IPRPD
International Journal of Business & Management Studies
ISSN 2694-1430 (Print), 2694-1449 (Online)
Volume 05; Issue no 04: April, 2024
DOI: 10.56734/ijbms.v5n4a1

THE EFFECTS OF COMPLEXITY AND COUPLING ON SUPPLY CHAIN DISRUPTIONS

Marco Habermann. Ph.D.[1], Ashley Y. Metcalf, Ph.D.[2], Dr. Alex Michel[3]

[1]*Associate Professor of Operations Management, College of Business, Ohio University*

[2]*Associate Professor of Operations Management, College of Business, Ohio University*

[3]*Professor, International School of Management (ISM), Frankfurt, Germany*

Abstract

Business executives have recently indicated that supply chain disruptions represent a major threat to their firm's profitability and revenue growth (Smyrlis, 2006; Hendricks and Singhal, 2009). In the literature, a number of conceptual studies have suggested that supply chain complexity is a main driver of supply chain disruptions (Choi & Krause, 2006; Christopher & Lee, 2004; Juettner et al., 2003). Other studies have suggested that the degree of coupling in the supply chain is a major determinant of supply chain disruptions (Agrawal and Nahimias, 1997; Ahuja, 2000). Building on the theoretical foundation of Normal Accident Theory (NAT), this paper proposes a nuanced relationship between supply chain complexity and coupling and their collective impact on supply chain disruptions. Through an empirical examination, we seek to validate the theoretical proposition that complex, tightly coupled systems are inherently prone to failures or accidents. This study contributes significantly to the supply chain management discourse, providing a detailed analysis of the mechanisms underlying supply chain vulnerabilities and offering practical guidance for developing more resilient and responsive supply chain systems. Our findings invite future research to further explore the intricacies of supply chain disruptions, complexity, and coupling, aiming to refine and expand upon the mitigation strategies discussed herein.

Keywords

Supply Chain Disruption Risk, Supply Chain Complexity, Coupling, Risk Management, Disaster Management, Supply Chain Design, Network Design

1.0 Introduction

As the world grapples with unprecedented challenges, ranging from health crises to geopolitical tensions, the stability and efficiency of supply chains have come under significant scrutiny. Such disruptions are not only obstacles to the smooth functioning of supply chains but also present considerable risks to the global economy at large. This document aims to delve into the complexities of supply chain interruptions, exploring their causes, consequences, and the effectiveness of various countermeasures, as illuminated by recent academic research. Our objective is to identify practices that bolster the resilience and flexibility of supply chains, thereby ensuring uninterrupted business operations and maintaining competitive advantages during periods of instability.

Supply chain interruptions encompass a wide array of incidents, including natural disasters, political conflicts, technological breakdowns, and public health emergencies, each capable of severely hampering supply chain operations. Contemporary studies stress the importance of distinguishing among different types of disruptions to implement tailored management strategies effectively. Alok and Ramanathan (2021) highlight the need for dynamic, sturdy supply chain models designed to quickly rebound from disruptions, emphasizing the critical roles of resilience and agility.

The COVID-19 pandemic, a defining event of recent years, underscored the vulnerability of global supply chains, prompting companies to reevaluate and strengthen their supply chain frameworks. Ivanov and Dolgui (2020) discuss the ripple effect of the pandemic on supply chains, demonstrating how disruptions in one part of the world can lead to significant shortages and operational challenges globally. Their work emphasizes the need for supply chain visibility and digital transformation as critical components of a resilient supply chain strategy.Queiroz et al. (2020) investigate the pandemic's extensive effects on supply chains and propose digital transformation, including the use of AI and machine learning for predictive analytics and improved decision-making, as a crucial adaptive strategy.

Technological innovation is key to safeguarding supply chains from interruptions. The deployment of blockchain technology, for instance, is seen as a means to enhance transparency and trust between supply chain parties, as discussed by Saberi et al. (2019). Additionally, the adoption of IoT devices enables the real-time monitoring of supply chain activities, significantly mitigating disruption risks (Wang, Gunasekaran, Ngai, & Papadopoulos, 2016; Choi, 2020).

Beyond technological interventions, the role of human factors in managing supply chain disruptions is indispensable. Leadership, strategic foresight, and a culture emphasizing resilience are essential components in overcoming the challenges posed by disruptions (Pettit, Fiksel, & Croxton, 2019; Tukamuhabwa et al., 2015). This points to the necessity for an integrated approach that melds technological advancements with strategic management and people-focused strategies.

Early research into supply chain management often focused on the minimization of costs due to transportation and dealt with small individual pieces of what is now referred to as the supply chain system. Such topics as facility location, transportation, logistics and outsourcing, to name a few, received much attention in the operations management literature. More recently, research utilizing a systems engineering viewpoint has treated a supply chain as a complicated system recognizing that it is no longer adequate for businesses to operate as standalone pockets of operation. Indeed, firms today must manage relationships, information flows, and material flows between geographically disperse suppliers and customers, each with their own technologies, cultures, goals, and objectives. Given this systems view, it is not surprising that recent research has utilized such systems engineering concepts as reliability, complexity, coupling, linkages, and redundancy when discussing supply chain management and design. For example, Choi et al. (2001) uses engineering systems theories to model supply chains as complex adaptive systems (CAS). Surana et al. (2005) presents an analytical framework for applying CAS to supply chain research. Bozarth et al. (2009) argue that supply chain complexity is the degree of detail and dynamic complexity in the system where detail complexity is the number of components in the supply chain while dynamic complexity is the unpredictability of the system. Choi et al. (2006) define complexity in a supply base as the number of suppliers, the level at which these suppliers interact, and the variety of these suppliers in terms of size, location, technology, etc. In a similar vein, Vachon and Klassen (2002) describe supply chain complexity as a function of numerousness (the number of firms), interconnectivity (how closely these firms are linked), and unpredictability (unanticipated outputs given a set of inputs).

