respondents' view of causal relationships amongst future events (Turoff 1971a). Also, along with many other forecasting methods, its shortfall is its inability to identify potential relationships between the forecasted events and that forecast might well contain mutually reinforcing or mutually exclusive terms (Gordon and Hayward 1968). CIA allows for the adjustment of the expected probability of each item in the set on the basis of perceived interdependencies amongst the items (Gordon and Hayward 1968). To be parsimonious, we do not go into the great detail concerning the history, evolution and formulation of the CIA methodology. Instead, we provide a brief practical illustration of the technique in a global supply chain context. A more in-depth discussion and analysis of the origins of the CIA technique, can be found in (Gordon 2004; Gordon and Hayward 1968; Turoff 1971a).

4 Cross-Impact Analysis in a supply chain setting

The primary aim of CIA is to forecast events based on the idea that event occurrence is not independent (Bañuls and Turoff 2011). We assume, like Turoff, (1971), that each event occurs only once during the event time frame. . We then proceed with the CIA by following the steps below which are outlined in (Bañuls and Turoff 2011). Initially, a group or individual must come up with a set of interrelated events that can be matched with a set of exogenous events that are not influenced by the interrelated set (Bañuls and Turoff 2011). In our numerical example we consider a supplier i to be associated its own peculiar set of exogenous events that can directly,

or indirectly in a domino-like fashion, trigger a supply chain disruption event. This set represents a user's initial worldview. CIA will involve the iterative perturbation of this world view in the manner described below.

1. Derive an initial event for a supplier i and estimate the subjective probability that an event will occur some time during the time horizon T (in the numerical example we pick a period of ten years). Then perturb the estimator's worldview in the manner described below:
 - a) Set a probability threshold (for example, 0.5) and ask the estimator to assume that events with probabilities above the threshold will happen with certainty. Then ask the estimator to re-estimate the probability that the rest of the other events will occur under this assumption.
 - b) Ask the estimator to assume that events with probabilities above the threshold will *not* occur. Then ask the estimator to re-estimate the probability that the rest of the other events will occur under this hypothesis.
2. The result is a set of $n(n-1)$ estimates for the n events. A computer can be used to generate a complete structural model of the estimates.
3. In a group setting, the individual is encouraged to first experiment with the model to reach consistency with their own estimates. Each individual's final estimates are then used to compile a collaborative model through an averaging process.
4. If the event set is interdisciplinary in that it traverses many professional areas, users may instead be advised to only estimate the probabilities related to their own area of expertise. This can be facilitated through a group decision process such as Delphi.

The successful choice of the initial event set is entirely dependent upon the knowledge of the individual. Therefore, our recommendation is that the initial event set be compiled through something like a Delphi process by a group comprising supply chain and other relevant subject matter experts. We constructed the initial event set using our own expertise and judgment.

Following this process, participants are able to estimate the influence (causality) resulting from the assumptions made about the occurrence or non-occurrence of events. Causality is measured using a correlation coefficient C_{ik} which represents the impact of the k^{th} event on the i^{th} event. A positive C_{ik} means that event k *enhances* the probability of event i whereas a negative C_{ik} implies that event k *inhibits* or reduces the probability of event i . We can calculate C_{ik} using a variation of the Fermi-Dirac or logistic distribution function by asking subjects about the probabilities (P_i) as determined by the following relationship (Bañuls and Turoff 2011; Turoff 1971a):

$$P_i = \frac{1}{[1 + \exp(-G_i - \sum_{i \neq k} C_{ik} P_k)]} \quad (3.1)$$

where:

P_i is the probability of the occurrence of the i^{th} event, ($i = 1, 2, 3, \dots, n$)

G_i (the gamma factor) effect of all the events not explicitly specified in the model.

C_{ik} impact of the k^{th} event on the i^{th} event (positive \Leftrightarrow enhancing, negative \Leftrightarrow inhibiting).

G_i is a constant of integration for all the n differential equations for P_i when they are all integrated as a solution set (Bañuls and Turoff 2011). It is equivalent to the sum of individual

products of $C_{ik} * P_{ik}$. Thus it accounts for the effect of all external events not specified in the model. This allows us to infer that it contains all the other influences of the outcome for any given P_i value which is the sum of all which were not made explicit in the events given in the model (Bañuls and Turoff 2011). Once a model is established, the initial probabilities can be varied to assess the degree of influence that it has on the occurrence of the events (Bañuls and Turoff 2011). Internal measures exist that can determine if there are events that are missing and should have been included in the initial event set. For further details of this see (Turoff 1971a).

5 A numerical example

In this section we provide a SCRM-oriented numerical example of a completed CIA exercise. We propose a scenario whereby a supplier to a large manufacturer wins a bid to become the sole provider of an important assembled part such as an automobile engine that is needed by the automobile manufacturer under a strict Make-To-Order (MTO) agreement. We consider this major supplier to be the focal firm in a three-tier supply chain. The focal firm is required to fully satisfy the demands of its important customer through a just-in-time (JIT) delivery of customer orders over the next decade or face sanctions in the form of fines or even the eventual loss of the customer's business. The focal firm can choose to source a critical component needed to assemble the engine (such as the main engine block) from a set of 10 potential suppliers each located in a geographical region \mathbf{r} where $\mathbf{r} \in \mathbf{R}$. We assume that once the focal firm settles on a supplier to fulfill the demand for this critical component, the supplier-buyer agreement cannot be revoked or replaced with another until the end of $T = 10$ years, the duration of the demand horizon for the product under consideration. The selection of a sole supplier in a context like this is critical. For example in recent news Ford Motor Company was forced to halt production of its flagship F150 truck due to supplier failure while it reconsidered options (Krisher 2018).

1.2.1 Determining the initial event set.

The first step in the cross-impact analysis is determining an appropriate event set. This is usually done by committee through a Delphi process. For our example we consider a potential US-based supplier. We assume that historic empirical data and expert opinion pinpoint economic policy and its interrelated events as the main antecedent for the success and failure for firms in this particular geographical region. With this knowledge, supply chain strategists, (along with other appropriate subject matter experts) will be asked to predict the supplier’s probability of being negatively affected by a supply chain disruption during the next ten years.

Table 2 Disruption event set

Event Number (E _i)	Description
1	The US presidency changes hands and political parties more than once (Successive 1 term presidencies)
2	There is a marked increase in worldwide natural disasters and freak devastating weather occurrences
3	Advances in alternative clean energy sources exerts downward pressure on oil prices at the rate of 4%
4	Labor activists successfully lobby for a minimum federal wage increase of 80%
5	National automobile safety standards are tightened
6	Loses class action lawsuit due to multiple personal injury incidents resulting from product defect
7	National demand for cars weakens by 10%
8	Regulatory barriers to autonomous vehicle commercialization are removed
9	A general port strike on the east coast interrupts the flow of goods by ship into the US
10	Washington DC experiences a major terrorist attack similar to the 2001 September 11 attacks on New
11	The US experiences at least a 4% annual decline of real GNP for the time frame
12	High Disruption - Plant production is halted for a continuous period of more than six weeks
13	Low Disruption - Plant production is halted only for brief periods (Slack made up by normal inventory
14	Complete Disruption – Production is permanently halted

The initial event set (see **Table 2**), or current “world” view, for this or any supplier should correspond with its particular geographical region’s main disruption threat based on expert knowledge and past data. Each event is either a direct economic policy change or an event that can be reasonably associated with economic policy changes. Following this, we can refer to events in the event set by their number. For our application of CIA in SCRM, we consider events 12, 13 and 14 to be a special category of SCRM-related events. Event 12, 13 and 14 are manifestations of different levels of supply chain disruption whose occurrence is triggered

directly or indirectly by the rest of the events in the set. In our example of a US-based focal firm, we assume that a large proportion of the values of p_i^L , p_i^H and p_i^X is, indirectly or directly, driven by economic policy changes and the business environment. Ultimately, the novelty of this study is that we consider the cascading nature of events occurring outside of the supply chain that negatively affect its performance. The focal firm is negatively affected when its supplier is unable to deliver components on time.

6 The Cross-Impact matrix and disruption prediction

The CIA process results in a cross-impact matrix A (see Table 3). A quick analysis of the cross-impact matrix shows that E_{10} (major terrorist attack) has a relatively strong (2.54) causal influence or enhancing effect on E_{14} (total disruption). While there may be nothing a firm can do to prevent a terrorist attack, they can either choose not to locate a potential supplier in a region where such attacks may be likely to cause a complete supplier outage or create a business continuity plan for that supplier containing contingency measures if an attack were to occur. In an enhancing linkage such as that between a supplier outage and a terrorist attack, the terrorist attack is considered to have a positive Hahn-Strassman effect on supplier outage in that it creates the conditions that enable a supplier outage to happen (Gordon and Hayward 1968). A terrorist attack necessitates that effort be expended to counteract its negative effect on firm performance. The amount of effort needed to counteract events that enhance a negative supply chain outcome could then be used as a measure a measure of risk mitigation costs and incorporated into a multi-objective optimization model as a parameter and/or a constraint.

The output of the cross-impact matrix gives the user an opportunity to reassess whether the causal relationships make sense. If not, the user can then go back and adjust the initial probabilities in the original event set until she is satisfied with the final results. Had this exercise

been part of a group or Delphi process, all the participant's estimations will then be averaged to come up with a new, and

presumably better, cross-impact matrix. This interaction will result in new probabilities for the initial event set.













Table 3 Cross-impact matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	G_j
1	OVP	0.00	0.44	0.44	0.00	-0.44	0.00	0.44	1.39	-0.44	0.00	0.00	0.00	0.00	-0.58
2	-0.85	OVP	0.41	0.00	-1.79	-1.79	-1.79	-0.85	0.00	-1.79	-0.44	0.00	0.00	0.00	0.64
3	0.00	0.41	OVP	0.00	0.41	0.00	-0.41	-0.41	0.00	-0.81	0.00	0.00	0.00	0.00	-1.24
4	0.00	0.00	-0.41	OVP	0.00	0.00	0.00	0.00	0.00	-1.39	-0.44	0.00	0.00	0.00	-0.91
5	0.00	0.00	0.00	0.00	OVP	-0.54	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.36
6	0.00	0.81	0.00	0.00	1.25	OVP	0.81	0.00	0.41	0.00	0.44	0.00	0.00	0.00	0.78
7	-0.44	-0.85	1.79	0.41	0.00	0.00	OVP	0.00	-0.44	0.44	0.00	0.00	0.00	0.00	0.95
8	1.79	0.00	1.39	0.00	1.79	-0.44	-0.44	OVP	0.00	1.25	-0.44	0.00	0.00	0.00	-0.87
9	0.41	0.44	0.00	0.00	0.44	0.00	0.44	0.00	OVP	-1.35	0.00	0.00	0.00	0.00	-1.43
10	1.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	OVP	0.00	0.00	0.00	0.00	0.00	-0.84
11	-0.44	0.00	-0.85	0.00	0.54	0.00	-0.44	0.54	-0.98	-1.35	OVP	0.00	0.00	0.00	0.23
12	0.44	0.41	-0.44	0.00	0.41	0.00	0.00	0.44	0.00	1.39	-0.85	OVP	3.04	0.00	-1.74
13	0.00	-1.69	0.00	0.00	-0.54	0.00	0.00	0.00	0.54	0.00	-0.54	0.85	OVP	0.00	-0.08
14	-0.38	-1.35	-0.44	0.81	-0.54	0.00	0.54	0.98	0.44	2.54	-1.35	2.10	0.12	OVP	-34.00
G_i	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

When finalized, the CIA results could be presented in manner such as we suggest in **Figure 1** below. **Figure 1** represents a plausible future world view based on the user's understanding of the present context. The given time frame is 10 years. Figure 1 presents the overall probabilities assigned to events in the set and the resulting CIA outcomes or predictions. Of particular interest are events 12, 13 and 14 which represent p_i^H , p_i^L , and p_i^X , respectively. This approach provides results for the impact of high-level economic issues. The assumption is that the experts who ultimately quantify the relative impact of event types are competent at this activity. Their assessment will be based on previous data and the expert's idea of the causal relationships between the different types of events. One possibility that could increase the efficacy of this approach would be to use event studies methodology to provide more robust numerical input.

In this case, the output indicates that it is highly unlikely that a US supplier will become insolvent due to projected changes in the economic environment within the next ten years. Events 3, 4 and 5 are predicted to almost certainly happen. The strategist can then use this insight to help decide whether to initiate a contractual relationship with this supplier. The user's understanding of the current context is greatly enhanced through the CIA process because the resulting outcome considers the interrelatedness of the factors or events.

Figure 1 Summary of probability estimates

SUMMARY OF PERTURBED OUTCOMES FOR CROSS IMPACT SET OF ECONOMIC EVENTS				
THE DATA BARS INDICATE THE ACTUAL CONTINUOUS PROBABILITY LEVEL (0 to 1)		OVERALL PROBABILITY	RESULTING OUTCOME	PROBABILITY LEVEL
1	A Republican presidency in 2024	0.4	Low probability	
2	OPEC reduces oil production by 20%	0.4	Medium probability	
3	Major advances in clean energy technology	0.5	Very high probability	
4	Labor activists successfully lobby for a minimum federal wage increase of 80%	0.4	Very high probability	
5	National automobile safety standards are tightened	0.3	Very high probability	
6	Tort laws are restricted and judgment awards are capped	0.4	Very high probability	
7	Demand for gas-driven cars weakens by 10%	0.6	Medium probability	
8	Regulatory barriers to autonomous vehicle commercialization are removed	0.3	Low probability	
9	A general port strike on the east coast interrupts the flow of goods by ship into the US	0.3	Low probability	
10	The US experiences a major terrorist attack similar to the 2001 September 11 attacks on New York City	0.1	Very low probability	
11	The US experiences at least a 1% annual decline of real GNP for the time frame	0.3	Low probability	
12	High Disruption - Plant production is halted for a continuous period of more than six weeks	0.3	Low probability	
13	Low Disruption - Plant production is halted only for brief periods (Slack made up by normal inventory management)	0.7	Medium probability	
14	Complete Disruption - Production is permanently halted	0.1	Very low probability	

Instead of considering the event probabilities in isolation, the practitioners can now view them more holistically and objectively in through a cascading effects lens. This reduces bias by preventing the practitioner from arbitrarily weighing one factor over another. The user can

choose to use a scale to determine probability level like in **Figure 2** below.

Figure 2 Probability thresholds

Level of probability	Probability value
Very Probable	$P_i \geq .75$
Probable	$.75 \geq P_i \geq .50$
Neutral (could go either way)	$P_i = .50$
Improbable	$.25 \leq P_i \leq .50$
Very Improbable	$P_i \leq .25$

2 Discussion

2.1 Prediction with CIA vs. Bayesian Statistics

Skeptics in SCRM with their roots in Bayesian theory may still doubt the efficacy of the CIA method because they may still view it as a predictive tool in the classical probability sense. However, CIA by itself does not provide the user with a predictive measure in the strictest classical sense of “frequency” probability (Gordon and Hayward 1968). However, when combined with contingency theory, the CIA approach possesses some magnitude of statistical predictive power. This can be the case if the occurrence of one or more events in the set is within the power of the decision-maker. In another example, the decision-maker may be absolutely certain that an event may or may not occur in future. In SCRM, prior knowledge of when a disruptive event will occur is not the norm. Thus, for the most part, CIA can be regarded as a consistency analysis tool that simplifies the supply chain strategist’s task by drastically reducing what would be an infeasible amount of information into a more palatable quantity. Events in the CIA are defined by two important properties:

1. They are strictly non-recurrent, i.e., can only happen once in the time horizon under consideration
2. They can be transient, i.e., they may not even happen at all.

Because of the property of non-recurrence, it is not possible to derive an event's associated probability distribution function. However, it becomes more feasible to apply the concept of subjective probability for an event that occurs only once (Turoff 1971). Given a set of N non-recurrent interrelated events, there exists 2^N distinct scenario outcomes and $N2^{N-1}$ outcomes that span the range of none the events occurring and all of them occurring in a given time frame (Turoff 1971). Interestingly, human beings on their own are not even capable of estimating the outcomes of event sets where N is a single digit number in a meaningful manner. Even for a mere $N = 4$ events, a decision maker would have to decide amongst 32 possible outcomes and 512 possible distinct transition paths. In reality, human beings estimate these probabilities by subconsciously analyzing non-recurrent and transient relationships of this nature on a daily basis (Turoff 1971). Sometimes these rudimentary estimates may even be used to make important decisions such as selecting a long-term supply chain partner. The power of CIA lies in its ability to limit the user to N^2 outcomes or questions for N interrelated events (Turoff 1971a).

7 Managerial implication

The main practical implication of our study is that we provide strategist tasked with building inflexible supply chains with a useful tool with which they can better prepare for unpredictability. Some researchers have stated that predicting and then avoiding disruptions are impossible tasks, especially in the case of exogenous events. Their basic approach to SCRM has been to assume that disruptions are an inevitability and that SCRM should focus on mitigation and business continuity in the advent of disruptions. We partially agree with this assertion because no one can ever completely and accurately predict the future. However, we contend that practitioners should at least try to take steps to understand their business environments and the possible impact on their firms' performance when exogenous events do occur.

8 Limitations

For this study, we arbitrarily picked economic policy as being a major potential disruptive factor in the US. This may not necessarily be reflective of reality. Furthermore, the process of deciding which types of exogenous disruptive events to include in the event may be more complicated than just choosing a single risk category such as economic events. Since we acknowledge that the event set is crucial to the estimation of risk, we deem this aspect to be a limitation of this particular study. We do point that the approach of considering a different context for each geographical region is correct and has been supported in SCRM risk management contingency theory literature (see Sodhi and Tang, (2014)). Thus, potential suppliers in different geographical areas will most likely have a unique event set (Sodhi and Tang 2014). To arrive at plausible and useful event sets, we suggest a contingency theory approach whereby the user with the help of other experts would consider the context in which the strategy is to implemented (S. M. Wagner and Bode 2008). Events 12, 13 and 14 in Table 3 will be common in all the event sets. It is a comparison of these across all the summary outputs for all the potential suppliers under consideration that arm the strategist with a better idea of the relative exposure to disruption risk of each site.

Another limitation is that the actual outcome of CIA can only be analyzed in the aftermath of the predicted event set and not before. With each event set being unique, it may be difficult to generalize the results of the exercise. What is undeniable however is that CIA greatly reduces the complexity of analysis by limiting the user to N events and N^2 event pathways as opposed to a possible $2N$ distinct outcomes and $N2^{N-1}$ pathways that span the range of none of the events occurring and all of them occurring in a given time frame.

9 Conclusion

The objective of this research was two-fold: (1) to demonstrate modeling of supply chain disruptions caused by exogenous events when it is assumed that events do not happen in a vacuum but rather are triggered by other events. (2) to reduce the complexity practitioners can face when deciding amongst a great number of possible pathways. We were able to accomplish both objectives by introducing CIA as a potential analytics tool in SCRM. We show how the causal relationship between exogenous events can be analyzed resulting in a prediction of supply chain outcomes. In future research we will demonstrate how both efficiency and effectiveness goals can be simultaneously achieved through the hybridization of CIA with a stochastic MMOP supplier selection technique. The output of the CIA matrix could be used to reduce uncertainty by providing informed probability estimates, as opposed to random distributions. Another research direction could encompass defining the linkages between the cost of mitigation and supply chain outcomes in the aftermath of exogenous disruptive events. For example, the effort necessary to fend off the negative effects of a certain disruption could be calculated as a function of its probability and disruption-enhancing effect. Ultimately, a futures approach should provide the practitioner with a better understanding of future disruption mitigation costs and outcomes. The analyst may be able to better predict the performance of different mitigation strategies, i.e., the extent to which a particular mitigation strategy will enhance or inhibit the occurrence of a particular disruption type. In other future studies, strategists could elect to base the risk assessment of a supplier on the results of just one CIA exercise using just one event set. However, we recommend that this process be repeated with other types of disruption threats. The results of the analyses would then be aggregated to derive a more complete composite risk profile index for a particular site with an appropriate weighting of individual disruption types.

Overall, we hope that this study will motivate SCRM researchers to delve into futures-oriented research.

Chapter 3

Supplier Selection Under Disruption Risks: A Hybrid Cross-Impact Analysis/Stochastic Mixed-Integer Approach.

Abstract

Global supply chains are becoming more vulnerable to increased supply chain-related cost due to supplier operational failure and that increase component costs due to political/macro-economic disturbances. In this paper we address the shortage in the literature of mathematical supplier selection models that account for both types of supply chain risks. Using a combined Cross-Impact Analysis and Stochastic Mixed-Integer Programming approach, we introduce a single-source supplier selection model that accounts for both operational and political/economic disruption risk. Our computations indicate that a model considering the probability and impact of future political/macro-economic events can result in the selection of a different supplier from that of a model that only considers costs borne from supplier operational delays. We hope that our model will motivate researchers to adopt mixed-methods approaches and incorporate political/economic risk into future global supplier selection mathematical models

1 Introduction

In 2018, President Trump sparked a series of tariff wars that caused many company executives to reconsider the composition of their supplier portfolios in order to minimize supplier risk exposure (Conerly 2018). The idea that supplier risk-related costs are an important consideration during the selection of an optimal supplier portfolio is not new (see de Boer et al., 2001; Chen et al., 2006; Kuo et al., 2010; Li and Zabinsky 2011; Ruiz-Torres et al., 2013). The broad view in the literature is that decreased on-time delivery rates due to supply chain-related disruptions

increase cost of production. In essence, supplier risk is realized when a firm is fined by its customer for failing to deliver on time (Sawik 2011). Such a delay is often due to failure of the supplier's own supplier to deliver necessary components in a timely manner. Increase in variable costs due to the manifestation of supply chain risk has been used to quantify supplier selection risk in stochastic supplier selection models (see Sawik 2011). However, the literature does little to account for increased supply chain-related costs resulting from disruptive external economic events; for example, tariff wars. Such external events do not necessarily result in delays in the supply chain. However, they have been shown to increase supply chain costs. For example, in retaliation for similar measures imposed by the Trump administration, Canada hit steel imports with a 25% tariff in mid-2018 (Allix 2018). The Trump administration also imposed a 25% steel import tariff on Mexico; along with a 10% general worldwide aluminum import tariff (Allix 2018).