In addition to research on the complexity of supply chain design, several authors have looked at the degree of coupling in the system. In engineering terms, coupling is basically the strength of the linkages and dependence between components in the system. Agrawal and Nahimias (1997) and Ahuja (2000) suggest that reducing the number of suppliers in a supply base will increase the coupling in the system. Speir et al. (2011) found that the degree of coupling in the supply chain increased management awareness and efforts to ensure supply chain security. Generally speaking, complexity and coupling refer to the design of the system in that the number and selection of suppliers in the supply base, the number and location of manufacturing plants, the number of products provided, the number and geographic dispersion of customers, the degree of outsourcing, the size and location of inventory and capacity buffers, etc. are all supply chain design related issues that contribute to the overall complexity and coupling of the system.

A primary intent of this research is to develop an understanding of the design characteristics, complexity, and coupling, of the supply chain that contribute to, or result in, failures or disruptions. Craighead et al. (2007) define a disruption as anything that "interferes with the normal flow of goods and/or materials within a supply chain." For our purposes, we define a disruption as *an unplanned stoppage of the material flow within a supply chain*. While the definition by Craighead et al. (2007) could include events that may interfere with the flow of materials but not result in a complete stoppage, we take the more stringent view that a disruption, if it is truly a disruption, will result in the actual interruption/stoppage of the flow of materials. Due to the negative impacts of such disruptions in a firm's supply chain, supply chain disruptions have become a critical issue for many managers (Powell, 2011) and researchers alike (Blackhurst et al., 2005; Craighead et al., 2007; Choi et al., 2001; Bozarth et al., 2009; Kleindorfer & Saad, 2005, to cite a few). Sheffi and Rice (2005) suggest that disruptions may have an immediate or delayed negative effect on the performance of the buying firm depending on the severity of the disruption and the ability of the firm to recover. In addition, disruptions have been shown to impact financial and operational performance (Kleindorfer et al., 2003), reduce shareholder value (Hendricks & Singhal, 2003), result in a drop in stock price (Hendricks & Singhal, 2005), and erode brand equity and consumer confidence (Speir et al., 2011). Much of this research has focused on the source and magnitude of these disruptions. For example, disruptions can be intentional, such as terrorist attacks (cyber hackings or bombings) or theft (the increased prevalence of open seas piracy or the hijacking of cargo carriers), as well as unintentional natural disasters such as fires, floods, hurricanes and tsunamis (Kleindorfer & Saad, 2005; Dobie et al., 2000, Speir et al., 2011). Likewise, disruptions can be more mundane and numerous such as transportation delays, machine failures, and poor communication (Blackhurst et al., 2005).

Several researchers have proposed a link between these disruptions and the level of complexity within the supply chain (Choi & Krause, 2006; Christopher & Lee, 2004; Juettner et al., 2003). Utilizing results from a survey of 209 manufacturing plants, Bozarth et al., (2009) found that supply chain complexity negatively affects plant costs and performance. Vachon and Klassen (2002) state that supply chain complexity is the primary construct affecting a firm's delivery performance.

This paper proposes that the relationship between the complexity and coupling of a supply chain and subsequent supply chain disruptions can be theoretically grounded in Normal Accident Theory (NAT). Developed by Perrow (1984), NAT suggests that complex and tightly coupled systems will eventually fail or experience an accident. In this sense, an accident is any unintended event that disrupts the ongoing or future output of a system (Perrow, 1981). Initially proposed for complex technological systems such as nuclear power generation, Perrow (1994) later suggested that NAT is applicable to any system, such as a supply chain, that is error- inducing. According to Perrow (1984), complexity is the unplanned and unanticipated sequence of events that are not readily understood, while a tightly coupled system is one where one event follows another in a rapid fashion, often without the possibility of an intervention. In this paper, we explore the relationship between supply chain complexity and degree of coupling on the frequency of supply chain disruptions. Building on conceptual work in organizational theory (Perrow, 1984; Rijpma, 1997; Weick et al., 1999; Roberts, 1993), we empirically examine the impact of complexity and coupling on the frequency of disruptions.

2.0 Theoretical Background

In this section, we discuss the basic premise of Normal Accident Theory (NAT). We then review relevant literature on supply chain complexity and discuss how NAT provides a unique perspective on supply chain management.

2.1 Normal Accident Theory

Normal Accident Theory (NAT) provides a theoretical framework from which to view disruptions in the supply chain and supply chain design factors such as complexity and coupling. NAT suggests that complex systems that are tightly coupled, such as many supply chains, will inevitably fail despite managerial efforts. Based on an in-depth study of the Three Mile Island nuclear plant accident, Perrow (1984) concluded that accidents are normal when systems are both complex and tightly coupled. In this sense, complexity refers to the interactions between components in the system such that the impact of unexpected events on system processes is neither readily visible nor understood. Several factors contribute to the level of inherent complexity (Perrow, 1994). For example: the existence of multiple function components that can fail from many directions (in a supply chain, this is analogous to outsourcing several components to the same supplier whereby an accident at this supplier can impact the supply chain at multiple points); close physical proximity of components (such as when suppliers are geographically located close together or use common transportation methods); and several control parameters with potential interactions (such as changes in lead times affecting forecasting accuracy or safety stock requirements).

Tight coupling exists when components are highly interdependent in the sense that materials/capacity are not easily interchangeable (such as single source suppliers), invariant sequence of production processes (such as defined by bills of materials), any buffers or slack are inbuilt with little chance of adding them later (such as increasing delivery lead times in response to a late shipment), and little slack in capacity, materials and personnel (such as short delivery lead times or inadequate safety stocks). Sagan (1993) extended NAT by suggesting that while accidents are inevitable due to inherent complexity and tight coupling, accidents also occur due to production and economic pressures that take precedence over stated safety goals. In such cases, should an accident occur, the organization fails to learn from such events, choosing instead to pass the blame to operators, thus not addressing the real causes of the failure.