Tariffs can result in abrupt and unexpected changes in supply chain costs. Unexpected increases in costs realized from economic disturbances like tariffs are a special type of supply chain disruption that is often overlooked in the literature. We differentiate between two types of supply chain disruption costs: 1) *operational costs*, which result from fines imposed on a firm for failure to deliver on time, and 2) *non-operational* or *economic costs*, which are a result of external global or regional economic events. We define the threat of economic event or disturbances to the supply chain as economic disruptions risk. In this case our definition of economics is based on the broad definition of economics i.e. "the academic study of the production, distribution, and consumption of goods and services" (Merriam-Webster 2015). In particular, we focus on the impact on the supply chain of human-driven events on the macroeconomic level. Examples of this are possible government policy changes in influential countries such as the United States that

may affect global market efficiency. Disruptive external economic events may not necessarily result in a slowdown of the supply chain. However, they are an important supply chain risk consideration because they can negatively affect supply chain efficiency.

To illustrate the main idea in this study, we use the special case of a firm with a single source supplier strategy. The problem of supply chain risk is interesting to study in such a setting because the problem of supplier risk is exacerbated when a firm is unable to spread the risk of non-delivery across a portfolio of suppliers. Despite this danger, some firms may still prefer single-sourcing in order to increase supply chain flexibility (Chappell 2018) or for achieving efficiencies borne from buyer-supplier collaboration (Bode et al., 2011) and/or economies of scale. Our own investigative interviews with actual supply chain professionals and industry executives reveal that sometimes these two generally accepted and prescribed methods are not always practical or economically viable.

In one case, the Chief Executive Officer of a major supplier to one of the top three automobile manufacturers described to us how certain buyer-supplier relationships may involve extremely critical high-cost components such as engine blocks. He said that in the automobile industry it is not uncommon for supplier sites to have extremely high Cost of Assets to Total Cost (COA/TC) ratios.. Thus, an extremely high COA/TC ratio can render mitigative strategies such as dual or cross sourcing economically infeasible. Furthermore, he added that the extremely high unit cost of production of a single specialized component may necessitate a strict make-to-order demand-driven Just-in-time (JIT) production and delivery process. He added, “once a buyer picks a supplier, it has to hope that the probability of future disruption of this supplier is minimal for the complete duration of a product’s life cycle.”

In cases, where buyer supplier production activities are highly co-dependent and integrated, buyers often invest financial and human capital into supplier resiliency in a bid to reduce supplier *operational risk* (See Colicchia and Strozzi 2012; Jüttner 2004; Kleindorfer and Saad 2009). This practice is common in the automobile industry. In Japan, these types of exclusive, closely-integrated buyer-supplier partnerships borne from long-standing relationships are generally known as *keiretsu* (Matsuo 2015). A prominent example of this is Toyota's supplier structure strategy: Despite parts shortages in the aftermath of the Tohoku earthquake/tsunami catastrophe, Toyota announced that it would continue to stick to its single sourcing strategy because the benefits of doing so significantly outweighed the negatives (Chappell 2018). Toyota cited the reliance on some of 150 critical single-source suppliers with whom it had a very close collaborative relationship and who could not be easily replaced due to their very high engineering capabilities (Chappell 2018). In a similar move, Tata Motors, India's largest auto maker, announced a new one-part one-vendor strategy aimed at cutting cost through economies of scale achieved from close and exclusive long term collaborative supply chain buyer-supplier partnership (Fintech 2013).

Long-term collaborative partnerships typically involve extensive interfirm integration and investment into human and sometimes physical capital (Bode et al., 2011). Thus, once fully established, efficacious collaborative buyer-supplier relationships are usually not easily or readily replicable (Friedl and Wagner 2012). The problem arises when a single-source supplier is disrupted in some way. In the case of operational disruptions, the buyer may have no choice but to invest, at great expense, to help the supplier regain full production capacity. In the interim, demand may remain unsatisfied and market share could be permanently lost as customers balk at waiting times and begin to defect to competitors' substitute products. In the case of economic

disruption, the buyer may have to absorb the resultant increased costs and forgo the ability to find a cheaper alternative source.

It becomes obvious that for long-term single-sourcing buyer-supplier relationships, selecting the right supplier from the start is an extremely important decision that could save a buyer from the negative effects of supplier disruption in the long-run. Single sourcing dependency exposes the buying firm to an elevated level of risk (Burke et al. 2007). Despite this fact, there is a lack of research dedicated to sole supplier selection under external economic risk and uncertainty (Cao et al., 2016; Hammami et al., 2014). More specifically, there is need for supplier selection mathematical models which also quantify the impact of macro-economic disruptions on supply chain.

The problem of the macroeconomic impact of human activity on supply chains has been studied extensively in the field of economics. Some examples of the macroeconomic effect of trade policy on global supply chains can be found in literature on vertically linked product trade policy schemes and cascading trade protection (Erbahar and Zi 2017). Cascading trade protection occurs when countries administer forms of protection such as import tariffs (Anis et al. 2002) and anti-dumping (AD) law (Hoekman and Leidy 1992) to protect local industry from foreign competition. While these studies address global supply chain efficiencies, they are more focused on the broad benefit of government policy to a particular country's firm in general. Relatively few studies focus on the SCRM activities of individual firms. While the macroeconomic effect is prevalent in economics and trade policy journals, it is not as well addressed in SCRM. To be precise, and as outlined in the literature review section, there are very few SCRM studies that specifically consider the potential risks that macroeconomic activity poses to supply chain viability when firms are faced with supplier selection decisions. To contribute towards

addressing this void in SCRM, we introduce a single-source supplier selection model that assists in decision-making in the face of both operational and economic disruption risk.

We propose the dual use of Cross-Impact Analysis (see Gordon and Hayward, 1968) , a futures-oriented scenario generation technique, and Stochastic Mixed-integer Programming (SMIP) in a robust hybrid CIA-SMIP model. The CIA component can enhance the ability of practitioners to predict economic disruption risk. We illustrate this new technique using an example of a focal firm (a first-tier supplier) which must decide on a single-source supplier from a set of potential partners, all in different global regions. Using this example, we formulate and solve a dynamic stochastic mixed integer programming (SMIP) model in which the risk of operational disruption is measured using an extant SMIP model developed in (Sawik 2018). As our contribution, we adapt one of Sawik's (2018) SMIP models to include consideration for economic disruption risk using the scenario-generation capabilities of the CIA technique. The CIA-SMIP technique combines the two approaches most commonly used in optimization under uncertainty: (1) stochastic optimization where random parameters have known distributions and (2) robust optimization where the probabilities and distributions are unknown (Snyder and Daskin 2006). In SCRM, robust optimization often utilizes scenario generation to find solutions that, on average, perform well while allowing for some periods of bad performance (Snyder and Daskin 2006). The problem is that supply chain decision-makers are often evaluated *ex post*, i.e., after the cost of their decisions have been actualized (see Snyder and Daskin 2005). Thus, a side effect of *ex post* evaluation is that decision-makers are incentivized to use robust optimization to seek minimax regret solutions that have the appearance of effectiveness regardless of the situation (Snyder and Daskin 2006) i.e., their models will assume the worst-case scenarios and be overly conservative every time. This tendency could result in lost opportunities.

Another general concern in robust optimization under uncertainty has to do with the sheer number of possible scenarios. Because of their random nature and interrelatedness, analyzing the set of events that result in supply chain disruption requires the generation of multiple scenario configurations. Unfortunately, the mathematical tractability necessary to determine dominance relationships is quickly diminished as the number of possible scenarios under consideration increases (Gutierrez and Kouvelis 1995).

CIA can be categorized as a special type of robust technique. It has some distinct advantages over other robust techniques in that it accounts for the interrelatedness of risk factors. It also provides a systematic approach to reducing the number of possible scenarios into a more manageable and plausible set. Other robust techniques exist in the literature, but they do not possess some of CIA's advantages. For example, Häntsch and Huchzermeier (2013) use a robust approach that incorporates scenario building. However, their approach does not consider the interrelatedness of the factors they consider. Furthermore, it neither provides a systematic replicable approach to scenario generation nor does it explain how the number of scenarios was, or could be, reduced.

In this paper, we show CIA's approach to scenario building can be incorporated into an extant SMIP model. Therein, we demonstrate CIA's ability to reduce an otherwise mathematically intractable number of possible outcomes resulting from a combination of plausible future events to a more manageable set of plausible scenarios in an uncertain supply chain risk management environment. Our CIA-SMIP approach is designed to help decision-makers in firms that employ single-sourcing strategies to correctly choose the supplier that presents the lowest long-term overall supply chain risk. The rest of this study comprises the following sections: Section 2 is a literature review of our general topic area; in Section 3, we present the proposed CIA-SMIP

model formulation used to solve the supplier selection problem; Section 4 comprises a detailed computational example; and lastly, Section 5 contains the conclusion and suggestions for future research.

2 Literature Review

The supplier selection problem has received much attention in the literature. Dickson (1966) conducted a groundbreaking survey in this area and found that there were three main criteria used in supplier selection decision-making: the ability to meet quality standards, the ability to deliver the product on time, and performance history. Many tools and approaches have been subsequently developed based on these criteria to address supplier selection under uncertainty. In general supplier selection literature can be classified into 3 categories (De Boer et al., 2001; Wu et al., 2006):

- 1) A conceptual approach that highlights supplier selection strategies
- 2) Empirical studies that examine relationships between attributes of the supplier selection process
- 3) An analytical approach that presents models used to solve the supplier selection problem

In this is paper we present an analytical model. Thus, we concentrate our literature review on this approach. More precisely, we present an analytical model for the *final selection* of a supply chain partner (Wu and Barnes 2011). Whereas some supplier selection decision models address different stages of the supplier selection process such as formulation of criteria and supplier qualification, the majority of supplier selection models fall under the final selection category (Wu and Barnes 2011).

A variety of approaches that can be found in the literature to address that final selection of a supplier. They include: Mathematical programming; Analytical hierarchical/ network process

(AHP) and (ANP); Fuzzy Set Approach; and combined methods which do not necessarily fall neatly into any particular category (Wu and Barnes 2011).

In mathematical programming, goal programming has been applied to attain multiple goals for different levels of performance (Hajidimitriou and Georgiou 2002). Multi-objective programming (MOP) is used to help decision-makers during the negotiation stage (Cakravastia and Takahashi 2004). Wu et al., (2010) propose a stochastic fuzzy multi-objective programming model that takes supply chain risk factors into consideration. Another subcategory of MOP that is common in the literature is integer programming. An example of this is Zhang and Zhang (2011) who address a supplier selection and purchase problem under stochastic demand by applying a Mixed Integer Programming technique incorporating a branch-bound algorithm. Distinct from MOP are AHP and ANP. Examples of these include: Tam and Tummala (2001) who applied an AHP-based model to in a real setting to select a vendor for a telecommunications system. Chan (2003) uses AHP to identify buyer-supplier interactions and to validate data collection methods in order to select the best possible suppliers. AHP however falls short in that it may be too simplistic and fails to account for the complexity presented by hierarchical relationships between factors under consideration (Wu and Barnes 2011). ANP is used to address this deficiency in for example (Coulter and Sarkis 2006) who propose a strategic model for partner selection that accounts for more complex relationships and also the possibility of bi-directional hierarchical relationships.

Fuzzy set models have also been used in final supplier selection literature and have been applied to both MOP and AHP techniques. They have been particularly useful for accounting for uncertainty and imprecision in supplier selection. For example, Sarkar and Mohapatra (2006) introduce a fuzzy MOP supplier selection model that measure the imprecision of suppliers'

subjective characteristics. Bevilacqua et al., (2006) introduce a fuzzy algorithm that evaluates that importance of product features in supplier selection.