Therefore, when circumstances such as a failure occur, complex interactions cascade rapidly in a tightly coupled system and offer little chance to recover. Inevitably, a disruption results in the supply. The basic premise of NAT is that a contradiction exists between the level of authority needed to operate a tightly coupled system and that needed to operate a complex system. According to Perrow (1984), a tightly coupled system requires centralized decision- making to respond to an immediate threat due to the need for a total view of the system, while a complex system requires decentralized decision making since those individuals closest to the action are better able to cope with the event due to their local knowledge. Therefore the decision- making needs between complexity and coupling contradict, thus systems will inevitably fail. In addition, according to Weick (1990), all organizations are moving toward complex and tightly coupled systems because of interconnected technologies and resource demands.

The challenge to any organization and its supply chain is to develop coping mechanisms that will allow for ongoing operations without fear of disruptions (Shrivastava et al., 2009). From a NAT perspective, these coping mechanisms focus on the design of the system in such a way as to eliminate complex interactions and tight coupling. Perrow (1999) emphasizes this view by suggesting that limits on the size of any component should be set to prevent any entity from becoming too large, insure that the system has numerous and adequately sized buffers, insure that information signals at all levels in the system are readily provided, and provide for a robust design with the assumption that all components in the system will fail at some point in time.

2.2 Supply Chains as Complex and Tightly Coupled Systems

Conceptualizing supply chains as complex systems is not a novel idea in the literature (Choi et al., 2001; Choi & Hong, 2002; Lamming et al., 2000; Stuart et al., 1998). Thompson (1967) defined systems as a collection of interrelated elements that acquire resources from outside, transform the resources, and deliver products back to the outside. Supply chain research adopted this view and looks beyond immediate suppliers to consider all companies within the value stream (Porter, 1985). A critical aspect of supply chain systems is their inherent complexity due to their sheer size and the interdependence of the supply chain elements (Choi & Krause, 2006). Choi et al. (2001) recognized supply chains as complex adaptive systems with extensive interconnectedness, which is an idea that has been used and extended (Surana et al., 2005; Pathak et al., 2007). This work lays the foundation for describing supply chains as complex systems and allows for the conceptualization of complexity in supply chain settings.

The majority of studies on supply chain complexity base their conceptualization of complexity on insights from the pure sciences, such as biology (Kaufman, 1993), and the organizational sciences (Simon, 1962; LaPorte, 1975; Daft, 1983; Senge, 1990). Consequently, there is significant overlap and acceptance of the critical complexity dimensions within the supply chain literature. Described by Vachon and Klassen (2002) as numerousness, the number of supply chain elements is a well-established dimension of complexity in the literature in that a larger number of suppliers results in a more complex supply base compared to a supply base with fewer suppliers (Bozarth et al. 2009; Choi & Krause, 2006; Handfield & Nichols, 1999). This dimension of complexity was defined by Senge (1990) as detail complexity and was later adopted by Bozarth et al. (2009).

Another dimension of complexity discussed in the literature is the inability to predict the behavior of the system when a set of unexpected events occur (Bozarth et al. 2009; Choi & Krause, 2006; Vachon & Klassen, 2002). This was defined by Senge (1990) as dynamic complexity such that "obvious interventions produce nonobvious results" and/or "when an action has one set of consequences locally and a very different set of consequences in another part of the system." Bozarth et al. (2009, p. 80) adopted this view and defined supply chain complexity as the "level of detail complexity and dynamic complexity exhibited by the products, processes and relationships that make up the supply chain".

In addition to detail and dynamic complexity, the interrelatedness of the elements within the supply chain represents a fundamental aspect of supply chain complexity. Choi and Hong (2002) and Dooley (2001) describe supply chain complexity using the degree of coupling and interaction between supply chain elements. Choi and Krause (2006) emphasize the importance of the resulting interrelationships and their impact on overall supply chain complexity. A supply chain with independently acting suppliers is less complex than a supply chain with inter-related or tightly coupled suppliers. This aspect of coupling, interrelatedness or interconnectivity, is widely accepted in the literature on supply chain complexity (Bozarth et al., 2009; Choi & Krause, 2006; Handfield & Nichols, 1999; Vachon & Klassen, 2002; Wilding, 1998). These insights regarding complexity and coupling from the literature illustrate the applicability of Normal Accident Theory (NAT) within the context of supply chains, as their conceptualizations of complexity and coupling strongly overlap. Consequently, we believe that it is beneficial to use NAT to examine the link between supply chain complexity, coupling, and supply chain disruptions.

To date, there has been limited research that has studied the link between supply chain complexity, the degree of coupling in the supply chain, and disruptions in the supply chain. Kleindorfer and Saad (2005, p. 56) suggest that useful practices for supply chain disruption management can be drawn from NAT. Choi and Krause (2006) postulate that supply base complexity is positively associated with supply base risk. In addition, the literature suggests that process improvement efforts within supply chains have resulted in increased interdependencies and complexity in global supply chains, which in turn have increased their overall vulnerability (Christopher & Peck, 2004; Harland et al., 2003; Hendricks & Singhal, 2005; Tang, 2006). More specifically, Craighead et al. (2007) have linked supply chain complexity with disruption severity using case- and interview-based evidence. They primarily focus on the number of nodes in the supply chain and the respective material flows between the nodes to capture complexity. At the same time, Wagner and Bode (2006) examine how customer/supplier dependence, supplier concentration, and local/global sourcing, as examples of supply chain complexity, affect supply chain vulnerability. The authors call for more research regarding how supply chain design characteristics, such as complexity and coupling, increase or decrease supply chain risk. More recently, Speier et al. (2011) use NAT to examine product safety and security risks in a supply chain. Their results show that firms with higher supply chain complexity invest more heavily in information sharing, process management, and partner security management. The results also show that more tightly coupled supply chains invested more heavily in partner security systems. However, it needs to be emphasized that the authors explicitly assumed that the premises of NAT hold in the supply chain setting as a major assumption for the hypotheses was based on the fact that more complex or coupled supply chains have an increased risk of experiencing a supply chain disruption. In other words, the direct link between complexity and coupling was not explicitly studied.

3.0 Hypotheses

In this study, we want to build on these insights and assumptions and empirically examine the theoretical relationship suggested by NAT. In much of the literature noted above, overall supply chain complexity is often modeled as a mixture of complexity, in the form of dynamic and detail complexity, and the interdependencies of the elements in the supply chain, in the form of the degree of coupling within the supply chain. For example, Choi and Hong (2002) and Dooley (2001) model supply chain complexity as the degree of coupling and the interaction of elements within the supply chain. Described as complex adaptive systems, several authors argue that complexity stems from the sheer number of different elements in the supply chain (i.e. numerousness) and the high level of interconnectedness (i.e. coupling) of elements in the supply chain (Choi & Krause, 2006; Handfield & Nichols, 1999; Vachon & Klassen, 2002; Wilding, 1998; Choi et al., 2001).

After reviewing the literature on supply chain complexity, it became apparent that complexity and coupling are often aggregated to create an overall supply chain complexity assessment. In some cases these two concepts seem to be used almost interchangeably, blurring any differentiation between complexity and coupling. However, adopting the NAT framework requires complexity and coupling to be treated separately. NAT postulates that a system has to fail if it is both highly complex and tightly coupled. For our purposes, a system failure results in a disruption in the flow of materials. Simply stated, a complex system will experience frequent minor incidences, some of which may lead to a supply chain disruption. When such a system is tightly coupled, it is likely that these incidences will quickly spread throughout the system before intervention efforts can intercede and correct the problem, thereby resulting in a disruption. This suggests that complexity alone may not significantly affect supply chain disruptions if the system is loosely coupled. Yet, likely due to the aggregating of complexity and coupling, much of the research noted above has reported a link between supply chain complexity and supply chain performance. To explore this further, we first examine the direct effects of complexity on supply chain disruptions. Consequently, our first hypothesis is:

Hypothesis 1: *Supply chain complexity is positively associated with the frequency of supply chain disruptions.*

Further, even though a supply chain may be complex in its design, it may be possible to limit disruptions if the system is loosely coupled in the sense that there are large safety stocks, long lead times, excess capacity, and little interdependence between elements in the supply chain. In this case, the system is so loosely coupled that it may have time to correct itself when unexpected events occur. However, the lack of buffers in a tightly coupled supply chain does not allow for these system corrections. As such, we examine the direct effects of coupling on supply chain disruptions. Stated formally,

Hypothesis 2: *Supply chain coupling is positively associated with the frequency of supply chain disruptions.*

As suggested by NAT, any system that is both complex and tightly coupled will experience normal failures or accidents. This implies that it is the interaction of complexity and coupling that leads to these system failures, or in our case, supply chain disruptions. With this in mind, our third hypothesis is:

Hypothesis 3: *The interaction of supply chain complexity and supply chain coupling is positively associated with the frequency of supply chain disruptions.*

4.0 Conceptual Model

Figure 1 presents a conceptual model that formally links complexity and coupling in supply chains with the frequency of disruptions. The model is comprised of three parts which represent our three hypotheses: the effect of supply chain complexity on the frequency of disruptions in the supply chain; the effect of the degree of coupling on the frequency of disruptions in the supply chain; and the interaction of supply chain complexity and coupling on the frequency of supply chain disruptions.

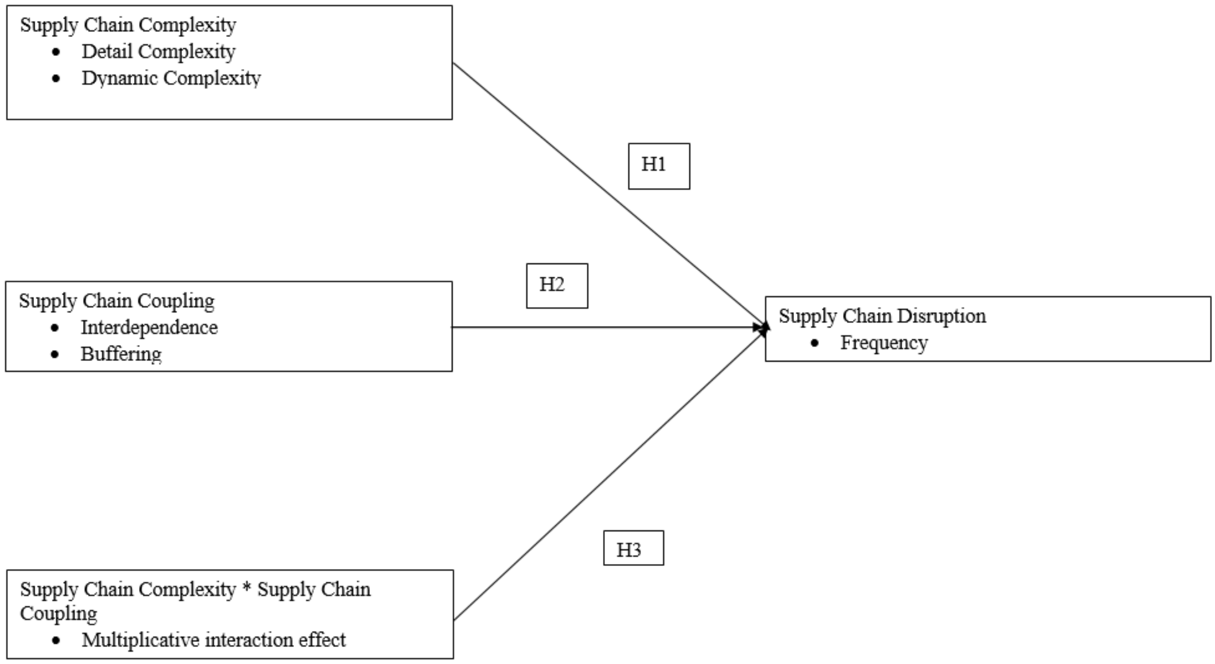

Figure 1: Conceptual Model

We assess supply chain disruption using a scale that captures the frequency of disruptions. As suggested by Ellis et al. (2010), the published literature provides little guidance for measuring the magnitude of supply disruption, the probability of supply disruption, and overall supply disruption risk constructs. While other dimensions of supply chain disruptions such as magnitude of disruption or duration of disruption could have been used, NAT focuses on the number of incidents or accidents that occur. As such, to be consistent with our NAT framework, we choose to model supply chain disruptions as the frequency of their occurrence.