There are models in the literature that do not belong to any of the aforementioned categories.

These models are mostly set in dynamic decision-making settings. Examples include Lau and Wong (2001) who use different technologies such as manufacturing resource planning (MRPII) , computer aided design (CAD) and computer aided process planning (CAPP) to solve the supplier section problem in dynamic networks; and Crispim and De Sousa (2010) propose an integrated approach for ranking virtual enterprises as prospective partner in a dynamic environment using TOPSIS (a technique for ordering preferences) in a dynamic environment.

Almost all the aforementioned approaches to supplier selection propose methods are operations-based in nature. Specifically, most of the research we describe is concentrated around operational supplier selection metrics such as quality and timely delivery. We found few analytical models that consider the uncertainty of supply chain viability as result of factors other than supplier operability such as increased cost due to external economic factors. We also found no stochastic model that simultaneously addresses internal operational and external non-operational supply chain risk. Furthermore, we found no studies that simultaneously consider the cascading effect of human-driven economic events that are external to the supply chain but may nonetheless threaten supply chain efficiency. This is what we introduce in this study

There are several studies such as Ruiz-Torres and Mahmoodi (2007) that consider economic factors exist in the literature. For example, Gutierrez and Kouvelis (1995) show, using a robust approach, how a buying firm's performance could be hedged against global supplier disruption caused by changes in macroeconomic parameters. They use realizable exchange rates as their unit of measurement and attempt to hedge the firm's performance against the worst-case

scenario. Kasilingam and Lee (1996) propose a stochastic mixed integer programming model to select vendors and determine order quantity. Bollapragada et al., (2004) examine system inventory dynamics and propose a decomposition approach using an internal service level to independently determine near-optimal stock levels for production components under demand uncertainty. Berger and Zeng (2006) use a decision tree approach to determine the optimal size of its supply base in the presence of risks. They focus on operational interruptions that occur when suppliers are unable to meet the buying firm's demand levels and offer exact and approximate optimal solutions for various scenarios.

Ruiz-Torres and Mahmoodi (2007) also utilize a decision tree approach to determine an optimal number of suppliers in the presence of supplier failure risks. Their study is different from previous research in that they consider partial failure and the possible operating cost gains that can be accrued from using less reliable suppliers. Sawik (2011) presents a study on supplier selection under disruption risk and proposes a method that uses two measures of risk: value-at-risk and conditional value-at-risk for order allocation optimization in a multiple vendor scenario. Li and Zabinsky (2011) identify supplier selection as an important strategic decision and propose a two-stage stochastic programming and chance constrained hybrid model to determine the minimal set of suppliers and optimal order quantities with consideration for business volume discounts. Ruiz-Torres et al., (2013) also use decision trees to model supplier failure and prescribe mitigation strategies. They consider all the possible states of nature when one or more suppliers fail. Their contribution is the consideration of contingency planning in the decision process in order to minimize the total network costs.

Most of the aforementioned methods use past empirical data to predict future events. The problem is that cascading events can result in unexpected outcomes. The reality is that the future

does not present itself in a manner such that these models can be conveniently superimposed onto strategic plans. Scenarios and conditions differ across different time periods. This means that past mitigation strategies may prove ineffective as new and different problems occur. Thus, there is need, in the literature, for more forward-looking futures-oriented predictive techniques that account for the possibility of multiple possible scenarios and their resultant outcomes. To address this gap, we draw inspiration from studies like (Gutierrez and Kouvelis 1995) who introduced a robust approach to international sourcing by developing supplier networks in such a way that hedges the firms' performances against the worst contingency in terms of foreign exchange rates shock over a planning horizon. They presented an algorithm that resulted in the N best sourcing networks to the international sourcing problem. Our approach is different from (Gutierrez and Kouvelis 1995) in that we also consider operational risk and the additional constraint of the single-source supplier. For this we utilize a widely accepted Stochastic Mixed Integer approach outlined in Sawik (2018). The result is a hybrid model that we contend is more robust than each the two techniques on their own. Our ultimate goal is to minimize *future* overall supply chain risk by choosing the single best sole source for a component in the presence of uncertainty and incomplete information.

3 Formulation of Model

We consider a three-echelon customer driven global supply chain very similar to one proposed by (Sawik 2018) in which comprises a customer, a buyer and a supplier. The buyer is the focal firm. The buyer can source a single critical component from a set of potential suppliers $I = \{1, \dots, \bar{I}\}$ located in different geographic regions across the globe (see Table 1 for notations used). The buyer must pursue a single-source strategy for this component over a 30 month planning horizon (five six-month planning periods). The product is to be manufactured and

provided by the buyer to meet customer demand over the entire planning horizon. The satisfaction of customer demand is contingent upon on the on-time delivery of the critical component to the buyer.

Using the general format in Sawik (2018), let $I = \{1, \dots, \bar{I}\}$ be the set of potential suppliers, $J = \{1, \dots, \bar{J}\}$ the set of \bar{J} customer orders for the product, and $T = \{1, \dots, \bar{T}\}$ the set of planning horizons. Then let b_j and d_j be the size and due date of customer order $j \in J$ respectively. Let b_j be the number of units of product ordered and d_j the latest period of their completion required to deliver the product to the customer by the required date.

We use a_j to describe the unit requirement for the critical part of the product in customer order $j \in \bar{J}$. The total demand for all parts is $A = \sum_{j \in J} a_j b_j$. In the same vein, the total demand for all products can be written as $B = \sum_{j \in J} b_j$. Orders for parts are presumed to be placed at the beginning of the planning horizon and customer demand is known ahead of time. Let o_i be the unit purchasing price of components from supplier $i \in I$. Under normal conditions, the supplier can deliver the components needed in any given period on time and with a negligible defect rate. All the parts ordered from a supplier are delivered in a single delivery. The order takes a constant τ_i periods to prepare and transport from supplier to buyer such that components ordered from supplier $i \in I$ are delivered in the period τ_i and then can be used for the assembly of the product in period $\tau_i + 1$, at the earliest (Sawik 2018).

3.1 Disruption Risks

The selection of a supplier comes with two types of disruption risks that may increase production costs for the buyer. The main contribution of this study is that we simultaneously measure additional cost borne from delays in the supply chain and also increased component cost arising from external economic factors. We define risk borne from delays as operational risk and risk

resulting from increases in component cost as economic risk. The events that result in the realization of either type of risk may be the same. For example a seaport strike may result in the delay of product delivery and result in the focal firm being fined accordingly by its customer. However, the port strike could result in an increase in component cost only if the focal firm uses air to transport the component instead. Note that what we actually measure in the end is the effect on supply chain operability or cost of the event and not the event itself. We achieve this by adapting a risk-neutral calculation of supplier-caused operational risk for a single-sourcing strategy introduced in Sawik (2018) to include an economic risk component. We define supplier-caused operational risk as the risk of increased production costs due to delays in the delivery of necessary production components for a supplier. This risk is realized when the buyer is fined by the customer for each order and unit that is late. The incurred costs are based on a contractual agreement that stipulates penalty cost for each delayed order delivery.

The second type of risk is political economic risk which is calculated using the CIA methodology. This risk encapsulates the political and economic disruption risks that affect global factor markets which is expressed as D_i^{CIA} , a constant or a cost factor by which the total cost (including operational risk-related costs) of ordering from a certain supplier is multiplied over a given planning horizon. This constant is always greater than one because economic risk can never be less than or equal to zero. Economic disruption risks do not necessarily manifest or present themselves as slowdowns or retardations in supply chain operability. They are, instead, expressed as per unit real increases in component costs due to things like currency fluctuations, increases in transportation costs due to increased oil prices, increases in the cost of imports due to changes in tariffs, etc.

3.1.1 Calculating Operational Risk (Sawik 2018)

The method for the calculation of operational risk is found in Sawik (2018). Below we briefly describe the **SPS1_E(c)** model and present its basic equation and refer the reader to Sawik (2018) (see p.g 112) for a more detailed and complete explanation. The suppliers are located in R disjoint geographic regions. Let $I^r \subseteq I$ be the subset of suppliers in region $r \in R = \{1, \dots, \bar{R}\}$ where $\bigcup_{r \in R} I^r = I$. Let p_i^o be the probability of *operational* disruption caused by localized phenomena such as fires, plant failure, freak weather occurrences or earthquakes for supplier i , i.e. $1 - p_i^o$ is the probability that the parts are delivered without disruptions and p_i^o is the probability that parts are not delivered.

Along with the local disruptions of each individual supplier, there are potential regional disasters that may result in correlated regional disruption of all suppliers with a probability of p^{r_o} .

Furthermore, global disaster super events such as worldwide environmental catastrophes that may affect all suppliers, regardless of region, with a probability of p^{*o} . p^{r_o} and p^{*o} can be interpreted as affecting the operations of supply chains. They are special and separate types of operational disruption not to be confused with p_i^o , which strictly refers to local disruptions at each site because they negatively affect internal supply chain operability and result in the inability of the supplier to deliver components on time. The aforementioned events are assumed to be independent.

In this study, a buyer must source all or part of any given order j from only one supplier over the entire planning horizon. In any disruption scenario S , zero or more suppliers can be disrupted and their ability to deliver parts will be disrupted for that period. The probability that disruption scenario s occurs is P_s^o , where $s \in S = \{1, \dots, \bar{S}\}$ corresponding to a unique subset $I_s \subseteq I$ of suppliers who deliver parts without interruption. For each scenario $s \in S$, the supplies from

every supplier $i \in I \setminus I_s$ can be disrupted either by a local, regional or global disruptive event.

The probability of P_s^o is presented in Sawik (2018) as:

$$P_s^o = \left\{ \begin{array}{ll} (1 - p^{*o}) \prod_{r \in R} P_s^{r_o} & \text{if } I_s \neq \emptyset \\ p^{r_o} + (1 - p^{*o}) \prod_{r \in R} P_s^{r_o} & \text{if } I_s = \emptyset \end{array} \right\} \quad (2)$$

Where $P_s^{r_o}$ is the probability of realizing disruption scenario s for suppliers I^r .

$$P_s^{r_o} = \left\{ \begin{array}{ll} (1 - p^{r_o}) \prod_{i \in I^r \cap I_s} (1 - p_i^o) \prod_{i \in I^r \setminus I_s} p_i^o & \text{if } I^r \cap I_s \neq \emptyset \\ p^{r_o} + (1 - p^{r_o}) \prod_{i \in I^r} p_i^o & \text{if } I^r \cap I_s = \emptyset \end{array} \right\} \quad (3)$$

In risk-neutral decision making, the effectiveness of the supply portfolio can be measured by the

expected cost per product (see equation (3)), of parts ordering $\frac{\sum_{i \in I} e_i u_i}{B}$, and purchasing of parts

$(\sum_{s \in S} P_s^o (\sum_{i \in I_s} A o_i u_i) / B)$, where the producer is not charged with ordered and undelivered

parts, plus two types of penalty costs 1) penalty cost of delayed orders

$\sum_{s \in S} P_s^o (\sum_{j \in J} \sum_{t \in T: t > d_j} g_j b_j (t - d_j) w_{jt}^s) / B$ and 2) cost of unfulfilled (rejected orders) due to

delays and disruptions of part supplies, $\sum_{s \in S} P_s^o (\sum_{j \in J} h_j b_j (1 - \sum_{t \in T} w_{jt}^s)) / B$ (Sawik 2018).