The complexity construct was assessed with multi-item scales for two sub-dimensions: *detail complexity* and *dynamic complexity* (Senge, 1990; Bozarth et al., 2009). Consistent with Senge (1990) and Bozarth et al. (2009), we measure *detail complexit*y as the numerousness of elements in the supply chain. The number of elements in the supply base is a well-established dimension of complexity in the literature in that a larger number of suppliers results in a more complex supply base compared to a supply base with fewer suppliers (Vachon & Klassen, 2002; Choi & Krause, 2006; Handfield & Nichols, 1999). With this in mind, we assessed the number of suppliers, the number of tiers in the supply chain, and the overall size of the supply chain compared to the industry norm. The comparison to the industry is critical as the industry drives the size of the supply chain (i.e. automotive supply chains are very deep and have many suppliers due the complexity of their product). The individual measurement items can be seen in Appendix A. The design of these measures was loosely based on the measures of numerousness in Bozarth et al. (2009) who used the number of suppliers to access upstream complexity, number of customers for downstream complexity, and number of products/parts for internal complexity.

Dynamic complexity refers to the ability to predict the behavior of the system when unexpected events occur in the sense that an intervention in one part of the system has an unexpected consequence in another part of the system (Senge, 1990; Bozarth et al., 2009). With this in mind, the measures for *dynamic complexity* used in this study focus on the differences between the elements in the supply chain. As suggested by Choi and Krause (2006), the main indicators of dynamic complexity are differences regarding operational techniques (e.g., one supplier operates in a push system and another in a pull system), cross-border cultural barriers (e.g., different languages are spoken), or varying levels of technical capability (e.g., if some suppliers lag in their technical capability, the focal company may need to conduct additional supplier development to make them more competitive). In this sense, it is easier for a focal firm to coordinate activities with suppliers that have a common culture and work norms. Dooley (2001) also observed that it is easier to manage similar elements in a supply chain than dissimilar elements.

Our construct for supply chain coupling is also comprised of two sub-dimensions: *interdependence* and *buffering*. Wagner and Bode (2006) suggest that the level of supply chain vulnerability is driven by the dependencies between elements within the supply chain. Specifically, supplier dependence has been viewed as the extent to which an organization sources inputs from one or more suppliers for which there are few alternative sources (Hallikas et al., 2005; Hibbard et al., 2001). In such a setting, the customer firm is vulnerable since the supplier is dominant and holds the majority of power (Bourantas, 1989). In the case of a supply-side disturbance, the buying firm may experience significant problems in substituting the supply from another supplier and the severity of the supply disruption is amplified by the critical nature of the purchased item (Giunipero & Eltantawy, 2004). A firm's ability to replace a supplier is a measure of the dependence on its partners (Heide & John, 1988) and has been used to assess *interdependence* in the supply chain (Buchanan, 1992; Heide & John, 1988). This situation increases dependence (Heide & John, 1988) and emphasizes the importance of the maintenance of that relationship and the associated risk of vulnerability (Jap & Anderson, 2007). The supply chain literature has recently increased its focus on such *interdependencie*s in supply networks (Subramani & Venkatraman, 2003; Wagner & Bode, 2014**).**

Our second sub-dimension of the coupling construct is the level of *buffering* in the supply chain. A supply chain with large buffers would be less tightly coupled than a supply chain with smaller buffers. Browning and Heath (2009) and Hopp and Spearman (2004) emphasize that buffers, specifically lead times, capacity, and inventory, decouple elements in the supply chain, especially when the environment is uncertain and unstable. Basically, buffering in a supply chain is a measure of the slack between system elements in that slack allows an organization to reduce workflow disruptions **(**Bourgeois, 1981) by providing a margin for error which might otherwise result in a disruption in an organization's processes (Cyert & March, 1963; Pondy, 1967; Thompson, 1967).

5.0 Sample Selection and Data Description

The data for this study were collected through a web-based survey with a sampling frame consisting of all manufacturing firms in North America (SIC Codes 21-39). Several rounds of pre-tests and pilot studies were used to establish the content validity of the survey items, refine the wording of the questions, and conduct preliminary measurement assessments using exploratory factor analysis techniques. The respondents of the main data collection effort belong to a national supply chain professional organization, and the contact lists for the survey were comprised of individuals that matched three criteria: 1) respondent worked for manufacturing firm, 2) respondent had high- or mid-level position within the organization, and 3) respondent was exposed to supply chain related activities in the organization.

The main data collection totaled 211 responses, resulting in a response rate of 7.6%. After eliminating responses with substantial missing data, our usable data set was comprised of 189 responses. This response rate is consistent with that reported in similar studies, e.g. Salvador et al. (2014) with a response rate of 10.6%, Kristal et al. with a response rate of 9%, Nahm et al., (2003) with a response rate of 7.47%, Braunscheidel and Suresh (2009) with 7.4%, and Li et al. (2005) with a response rate of 6.3%.

6.0 Measurement Designand Analysis

While the four first-order factors in our model: dynamic complexity; detail complexity; interdependence; and buffering, are reflective constructs based on prior literature, it is necessary to consider the theoretical makeup of the higher-level factors: overall complexity and overall coupling. Whether overall complexity and overall coupling should be modeled as reflective or formative measures is of particular importance. Diamantopoulos and Winklhofer (2001) illustrate that reflective constructs of latent variables often mistakenly prevail in the literature. In reflective construct specifications, higher-order constructs are assumed to cause their dimensions, while in formative construct specifications, the higher-order constructs are caused by their dimensions. Consequently, dimensions of reflective constructs are viewed as strongly correlated and interchangeable facets of the underlying phenomenon construct (Bollen & Lennox 1991). From a formative perspective, the higher-order construct is defined by its dimensions, which do not need to be highly correlated with one another. According to Diamantopoulos and Winklhofer (2001), the choice between a formative and a reflective specification should be based primarily on theoretical considerations. The findings of our literature review on complexity and coupling suggest a formative measurement approach to capture these higher-order constructs in our study. Hence, in this study we model overall complexity and overall coupling as second order formative factors. Complexity consists of detail and dynamic complexity, which are two sub-dimensions of the overall complexity construct. Coupling consists of interdependence and buffering, which are the two sub-dimensions of the overall coupling construct.

Indeed, the decision rules presented by Jarvis et al. (2003) to determine whether a construct is formative or reflective suggest the use of a composite latent construct model in our context. For example, in our study, causality flows from the measures to the construct. In addition, the value drivers do not need to be highly correlated with one another either within each of the value sources specified in our framework or between them. Therefore, we suggest that complexity is a second-order formative construct in that a supply chain can be high on detail complexity but low on dynamic complexity, or vice versa. This indicates that the construct is formative and not reflective. Furthermore, this also supports the use of a second order factor to capture overall complexity. Similarly, interdependence and buffering can be either high or low, irrespective of the other construct. Hence, overall coupling is also treated as a second order formative construct.

Consequently, the literature suggests that from a methodological point of view, a formative measurement approach should be used rather than reflective measures when supply chain complexity is modeled as a multidimensional construct. More precisely, using the Jarvis et al., (2003) classification of second-order factor models, a Type IV model (i.e., a reflective first-order, formative second-order model) should be specified when supply chain complexity and supply chain coupling is modeled. These insights have important consequences for the data analysis methods used in this study.

Rather than using structural equation modeling (SEM), which has been used in other similar studies (Shah & Goldstein, 2006), we adopt the partial least squares (PLS) approach as used by Peng and Lai, (2012). SEM is primarily designed to handle reflective constructs and requires a substantial sample size to test large models. In the previous section we established the reflective and formative nature of our research model, which makes the use of SEM problematic. One advantage of PLS is that it has the ability to estimate research models using relatively small samples without any strict assumptions regarding the distributions of the constructs, which is not a capability in SEM. Further, it can model both reflective and formative constructs within the same research model (Hair et al., 2014), which is specifically important in this study. The use of PLS in the OM literature has seen a steady growth as evidenced by Peng and Lai, (2012), who examined 42 OM-related articles using PLS published in top level OM and Management Journals between 2001 and 2011. Other related fields have also shown an increased use of PLS in their research studies, e.g. Marketing (Hair et al., 2012), Strategic Management (Hair et al., 2012), Management Information Systems (Ringle et al., 2012), and Accounting (Lee et al., 2011). Furthermore, Hair et al. (2014) examine the growing importance and use of PLS across all business disciplines and state that non-normal data, small sample sizes, and formative constructs are the most prominent justifications for the use of PLS methods.

7.0 Assessment of Measures

We use PASW 17 for the measurement assessment of our research model. The assessments of reflective and formative constructs are different and require the separate assessment of the two types of constructs. This section begins with a general assessment of the measures and then assesses the reflective first-order constructs in detail and, separately, the formative second-order constructs.

Common method bias is a concern in measurement design and refers to the spurious covariance shared by variables across different constructs that potentially biases empirical findings (Podaskoff et al., 2003). Common method bias is usually a greater problem in self-report studies on socially sensitive topics, or about someone the respondents know well, but is less likely in studies where respondents are asked to express their opinion about more impersonal topics such as those in this study (Malhotra et al., 2006). Nevertheless, we focus on reducing the potential impact of common method bias by using different scale formats and anchors for the independent and dependent variables. In addition, we simplify the formulation of items, using multi-item scales, and reduce social desirability by emphasizing the system design as the driver of disruptions as opposed to human error. To detect common method bias in this study, we use Harmon’s one factor test that assesses common method bias through factor analysis. If the factor analysis using all relevant measurement items results in a single factor, common method bias is assumed to exist (Shah and Ward, 2007; Podaskoff and Organ, 1986; Miceli et al., 1991). The factor analysis, including all items without any rotation of the factors, yielded several factors with an eigenvalue in excess of 1.0. This suggests that common method bias does not seem to be problematic in this study.

Five-point Likert scales are used for all first order constructs: detail complexity, dynamic complexity, interdependence, and buffering. The specific items can be seen in Appendix A.

	1	**2**	**3**	**4**
DetC1	-.051	**.922**	-.076	-.187
DetC2	-.355	**.764**	-.119	.263
DetC3	.075	**.825**	-.07	.266
Interd1	-.181	.162	**.831**	.045
Interd2	.122	-.178	**.857**	-.196
Interd3	-.075	-.247	**.797**	.064
Coupl1	.353	.214	.073	**.735**
Coupl2	.156	.085	.097	**.775**
Coupl3	.158	-.016	-.263	**.811**
DynC1	**.750**	-.126	-.116	.180
DynC2	**.896**	-.049	-.082	.248
DynC3	**.821**	-.020	.031	.144
Eigenvalues	3.279	2.727	1.925	1.085
Variance	27.32	22.72	16.03	9.04

Table 1: Factor Loadings

An exploratory factor analysis (EFA) using principle components extraction and a varimax rotation was used to empirically explore the underlying dimensions of complexity and coupling. The exploratory factor analysis resulted in the identification of four underlying factors: two first-order factors to capture the dimensions for complexity (detail complexity and dynamic complexity), and two first-order factors to capture the dimensions for coupling (interdependence and buffering), which aligns with our theoretically-driven dimensions of supply chain complexity and coupling. Three measures (see Appendix A) loaded on the common factor to form dynamic complexity with 27.32% of variance explained, while the three measures for detail complexity loaded on one common factor explaining 22.72% of the variance. The three interdependence measures loaded on a common factor with 16.03% of variance explained, while the three items for buffering loaded on one common factor with 9.04% of variance explained. Items were inspected regarding significant loadings on their respective constructs. All item loadings are greater than 0.70 and significant at the 0.001 level, indicating convergent validity at the indicator level (Peng & Lai, 2012).