Table 4 below contains the notation input parameters and indices that will be used throughout this paper.

In risk-neutral decision making, the effectiveness of the supply portfolio can be measured by the expected cost per product (see equation (3)), of parts ordering $\frac{\sum_{i \in I} e_i u_i}{B}$, and purchasing of parts $(\sum_{s \in S} P_s^o (\sum_{i \in I_s} A o_i u_i) / B)$, where the producer is not charged with ordered and undelivered parts, plus two types of penalty costs 1) penalty cost of delayed orders $\sum_{s \in S} P_s^o (\sum_{j \in J} \sum_{t \in T: t > d_j} g_j b_j (t - d_j) w_{jt}^s) / B$ and 2) cost of unfulfilled (rejected orders) due to delays and disruptions of part supplies, $\sum_{s \in S} P_s^o (\sum_{j \in J} h_j b_j (1 - \sum_{t \in T} w_{jt}^s)) / B$ (Sawik 2018).

Table 4 Notation: selection of supply portfolio and scheduling Indices (adapted from Sawik 2018)

Symbol	Indices
i	= supplier, $i \in I$
j	= customer order, $j \in J$
r	= geographic region, $r \in R$
s	= disruption scenario, $s \in S$
t	= planning period, $t \in T$
a_j	= per unit requirement for parts of each product in customer order j
b_j	= size (number of products) of customer order j
F_i	= Tariff costs risk factor (derived from CIA)
A	= total demand for parts
B	= total demand for product
c_j	= per unit capacity consumption of producer for customer order j
C_t	= capacity of producer in period t
d_j	= due date for customer order j
e_i	= fixed cost of ordering parts from supplier i
g_i	= per unit and per period penalty cost of delayed customer order j
h_j	= per unit penalty cost of unfulfilled customer order j
I^r	= subset of suppliers in geographic region r
o_i	= per unit price of parts purchased from supplier i
p_i^o	= local operational disruption probability for supplier i
p^{ro}	= regional operational disruption probability for all suppliers in region r
p^{*o}	= global disruption probability for all suppliers α
p_i^{Hc}	= low impact economic disruption probability \Rightarrow Cost of production is increased by $5\% \geq x \geq 3\%$
p_i^{Lc}	= high impact economic disruption probability \Rightarrow Cost of production is increased by $10\% \geq x \geq 5\%$
p_i^{Xc}	= very high impact economic disruption probability \Rightarrow supplier becomes insolvent $10\% \leq x$
α	= confidence level
τ_i	= delivery lead time from supplier i

The complete SPS1_E(c) model is formulated below.

Minimize

$$\begin{aligned}
 & \sum_{i \in I} e_i u_i / B + \sum_{s \in S} P_s^o \left(\sum_{i \in I_s} A o_i u_i \right) / B \\
 & + \sum_{s \in S} P_s^o \left(\sum_{j \in J} \sum_{t \in T: t > d_j} g_j b_j (t - d_j) w_{jt}^s \right) / B \quad (4) \\
 & + \sum_{s \in S} P_s^o \left(\sum_{j \in J} h_j b_j \left(1 - \sum_{t \in T} w_{jt}^s \right) \right) / B
 \end{aligned}$$

Table 5 Variables: selection of supply portfolio and scheduling (from Sawik 2018)

First stage variables	
u_i	= 1, if supplier i is selected; otherwise $u_i = 0$ (supplier selection)
Second stage variables	
w_{jt}^s	1, if under disruption scenario s customer order j is scheduled for period t ; otherwise $w_{jt}^s = 0$ (production scheduling)

In order to ensure selection of a maximum of one supplier, we introduce the constraint u_i shown in Table 2, an order-to-period assignment constraint, w_{jt}^s . That is, for each disruption scenario s , and each customer order j is scheduled during the planning horizon ($\sum_{t \in T} w_{jt}^s = 1$), or unscheduled and rejected ($\sum_{t \in T} w_{jt}^s = 0$). For a more detailed explanation of this model which includes the other constraints, we direct the reader to Sawik (2018).

3.1.2 Measuring Non-Operational (Cost) Risk Using Cross-Impact Analysis

So far we have outlined the calculation of *operational* supplier risk in a supplier selection model as proposed by (Sawik 2018). Instead of just considering operational risk we now consider *political-economic* risk. We define political-economic risk as risk of increased production costs as triggered by changes in the regional or global political and economic environment. This type of disruption event does not necessarily cause an *interruption* of the flow of goods in the supply chain but rather an *increased cost* of the component to the buyer.

Let p^{H_c} , p^{M_c} and p^{L_c} represent the probability of occurrence of high impact, medium and low impact economic disruption that cause increases in the cost of component sourced from suppliers for the buyer. Economic disruption which result in increased supply chain-related costs can happen when, for example, human induced global political/economic events trigger currency value fluctuations (Gutierrez and Kouvelis 1995), introduction or increase in costs related to import tariffs or when the buyer has to ship cargo using air as opposed to sea during a sea port/harbor strike; as opposed to operational disruptions which are random occurrences that directly result in delays in the supply chain we consider economic disruptions to be deterministic in nature. We posit that cost increases resulting from economic disruptions cascading culmination of preceding events that either enhance the or inhibit the occurrence of subsequent events. This is why we propose the use of a deterministic methodology like CIA to determine the magnitude of the causal relationships between such events and thus estimate their conditional probabilities.

3.1.3 Calculating Economic Event Probabilities Using CIA

The CIA method is an analytical approach to the calculation of probabilities of an item in a forecasted set (Gordon 2004). A set of future plausible events is usually generated through a

literature search and conducting interviews with experts in the field. In this study (for illustrative purposes), our event set is adapted from the Chartered Institute of Procurement and Supply (CIPS) report on the global supply chain risk index (Ganguli 2018). Using the provided list of global supply chain political-economic risks, we derive a plausible set of future events for each region in the supply chain based on our knowledge and expert opinion. We suppose that the setting is in January 2016 and the supplier under consideration is located in the Asia-Pacific region. We consider a total time period T of ten years to correspond with the projected life cycle of the product in question, implying that production of this product and its related inputs will be halted after ten years.

The event sets are situational and unique to each supplier based on its global location. Each event is assigned initial probabilities, P_i , $i = 1, 2, \dots, 14$, of occurrence sometime within any period $t \in T$, $t = \{1, \dots, 10\}$. For this example each period represents a year beginning with 2016. The general idea is that events in a well-defined set should influence or cause each other by some degree or magnitude. We estimate the influence (causality) resulting from the assumptions made about the occurrence or non-occurrence of events and thus calculate p^{Hc} , p^{Mc} , and p^{Lc} . Causality is measured using a correlation coefficient C_{ik} which represents the impact of the k^{th} event on the i^{th} event. The events are not necessarily timestamped. C_{ik} simply represents a quantification of how the occurrence of one event k will affect the probability of occurrence of another event i . A positive C_{ik} means that event k *enhances* the probability of event i , whereas a negative C_{ik} implies that event k *inhibits* or reduces the probability of event i . We can calculate C_{ik} using a variation of the Fermi-Dirac or logistic distribution function by asking subjects about the probabilities (P_i) as determined by the following relationship (see Bañuls and Turoff 2011; Turoff 1971):

$$P_i = \frac{1}{[1 + \exp(-G_i - \sum_{i \neq k} C_{ik} P_k)]} \quad (5)$$

where

P_i is the probability of the occurrence of the i -th event, ($i = 1, 2, 3 \dots n$)

G_i (the gamma factor) the effect of all the events not explicitly specified in the model.

C_{ik} impact of the k^{th} event on the i^{th} event (positive \Leftrightarrow enhancing, negative \Leftrightarrow inhibiting).

9.1.1.1 The Cross-Impact Matrix

The cross-impact matrix (see Table 3) is a tabular representation of all the possible relationships between the events in a given event set. It contains the values for each

C_{ik} which are calculated using the likelihood measure depicted in (Turoff 1971b). Each C_{ik}

represents the impact of the k^{th} event on the i^{th} event. The C_{ik} values in the body of the table, in

essence, represent the marginal utility factors that relate the utility of the k^{th} event to the i^{th} event

(Turoff 1971b). The last column in Table 3, called the G-vector which contains the G_i values, is

a constant of integration for of the n differential equations for P_i that allows us to collect all other

influences for P_i that are not explained by the causal relationships (Bañuls and Turoff 2011). The

result of calculating all the C_{ik} 's can be tabulated and displayed a cross-impact matrix such as

the one below; which we obtained for our computational example. The diagonal would present

the overall probabilities (OVP) for each event which are calculated using Equation 4. The OVP's

we used for our computational example are shown in Table 4.

Table 6 Cross-impact Matrix with G vector

i	k														G vector
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
1	OVP	0	0.44	0.44	0	-0.44	0	0.44	1.39	-0.44	0	-0.2	0	-0.81	4.50
2	-0.85	OVP	0.41	0	-1.79	-1.79	-1.79	-0.85	0	-1.79	-0.44	0	0	0	0.61
3	0	1.25	OVP	0	0.41	0	-0.41	-0.41	0	-0.81	0	0	0	0	-1.49
4	0	0	-0.41	OVP	0	0	0	0	0	-1.39	-0.44	0.44	0	0	-1.16
5	0	0	0	0	OVP	-0.54	0.44	0	0	0	0	0	0	0	0.50
6	0	0.81	0	0	1.25	OVP	0.81	0	0.41	0	0.44	0	0	0	1.61
7	-0.44	-0.85	1.79	0.41	0	0	OVP	0	-0.44	0.44	0	0	0	0	1.13
8	1.79	0	1.39	0	1.79	-0.44	-0.44	OVP	0	1.25	-0.44	0	0	0	-1.05
9	0.41	0.44	0	0	0.44	0	0.44	0	OVP	-1.35	0	0	0	0	-2.14
10	1.59	0	0	0	0	0	0	0	0	OVP	0	0	0	0	-0.50
11	-0.44	0	-0.85	0	0.54	0	-0.44	0.54	-0.98	-1.35	OVP	0	0	-0.09	0.38
12	0.44	0.41	-0.44	0	0.41	0	0	0.44	0	1.39	-0.85	OVP	3.04	0	-0.60
13	0	-1.69	0	0	-0.54	0	0	0	0.54	0	-0.54	0.85	OVP	0	-1.53
14	-0.38	-1.35	-0.44	0.81	-0.54	0	0.54	0.98	0.44	2.54	-1.35	2.1	0.12	OVP	-1.36

We refer the reader to Turoff (1971) for a more detailed explanation of the calculation. The conditional probability P_i of occurrence of each event is calculated using Equation. 4.

Calibration of the cross-impact matrix is an iterative process whereby the probability of each event is assumed to be 1 and then 0 while holding the rest of the events constant. This answers the question “If event m occurs (or does not occur) for certain, what is the new probability of n?”

The resultant new CIA-derived probabilities of events are checked for consistency and adjusted until the participants are satisfied with the results. Consistency of probability estimates can be checked using the rules governing conditional probabilities. One such rule is that there are limits to the range of overlap of conditional probabilities (Gordon 2004). Gordon (2004) gives the

following example: Consider two events, m and n , each with initial probabilities of occurrence of 0.6 and 0.5 respectively. Then imagine 100 hypothetical futures in which these events may or may not occur. It can be inferred that it is likely that m will occur 60 times and n will occur 50 out of the 100 futures. This implies that there is an overlap of at least 10 futures in which both m and n occur. Therefore, $P(n|m)$ can never equal zero because if n never occurred when m occurred the possible overlap of 10 events would not be possible. Thus, either the original estimate of the probability of n is estimated without any thought to the 0.6 probability of occurrence of m or $P(n|m) \neq 0$. One of the preceding judgments incorrect because both being true leads to inconsistency (Gordon 2004). It is left up to the participants to decide whether the initial estimate of $P(n)$ fully accounts for the influence of m or if $P(n|m)$ needs to be adjusted upwards. Therein lies the power of CIA. The learning process that occurs during the building of the cross-impact matrix is one of the reasons why this method is so beneficial (Gordon 2004).

9.1.1.2 The Event Set

In this study (for illustrative purposes), we derive a plausible event set based on the Chartered Institute of Procurement and Supply (CIPS) report on the global supply chain risk index (Ganguli 2018). Using the provided list of global supply chain political-economic risks, we derive a plausible set of future events for each region in the supply chain. In this example, the event set for a supplier i in country X in the Asia-Pacific region is used to generate a cross-impact matrix; the results of which are presented in Table 3. We use p_i to denote the original probability estimate for event i , whereas p_i^* is the probability estimate for the occurrence of event i after at least one iteration of the CIA estimation process. When faced with several choices of possible suppliers, the decision-maker will generate a CIA for each one. The output of each CIA will then

become one of the inputs for the final CIA-SMIP model (see Section 4: Computational Example).

9.1.1.3 Events of interest

We draw the reader's attention to events E_{12} , E_{13} and E_{14} . We designate these events to be our events of interest. The rest of the event set comprises enhancing (or inhibiting) events for E_{12} , E_{13} or E_{14} . We assume that these three events are mutually exclusive and will occur last in the "chain of causality" (Gordon 2004) from a temporal standpoint. p^{Hc} and p^{Lc} p^{*c} are the CIA-generated conditional probabilities for events E_{12} , E_{13} and E_{14} , respectively. E_{12} , E_{13} and E_{14} have associated probabilities p^{Hc} , p^{Mc} and p^{Lc} , respectively, which are used to calculate additional cost parameters in optimization models by converting them to economic disruption probability multipliers D_i^{CIA} where $i \in I$.

To calculate D_i^{CIA} , we weight the stated increase in the cost of production by the calculated CIA probabilities p^{Hc} , p^{Mc} , and p^{Lc} . We assume that $D_i^{CIA} > 1$ is a constant equal to 1 when the probability of political-economic disruption is equal to 0 and that $D_i^{CIA} > 1$ when we add to it the weighted probability factor accordingly (see Table 5). The weighted probability factor is calculated by multiplying the event's respective OVP by the estimated percentage increase in cost.

Table 7 Cross-Impact Analysis of Event Set for Asia -Pacific Region in January 2016

SUMMARY OF PERTURBED OUTCOMES FOR CROSS IMPACT ANALYSIS				
<i>i</i>	PROBABLE EVENTS (E_i)	ORIGINAL PROBABILITY p_i	CIA PROBABILITY p_i^*	RESULTING OUTCOME
1	US presidency changes hands next year	.99	1.00	Medium probability
2	Revision or cancellation of global trade agreements such as NAFTA and Trans-Pacific Partnership (TPP)	0.6	1.00	Very high probability
3	Increased tariffs on all US imports originating from Asia	0.5	1.00	Very high probability
4	Lower-for-longer oil prices	0.4	1.00	Very high probability
5	Increased regional political turmoil	0.7	1.00	Very high probability
6	Increased Banking-sector stresses	0.4	1.00	Very high probability
7	US demand for cars weakens by 10%	0.6	0.54	Medium probability
8	Britain's exit for EU is hard and sharp	0.3	0.00	Very low probability
9	A general seaport strike on the east coast	0.3	0.29	Low probability
10	The US experiences a major terrorist attack similar to the 2001 September 11 attacks on New York City	0.1	0.00	Very low probability
11	air delivery of critical component is necessary.	0.3	0.31	Low probability
12	Low impact economic disruption - Cost of production is increased by $\geq 25\%$ but $\leq 50\%$	0.5	0.53 (p^{Lc})	Medium probability
13	Medium impact economic disruption - Cost of production is increased by $\geq 50\%$	0.5	0.52 (p^{Mc})	Medium probability
14	High impact economic disruption - Cost of production is increased by $\geq 2000\%$ (arbitrarily large number to indicate supplier insolvency)	0.1	0.00 (p^{Hc})	Very low probability

The values shown in Table 5 were derived in this manner.

Table 8 Values for Economic Disruption Multiplier

Disruptive Event	Percentage increase in cost	CIA probability (p_i^*)	Disruption probability multiplier
High impact	2000%	0.00 (p^{Hc})	1
Medium impact	35%	0.53 (p^{Mc})	1.19
Low impact	12.5%	0.52 (p^{Lc})	1.07

In cases where p^{Hc} , p^{Mc} and p^{Lc} are decidedly different, we propose an arbitrary heuristic whereby if there is more than ten percentage points difference between them, the higher of either

p^{M_c} or p^{L_c} will be used for the calculation of the model's D_i^{CIA} . For our computational example, we propose the consideration of high impact only if the probability exceeds 0.50 (i.e. the D_i^{CIA} for supplier $i \geq 0.50$ we predict with certainty that that supplier will become insolvent and it is disqualified from consideration because of the arbitrarily high percentage increase in production cost). This is a similar approach to the Big M method sometimes used in in the Simplex method in linear programming. In the case where there is not a discernible difference between the probabilities, we default to the medium impact probability.

Future studies may improve upon the use of a heuristic to assume the occurrence or non-occurrence of event with more robust statistical techniques and that also employs the use of past empirical data to make this determination. For the time being, our aim is strictly to show how this disruption economic probability data can be formulated and incorporated into a stochastic optimization model. In this example we choose 1.19 (medium impact event) as the economic disruption multiplier for global supplier i under consideration in the preceding CIA calculation example.

1.1.1 Combined CIA-SMIP Model Formulation

In this section we introduce our proposed model. We demonstrate how Sawik's **SPS1_E(c)** can be hybridized into a CIA-SMIP model. The normalized functions are defined as:

$$\begin{aligned}
E^c = & D_i^{CIA} \left(\sum_{i \in I} e_i u_i / B + \sum_{s \in S} P_s^o \left(\sum_{i \in I_s} A o_i u_i \right) / B \right) \\
& + \sum_{s \in S} P_s^o \left(\sum_{j \in J} \sum_{t \in T: t > d_j} g_j b_j (t - d_j) w_{jt}^s \right) / B \\
& + \sum_{s \in S} P_s^o \left(\sum_{j \in J} h_j b_j \left(1 - \sum_{t \in T} w_{jt}^s \right) \right) / B
\end{aligned} \tag{6}$$

where $D_i^{CIA} = (1 + \Gamma)$, Γ is the expected percentage increase in cost

The multiplication of the first two terms of Sawik's **SPS1_E(c)** by the CIA-derived multiplicative factor D_i^{CIA} is our addition to the model and main contribution to literature. The multiplicative factor has the potential to enhance the predictive capabilities of Sawik's **SPS1_E(c)** because it explicitly accounts for the possibility of economic disruptions which are not expressed in extant supplier selection models that are based on mathematical modeling. Secondly, the factor operationalizes the idea of economic disruption in a mathematical model. As demonstrated in the CIA calculations, arriving at plausible value of the multiplier is not a trivial exercise.

4 Computational Example

We present a computational example as an application for the CIA-SMIP approach for the selection of potential global suppliers, order quantity allocation and the scheduling of customer orders in single-sourcing strategy. We evaluate the impact of the economic disruption multiplier by comparing the optimization of expected cost using the SMIP approach (Sawik 2018) to that of the CIA-SMIP. The parameters used in the example model were drawn from Sawik (2018) with the exception of a few numerical modifications and the addition of the economic disruption multiplier. The parameters used in the model are:

- \bar{I} , the number of suppliers was 5 and the number of disruption scenarios considered was 5.
- \bar{J} was the number of customer orders which was equal to 5
- \bar{R} , the number of geographic regions was 2
- \bar{T} , the number of planning periods was equal to 5;

- a_j the unit requirements for parts of products in customer orders were integers in $\{1, 2, 3\}$ drawn from $\text{int}(U[1;3])$ distribution, for all orders j ;
- the size of customer orders (required numbers of products); were integers in $\{500, 1000, \dots, 5000\}$ drawn from $500\text{int}(U[1;10])$ distribution, for all customer orders j
- c_j , the unit capacity consumptions of producer were integers in $\{1, 2, 3\}$ drawn from $\text{int}(U[1;3])$ distribution, for all customer orders j ;
- C_t , the capacity of producer in each period t , was integer drawn from $1000 \Gamma(2 \sum_{j \in J} b_j c_j / (\bar{T} - \max_{i \in I} \tau_i)) U[0.75; 1.25] / 1000 \Gamma$ distribution, i.e., in each period the producer capacity was from 75% to 125% of the double capacity required to complete all customer orders during the planning horizon, after the latest delivery of parts;
- d_j , the due dates for customer orders, were integers in $\{1 + \min_{i \in I} \tau_i(\tau_i), \dots, T\}$ drawn from $\text{int}(U[2;10])$ distribution, for all customer orders j ;
- e_i , the cost of ordering parts were integers in $\{5000, 6000, \dots, 10000\}$ and integers in $\{15000, 16000, \dots, 30000\}$, respectively for domestic suppliers $i \in I^1$ and for foreign suppliers $i \in I^2$;
- g_j , the unit daily penalty cost of delayed customer orders was equal to $\Gamma a_j \max_{i \in I} (o_i) / 350 \Gamma$ for all orders j , i.e., was approximately 0.28% of the maximum unit price of required parts;
- h_j , the unit penalty cost of unfulfilled customer orders was to $2 \Gamma a_j \max_{i \in I} (o_i) / \Gamma$ for all orders j , i.e., was approximately twice as large as the maximum unit price of required parts;
- o_i , the unit price of parts purchased from supplier i , was uniformly distributed over $[11, 16]$ and over $[1, 6]$, respectively for domestic suppliers $i \in I^1$ and for foreign suppliers $i \in I^2$
- p_i^o , the local disruption probability was uniformly distributed over $[0.005, 0.01]$ for domestic suppliers $i \in I^1$ and over $[0.05, 0.10]$ for foreign suppliers $i \in I^2$, i.e., the disruption probabilities were drawn independently from $U[0.005; 0.01]$ and from $U[0.05; 0.10]$, respectively for domestic and foreign suppliers.
- p^{r_o} The regional disruption probability was $p^1 = 0.001$ for domestic suppliers $i \in I^1$ and $p^2 = 0.01$ for foreign suppliers $i \in I^2$;
- p^{*o} , the global disruption probability was 0, i.e., no global disaster super event is considered.
- τ_i , delivery lead time from domestic suppliers $i \in I^1$, were integers in $\{1, 2\}$ drawn from $\text{int}(U[1;2])$ distribution and from international suppliers $i \in I^2$, were integers drawn $\{2, 3, 4\}$ drawn from $\text{int}(U[2;4])$ distribution. From a possible 5 suppliers, 2 were domestic (US-based) and 3 were international (all located in south-east Asia.)
- D_i^{CIA} , 1.3 based on CIA results.