We calculate a Cronbach's alpha to measure the internal consistency of the measurement construct and to assess reliability. The Cronbach's alpha for the disruption construct, the sub-dimensions of complexity (detail complexity and dynamic complexity), and the sub-dimensions of coupling (interdependence and buffering), are all greater than 0.7. As a further test of the reliability of our measurement scales, we compute a composite reliability (Escrig-Tena & Bou-Llusar, 2005). The value for the composite reliability for all dimensions exceeds the commonly used threshold of 0.7 (Shah &Ward, 2007). Further, we examined the average variance extracted (AVE) (Fornell & Larcker, 1981). The AVE exceeds the commonly used threshold value of 0.50 (Shah & Ward, 2007). Based on these reliability tests, the fact that all construct measurement items load on single factors and further explain more than 50% of the total variance, we can conclude that all measures indicate good construct reliability.

	Cronbach's Alpha	**Composite Reliability**	**AVE**
Detail Complexity	0.827	0.824	0.611
Interdependence	0.791	0.793	0.567
Coupling	0.757	0.761	0.523
Dynamic Complexity	0.813	0.851	0.662

Table 2: Reliability Results

The underlying dimensions and reliability for the reflective first order constructs were assessed above (see Tables 1 and 2). The square root of each AVE (shown on the diagonal in Table 3) is greater than the related inter-construct correlations (shown off the diagonal in Table 3) in the construct correlation matrix, indicating adequate discriminant validity for all of the reflective constructs.

Coupling	**0.723**			
Detail	-0.276639	**0.781**		
Dynamic	0.355433	0.074044	**0.813**	
Interdependence	0.262511	-0.202941	0.063664	**0.752**

Note: The square root of average variance extracted (AVE) is shown on the diagonal of the correlation matrix and inter-construct correlations are shown off the diagonal

Table 3: Construct correlations

Regarding the second-order formative construct, we examine the formative item weights, multicolinearity between items, and discriminant validity of the formative construct. For each formative item, we examine its weight (rather than its item loading), sign, and magnitude. Each item weight is greater than 0.10 (Andreev et al., 2009), and the sign of the item weight is consistent with the underlying theory. All items are significant at the 0.01 level. In addition, OLS regression was used to test for variance inflation factors (VIF). All VIF values are less than 3.3 (Diamantopoulos & Siguaw, 2006), indicating that multicolinearity is not problematic. To examine the discriminant validity of the formative construct, we compute the average of intra-construct item correlations for this construct and the average of intra-construct item correlations between this construct and other constructs. We find that the average of *intra*-construct item correlations is greater than the average of *inter*-construct item correlations. In other words, the correlations within constructs are larger than the between construct correlations.

2nd Order Construct	1st Order Construct	Item Weights	T-Stat.	VIF
Overall Complexity	Detail Complexity	0.80	4.89	1.146
	Dynamic Complexity	0.54	2.18	1.188
Overall Coupling	Interdependence	0.89	20.04	1.096
	Coupling	0.26	2.72	1.336

Table 4: Measurement properties of formative constructs.

8.0 Pls Analysis

Smart PLS 2.0 M3 software was used in the data analysis portion of our study to test the hypotheses in our reflective first-order, formative second-order model. We also use PASW 17 software for robustness checks via OLS regression.

8.1. Direct Effect Results

We first examine the direct effects of the second order factor model to test Hypotheses 1 and 2. The results of the structural model estimate are shown in Table 5. We run the structural model using the bootstrap procedure with 200, 500, and 1000 times of resampling and the magnitude and significance of the structural paths are consistent.

	PLS results			**OLS regression results**	
Path	**Coefficient**	**T-Stat.**	**95% Confidence Interval**	**Coefficient**	**T-Stat**
Overall Complexity → Disruption	0.035	0.406	(-0.135, 0.205)	0.031	0.398
Overall Coupling → Disruption	0.085	1.518	(-0.024, 0.194)	0.079	1.44

Table 5: Structural estimates direct model

As the t-statistics and 95% confidence intervals indicate, all path coefficients are non-significant at the 0.01 level. These results indicate that we don't have sufficient statistical evidence to support Hypothesis 1 that suggests a link between supply chain complexity to disruptions and further, there is no statistical evidence to support Hypothesis 2 that suggests a link between supply chain coupling to disruptions. Therefore, we reject the idea that supply chain complexity or supply chain coupling by themselves significantly impact disruptions.

Because our research model includes both reflective and formative constructs, we are unable to run SEM and compare PLS results with SEM results. Instead, for robustness, we calculate the average of the items within each construct and subject these average values to the OLS regression. The OLS regression results are largely consistent with the PLS results (see Table 5)

8.2 Interaction Effect Results

Hypothesis 3 suggests that the combination of supply chain complexity and supply chain coupling affects disruptions. To test this, we examine the interaction effect model and show the results in Table 6. We also run the structural model using the bootstrap procedure with 200, 500, and 1000 times of resampling and the magnitude and significance of the structural paths are consistent. As the t-statistics and 95% confidence intervals indicate, the path coefficient for the interaction effect is significant at the 0.01 level. The results of this model show statistical support for a multiplicative impact between complexity and coupling on disruptions. The results support Hypothesis 3 that postulated, based on NAT, a positive relationship between supply chain complexity, coupling and disruptions. In our robustness check, the OLS regression results are largely consistent with the PLS results (see Table 6).

Path	**PLS results**			**OLS regression results**	
	Coefficient	**T-Stat.**	**95% Confidence Interval**	**Coefficient**	**T-Stat**
Overall Complexity → Disruption	0.041	0.653	-0.082, 0.164	0.037	0.612
Overall Coupling → Disruption	0.028	0.642	-0.057, 0.114	0.022	0.601
Ov.Compl * Ov. Coupl. → Disruption	0.431	13.979	0.372, 0.491	0.421	13.118

Table 6: Structural estimates interaction model

9.0 Discussion and Conclusions

Numerous researchers have suggested that supply chain complexity impacts the frequency of disruptions (Choi & Krause, 2006; Christopher & Lee, 2004; Juettner et al., 2003; Vachon & Klassen, 2002). In much of this literature, supply chain complexity is often defined as a combination of coupling (*interdependence* or *buffering*) and complexity (*detail* or *dynamic)*. Combining these two concepts into a single assessment of supply chain complexity limits our ability to differentiate between supply chain complexity and supply chain coupling. Indeed, one can argue that with enough buffering (safety lead times, safety stocks, capacity cushions), a supply chain high in *detail* and/or *dynamic* complexity may be able to operate, at least for a period of time, with few supply disruptions even if it is tightly coupled through a high level of interdependence between elements in the supply chain. Further, a complex supply chain with few buffers may be able to operate if the *interdependenc*e of the elements within the supply chain is low, perhaps due to multiple sourcing options for each component, allowing for a rapid response to a supply shortage. To develop a better understanding of supply chain disruptions, we suggest that coupling, modeled in this study as *interdependence* and *buffering*, and complexity, modeled as *dynamic* and *detail*, should be viewed as two completely separate managerial issues. In this way, managers can strategically choose whether to design a less complex supply chain or whether to increase the coupling of the elements within the supply chain.