All the computational experiments were performed using the above data. For all the experiments the total demand is $A = 25,500$ and $B = 15,500$. Table 6 contains the results for the two objective functions; CIA-SMIP and the SMIP.

Table 9 Risk-Neutral Solutions: CIA-SMIP vs SMIP for Single-Sourcing Strategy

	Optimization Technique	
	CIA-SMIP	SMIP
Expected Cost (per unit)	6.010	5.028
Selected supplier	3	3
Number of variables	130	130

In both cases, the models used suggested supplier 3, a less expensive international supplier based in southeast Asia. All the southeast Asia suppliers were assigned the same multiplier

$D_i^{CIA} = 1.3$ based on CIA results; whereas US-based or local suppliers had a $D_i^{CIA} = 1$.

To test the sensitivity of supplier choice to D_i^{CIA} , we performed a parameter sensitivity analysis in order to observe the ranges of the D_i^{CIA} in which the selection of supplier 3 would remain optimal. As noted previously, the D_i^{CIA} value can range from 1 to 2; where $D_i^{CIA} = 1$ represents no influence in the model from the D_i^{CIA} multiplier and 2 represent the maximal possible influence. When $D_i^{CIA} = 2$, the probability of economic disruption is 1. When $D_i^{CIA} = 1$ the probability of economic disruption is 0. This implies that the CIA-SMIP and SMIP models are equivalent when $D_i^{CIA} = 1$ for both the local and SE regions.

Table 7 below shows the results of a sensitivity analysis for the SE Asia economic disruption multiplier denoted by $D_i^{CIA(SE)}$. The results displayed are for a range [1,2] for $D_i^{CIA(SE)}$ (holding a constant local disruption multiplier $D_i^{CIA(Local)} = 1$). Supplier 3 (in SE Asia) was the optimal supplier choice for $D_i^{CIA(SE)} < 1.5$ (approximately). Supplier 2 (local) was the optimal supplier choice for $D_i^{CIA(SE)} \geq 1.5$ (approximately). Supplier 3 (in SE Asia) was the supplier choice for the entire possible range of local dis $D_i^{CIA(Local)}$. The rest of the parameters and variable values were held constant. As was expected, the minimized cost per unit for each solution increased with the probability of economic disruption. The managerial implication of this is that decision-makers now have a way of systematically taking into consideration the probability of economic disruption as one of their supplier choice criteria. It is useful to note that, in this case, the first optimization in the sensitivity analysis series of optimizations can also be interpreted as the being

the results of the Sawik (2018)'s SMIP formulation, because, at this point, the CIA and SMIP models are equivalent.

What is obvious is that the optimal cost per unit is bound to increase with the D_i^{CIA} . Therefore, the purpose of the sensitivity analysis is to determine the point at which a different supplier becomes the optimal choice as the value of D_i^{CIA} increases.

Table 10 Sensitivity analysis for DCIA (SE Asia)

Note: $D_i^{CIA(LOCAL)} = 1$			Local Suppliers (1,2)		SE Asia Suppliers (3,4,5)		
Optimization (i)	$D_i^{CIA(SE)}$	Optimal Cost Per Unit (Minimized)	1	2	3	4	5
1	1	5.027612903	0	0	1	0	0
2	1.05	5.385632258	0	0	1	0	0
3	1.1	5.510103226	0	0	1	0	0
4	1.15	5.634574194	0	0	1	0	0
5	1.2	5.759045161	0	0	1	0	0
6	1.25	5.883516129	0	0	1	0	0
7	1.3	6.010245161	0	0	1	0	0
8	1.35	6.134716129	0	0	1	0	0
9	1.4	6.259187097	0	0	1	0	0
10	1.45	6.383658065	0	0	1	0	0
11	1.5	6.476553548	0	1	0	0	0
12	1.55	6.526447742	0	1	0	0	0
13	1.6	6.572512258	0	1	0	0	0
14	1.65	6.618576774	0	1	0	0	0
15	1.7	6.66464129	0	1	0	0	0
16	1.75	6.710705806	0	1	0	0	0
17	1.8	6.756770323	0	1	0	0	0
18	1.85	6.802834839	0	1	0	0	0
19	1.9	6.848899355	0	1	0	0	0
20	1.95	6.894963871	0	1	0	0	0
21	2	6.941028387	0	1	0	0	0

A parameter sensitivity analysis was also carried out in order to evaluate the model's sensitivity to the local disruption multiplier ($D_i^{CIA(LOCAL)}$). The baseline disruption multipliers for this particular analysis were $D_i^{CIA(LOCAL)} = 1$ and $D_i^{CIA(SE)} = 1.3$. This was based on the results of the CIA exercise. Holding $D_i^{CIA(SE)}$ at a constant 1.3 and increasing the $D_i^{CIA(LOCAL)}$ by .05 for each successive optimization, the effect on both minimal cost per unit and supplier selection is shown in Table 8 below.

Table 11 Sensitivity analysis for DCIA (Local)

Note: $D_i^{CIA(SE)} = 1.3$			Local Suppliers (1,2)		SE Asia Suppliers (3,4,5)		
Optimization (i)	$D_i^{CIA(Local)}$	Optimal Cost Per Unit (Minimized)	1	2	3	4	5
1	1	6.010245161	0	0	1	0	0
2	1.05	6.113574194	0	0	1	0	0
3	1.1	6.216903226	0	0	1	0	0
4	1.15	6.320232258	0	0	1	0	0
5	1.2	6.42356129	0	0	1	0	0
6	1.25	6.526890323	0	0	1	0	0
7	1.3	6.630219355	0	0	1	0	0
8	1.35	6.733548387	0	0	1	0	0
9	1.4	6.836877419	0	0	1	0	0
10	1.45	6.940206452	0	0	1	0	0
11	1.5	7.043535484	0	1	0	0	0
12	1.55	7.146864516	0	1	0	0	0
13	1.6	7.250193548	0	1	0	0	0
14	1.65	7.335983226	0	1	0	0	0
15	1.7	7.409067097	0	1	0	0	0
16	1.75	7.482150968	0	1	0	0	0
17	1.8	7.555234839	0	1	0	0	0
18	1.85	7.62831871	0	1	0	0	0
19	1.9	7.701402581	0	1	0	0	0
20	1.95	7.774486452	0	1	0	0	0
21	2	7.847570323	0	1	0	0	0

The results displayed are for a $D_i^{CIA(Local)}$ range [1,2] (holding a constant SE Asia disruption multiplier $D_i^{CIA(Local)} = 1.3$). The value for $D_i^{CIA(Local)}$ is obtained as a result of the CIA exercise. In this case, Supplier 3 (in SE Asia) was the optimal supplier choice for $D_i^{CIA(SE)} < 1.65$ (approximately). Supplier 4 (local) was the optimal supplier choice for $D_i^{CIA(SE)} \geq 1.65$ (approximately). The rest of the parameters and variable values were held constant. The results predictably show that an increase in $D_i^{CIA(Local)}$ will mean that the prescribed optimal choice in supplier will always be in SE Asia. What is interesting is that as minimal cost per unit increases, the choice of supplier in SE Asia will change from Supplier 3 to supplier 4 above a cost per unit of approximately \$7.25 per unit. Comparing the sensitivity of the model to $D_i^{CIA(SE)}$ to that of

$D_i^{CIA(Local)}$ we find that an increase in $D_i^{CIA(SE)}$ will more quickly result in a change of supplier ceteris paribus. Note that this behavior is unique to the mode and its parameters.

Parameter sensitivity analyses of supplier choice to Total Unit Demand (A) were also conducted for the CIA-SMIP and SMIP formulations. Table 9 below contains the results for the sensitivity analysis using that CIA-SMIP model formulation.

Table 12 Sensitivity analysis for Total Units Demanded (CIA-SMIP model)

			Local Suppliers (1,2) (DCIA Multiplier = 1)		SE Asia Suppliers (3,4,5) (DCIA Multiplier = 1.3)		
Optimization (i)	Total Unit Demand	Optimal Cost Per Unit (Minimized)	1	2	3	4	5
1	20000	5.757553548	0	1	0	0	0
2	20500	5.806166452	0	1	0	0	0
3	21000	5.854779355	0	1	0	0	0
4	21500	5.903392258	0	1	0	0	0
5	22000	5.919470968	0	0	1	0	0
6	22500	5.93243871	0	0	1	0	0
7	23000	5.945406452	0	0	1	0	0
8	23500	5.958374194	0	0	1	0	0
9	24000	5.971341935	0	0	1	0	0
10	24500	5.984309677	0	0	1	0	0
11	25000	5.997277419	0	0	1	0	0
12	25500	6.010245161	0	0	1	0	0
13	26000	6.023212903	0	0	1	0	0
14	26500	6.036180645	0	0	1	0	0
15	27000	6.049148387	0	0	1	0	0
16	27500	6.062116129	0	0	1	0	0
17	28000	6.075083871	0	0	1	0	0
18	28500	6.088051613	0	0	1	0	0
19	29000	6.101019355	0	0	1	0	0
20	29500	6.113987097	0	0	1	0	0
21	30000	6.126954839	0	0	1	0	0

The optimal supplier selection solutions are tabulated for a range of [20000, 30000] parts demanded for $D_i^{CIA(Local)} = 1$ and $D_i^{CIA(SE)} = 1.3$. Supplier 2 (local) was the initial supplier choice for $A \leq 21500$ (approximately). Supplier 3 (SE) was the optimal supplier choice for $A > 21500$ (approximately). As demand increased, so did the total cost attributable to disruptions. Initially, the supplier choice was local. However, as the volume increased, so did the cost

associated with disruptions. Assumedly, to compensate for this, the optimal supplier choice switched from 2 (a local supplier) to supplier 3 (a supplier in SE Asia).

For comparison purposes, a parameter sensitivity analysis of supplier choice to total parts demanded (A) was also conducted using the SMIP formulation. Table 10 below shows the results for this model.

Table 13 Sensitivity analysis for Total Units Demanded (SMIP model)

			Local Suppliers (1,2) (DCIA Multiplier = 1)		SE Asia Suppliers (3,4,5) (DCIA Multiplier = 1)		
Optimization (i)	Total Unit Demand	Optimal Cost Per Unit (Minimized)	1	2	3	4	5
1	20000	4.775623226	0	0	1	0	0
2	20500	4.806752258	0	0	1	0	0
3	21000	4.83788129	0	0	1	0	0
4	21500	4.869010323	0	0	1	0	0
5	22000	4.900139355	0	0	1	0	0
6	22500	4.931268387	0	0	1	0	0
7	23000	4.962397419	0	0	1	0	0
8	23500	4.993032258	0	0	1	0	0
9	24000	5.001677419	0	1	0	0	0
10	24500	5.010322581	0	1	0	0	0
11	25000	5.018967742	0	1	0	0	0
12	25500	5.027612903	0	1	0	0	0
13	26000	5.036258065	0	1	0	0	0
14	26500	5.044903226	0	1	0	0	0
15	27000	5.053548387	0	1	0	0	0
16	27500	5.062193548	0	1	0	0	0
17	28000	5.07083871	0	1	0	0	0
18	28500	5.079483871	0	1	0	0	0
19	29000	5.088129032	0	1	0	0	0
20	29500	5.096774194	0	1	0	0	0
21	30000	5.105419355	0	1	0	0	0

The optimal supplier selection solutions are tabulated for a range of [20000, 30000] parts demanded (holding a constant SE Asia disruption multiplier $D_i^{CIA(Local)} = 1$ and $D_i^{CIA(SE)} = 1$). Supplier 3 (in SE Asia) was the optimal supplier choice for Total Demand < 23500 . Supplier 2 (local) was the optimal supplier choice for Total Demand ≥ 24000 . The rest of the parameters and variable values were held constant.

Overall, in considering the sensitivity analyses and their results in totality, it is apparent that the key driver of supplier choice is cost per unit. Also apparent is that the choice of supplier is not immediately intuitive and would be very difficult to determine without the aid of this or similar models. When the cost of the possible impact of political-economic disruptions is considered, the buyer would face an enhanced probability of increased supply chain risk and cost of components over the duration of the planning horizon. This difference in cost may seem insignificant if only hundreds of components are ordered over the duration of the planning horizon. However, it is useful to consider that finished products like automobiles, for example, are made up of thousands of components which, in their totality, the aggregate impact of increase in component cost is a very important factor to consider in supplier selection.

We present a limited number of operational scenarios $i \in S, s = 1,2,3,4,5$ for demonstrative purposes. The number of scenarios \bar{S} , and scheduling variables w_{jt}^s increases linearly in the number of disruption scenarios (\bar{S}) and exponentially in the total number of suppliers (\bar{I}). Therefore, in the complete problem, a total of $\bar{S} = 2^{\bar{I}}$ potential scenarios will need to be considered. Excel and the add-in Risk Solver Platform were used on a MacBookPro (Retina, 15-inch, Mid 2014). CPU time for finding optimal solutions was negligible and ranged in the tenths of a second. However, we anticipate longer CPU times to prove optimality for complete models that consider all \bar{S} scenarios.

Figure 1 below is a visual depiction of the relationship between political-economic risk and price per part across international boundaries. In this example, political-economic risk is negligible for on-shore suppliers (1 and 2) and significantly increased for off-shore (southeast Asian) suppliers (3,4 and 5). Generally, there is a negative correlation between price per part and overall disruption risk. The connecting lines are not supposed to represent data continuity but

rather serve as aids that allow the reader to better visualize the difference in magnitude between data points. Note that the results in this scenario are a function of the event set and the assumptions made therein.

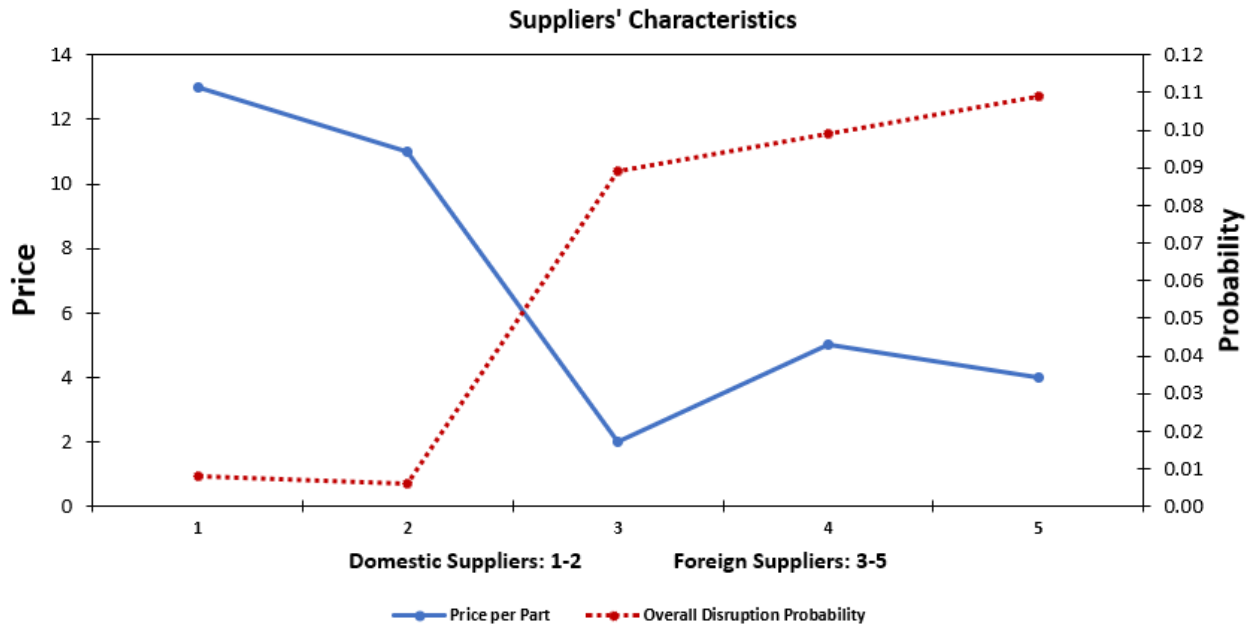


Figure 3 Supplier Political- Economic Risk Characteristics

The results show that as the economic disruption risk of less expensive off-shore suppliers increases, a firm is more likely to choose a less risky on-shore supply chain partner. We also note that as demand increases, the average cost of penalty costs decreases. This means that a firm may be able to choose a riskier off-shore supplier. This technique provides a decision-maker with an estimation of the inflection point at which a different choice in suppliers is recommended. It is important to note that this case and its variables and parameters is unique. Thus, decisions prescribed therein are not universally applicable. What is generalizable is the approach to the prediction of future scenarios.

5 Conclusion

We optimized the selection of a single source supplier using a combination of costs accrued from operational events that occurred within the supply chain and economic events that occurred outside of the supply chain. By adding the costs associated with economic events, we introduce a novel dimension to supplier selection optimization models. Any event that threatens supply chain efficiency, viability and functionality is, by default, a part of supply chain risk management and should be considered in supply chain models. In the special case of single source supplier selection, the geopolitical and geo-economic environment of a supplier is a key antecedent of risk management outcomes (Sheffi and Rice 2005). An example of such an external political/economic event is outlined in the study by Sheffi (2001) on the effects of international terrorism on supply chain management in the United States. Sheffi's (2001) study adopts an a posteriori stance towards supply chain risk management. Unfortunately, examining what managerial decisions could have been made in the aftermath of a catastrophic event would not be a very useful endeavor for an affected firm because such types of events are usually unique in nature. The catastrophic events tend not to repeat themselves. Thus, it is safe to assume that each future threat will be unique. It is noted that the unavoidable negative economic effects of the event on supply chain functionality were beyond the control of the affected. According to Sheffi (2005), it was the government's reaction to the event that created and exacerbated supply chain disruptions after September 11, 2001. Current optimization methods are not future-oriented and are not capable of predicting plausible scenarios in the face of uncertain futures. We have shown how incorporating it is possible using a hybridization example model such as CIA-SMIP could be the path to resolving this shortcoming.

In general, the outcome for SMIP-based models like the one in this study is dependent on parameters like unit cost of product and demand (see Sawik (2018)). This means that the results and optimal solutions are unique to each particular case. However, the advantage of the CIA-SMIP technique is that it allows decision-makers to view and account for the effect of a change in economic risk outlook. One of the past criticisms and known limitations of the CIA technique is lack of validation or testability in real time. This criticism is mainly due to the tendency for critics to apply Bayesian principles for not-yet-existent empirical data is a major problem encountered during the CIA exercises. However, it is important to point out that CIA does not claim to guarantee particular outcomes. Rather, it is a rather a tool for systematically organizing future possible scenarios.

One way to outline the advantage of using this systematic approach to mitigating against future uncertain scenarios is to contrast this approach to either doing nothing or leaving the fate of the firm's supply chain to ad hoc gut-feel instinct-driven decision-making. Merely estimating the probability of disruption is better than doing nothing (Chopra and Sodhi 2014). This is not to say that validation of the technique is not possible. The next step will be a validation study in which many supplier selection futures are generated and compared with real life supplier selection problems that are yet to be encountered. This approach to CIA validation is demonstrated in Bañuls et al., (2017). In this study, the impact of multiple risks on project performance was predicted using CIA-ISM; a combination of CIA and interpretive structural modeling (ISM). In the same manner, CIA-SMIP will be used to predict the correct supplier choice given a set of future multiple risks over a set time horizon. In the aftermath of the time horizon, the real-life outcomes will be compared with the CIA-SMIP predictions and the efficacy of the technique will be empirically measured. The model we propose in this study serves as an example of how the

human impact on supply chains and the management of their risk can be systematically evaluated on a macro-economic level. The data used as inputs in this model for the CIA part is derived from expert opinion. Empirical data and sophisticated statistical techniques could be used to bolster expert evaluation and remove a lot of the inherent subjectivity of expert opinion. Future researchers could examine ways in which the CIA methodology's predictive capabilities could be improved through machine learning techniques. The overreliance on expert's opinion and analytic capabilities, while reduced in CIA, is still problematic. The model is only as good as the accuracy of the data it utilizes. Future studies could utilize empirical data for real world examples to test the validity of this approach. The Delphi technique can also be utilized to draw on the knowledge of subject area experts to derive a more accurate event set. Future studies may also extend the proposed model to also consider multiple sourcing strategies including dual or cross-sourcing.

Summary

In this dissertation we presented three essays (Papers 1, 2 and 3) that served to develop our knowledge about the human impact in SCRM. Paper 1, proposed the delineation of studies centered around individual behavior in a SCRM context into a new topic area, BCSRM. Paper 2 introduced CIA as a new methodology for supplier selection for firms with a single sourcing strategy. Paper 3, extended Paper 2 and incorporated the output of CIA into an SMIP model. The result was a hybrid CIA-SMIP single source supplier selection model.

We hope that the three papers represent a step towards a new SCRM theoretical framework based on the impact of humans on the supply. Paper 1 is microeconomic in nature and is centered on the individual behavior. Papers 2 and 3 adopt a macroeconomic approach and serve to illustrate first how external macroeconomic events can result in supply chain disturbances.

Managerial implications

Supply chain viability and efficiency is becoming an increasingly important driver of firm success (Marley et al. 2014). In the past, SCRM models have been mostly quantitative and deterministic in nature. The emphasis was on countermeasures that ensured the uninterrupted flows of goods in the advent of operational disruption (Marley et al. 2014; Sheffi and Rice 2005). These countermeasures were overwhelmingly operational in nature. They included strategies such as buffering, postponement, outsourcing and supplier redundancy (C. Tang 2006). The problem is all these strategies were operations-based and lacked consideration of the human impact in supply chain. However, human activity and human decision-making have been shown to affect SCRM outcomes (Bode et al. 2011; DuHadway, Carnovale, & Kannan, 2018). By drawing the practitioner's attention to the potential benefits of considering the human impact in

SCRM both from a micro- and macroeconomic perspective, we hope to: 1) improve their understanding of the SCRM and 2) provide them with actionable methodologies such as CIA-SMIP, for example, to counter the risks posed by human activity in a SCRM setting.

Future research

In future, we hope to develop our BSCRM theoretical framework such that we can derive testable hypotheses that will inform decision makers about human behavior in a SCRM setting. We also aim to incrementally narrow the macro and microeconomic divide in SCRM. As a result, we will develop more effective new breed of hybrid models that simultaneously account for human behavior, human macroeconomic activity and quantitative SCRM performance parameters.

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