With this in mind, we suggest that the relationships between supply chain complexity, supply chain coupling, and supply chain disruptions can be explained using Normal Accident Theory (NAT). Under the NAT framework, complexity (*detail* or *dynamic*) and coupling (*interdependence* or *buffering*), are treated as two separate issues. In other words, a system such as a supply chain will fail (e.g., experience greater disruptions) if it is both complex and tightly coupled. To the best of our knowledge, this is the first paper to treat these two concepts separately, and further, our results suggest that complexity or coupling alone may not significantly affect the level of supply chain disruptions. Indeed, our results support the use of NAT in that it is the existence of both complexity and tight coupling that determines the level of supply chain disruptions.

Any empirical study has inherent limitations based on its research design. This study is no exception, and the reader needs to be aware of at least two limitations due to the chosen research design for this study. First, the use of a single informant for collecting information about a firm's supply chain is a limitation. Multiple informants provide the possibility for increased reliability for the study's findings through inter-rater reliability assessments. However, multiple respondents are often possible when data are collected within a single firm or a limited set of firms. In this study, the conceptual framework necessitated data collection that would allow for collection from a large number of firms to provide a heterogeneous sample for the assessments of different complexity, coupling, and disruption levels. Therefore, we approached professional management associations for data collection and accept the limitation of a single respondent design in favor of greater heterogeneity in the sample.

A second limitation of this study is the sole use of the focal firm's perspective. Many researchers favor the use of supplier-buyer dyads for their research designs. Using only the focal firm's perspective omits any analysis from the supplier's perspective of reported disruptions at the focal firm. As with the multi-respondent case, this research design was chosen to allow for the heterogeneity of the sample. A dyadic approach limits the study either to one focal firm, or one supplier-focal firm relationship. To the best of our knowledge, this is the first empirical study on supply chain disruptions using primary survey-based data, which led us to give the heterogeneity and size of sample priority over a dyadic approach.

This paper can serve as a stepping stone for future research aimed at a better understanding of supply chain disruptions, supply chain complexity, coupling, and the mitigation of supply chain risk. This paper offers a different view of supply chain complexity by treating complexity and coupling as two different issues. Our results suggest that it is the interaction of the two that has the greatest impact on supply chain disruptions. As such, future studies are needed to confirm our findings. And, if either complexity or coupling is found to significantly impact disruptions, determining whether *dynamic* or *detail* complexity has the greater impact is warranted. Likewise, determining which of the buffering techniques studied in this paper has the greatest impact on reducing disruptions is needed**.** Perhaps future researchers could develop quantitative measures of the level of supply chain complexity and degree of coupling in the supply chain. In this way, some type of tradeoff between complexity and coupling could be determined. Additionally, an extension of this research would be the examination of complexities and coupling in other parts of the supply chain on disruptions. As this paper was limited to complexities and coupling in the supply base, future research could analyze the complexities and coupling in the production and customer base. The integration of all complexity sources would generate a more complete and holistic view of supply chain complexities. Lastly, research is needed to expand our understanding of the impact of various mitigation techniques on supply chain disruptions. For example, research on the role of information availability (quantity of information, quality of information, type of information, accessibility to information; etc.) on the mitigation of disruptions is needed.

References

Alok, A., & Ramanathan, U. (2021). Supply chain resilience for performance: The roles of absorptive, adaptive, and innovative capabilities. Decision Sciences, 52(3), 516-547.

Anderson, J. C., D. W. Gerbing. 1988. Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103 (3), 411-423.

Bagozzi, R. P., L. W. Phillips. 1982. Representing and testing organizational theories: a holistic construal. Administrative Science Quarterly. 27 (3), 459-489.

Bagozzi, R. P., Y. Youjae, L. W. Phillips. 1991. Assessing construct validity in organizational research. Administrative Science Quarterly, 36 (3), 421-458.

Blackhurst, J., C. W. Craighead, D. Elkins, R. B. Handfield. 2005. An empirically derived agenda of critical issues for managing supply chain disruptions. International Journal of Production Research, 43 (19), 4067-4081.

Boyer, K. K., G. Keong Leong, P. T. Ward, L. J. Krajewski. 1997. Unlocking the potential of advanced manufacturing technologies. Journal of Operations Management, 15, 331-347.

Bozarth, C. C., D. P. Warsing, B. B. Flynn, E. J. Flynn. 2009. The impact of supply chain complexity on manufacturing plant performance. Journal of Operations Management, 27 (1), 78-93.

Braunscheidel, M.J., Suresh, N.C., 2009. The organizational antecedents of a firm's supply chain agility for risk mitigation and response. Journal of Operations Management 27, 119–140.

Brown, K. A., P. G. Willis, G. E. Prussia. 2000. Predicting safe employee behavior in the steel industry: Development and test of a sociotechnical model. Journal of Operations Management, 18 (4), 445-465.

Browning, T.R., Heath, R.D. 2009. Reconceptualizing the effects of lean on production costs with evidence from the F-22 program. Journal of Operations Management. 27 (1), 23-44

Buchanan, L. 1992. Vertical trade relationships: the role of dependence and symmetry in attaining organizational goals. Journal of Marketing Research, 29 (1), 65-75.

Choi, T., D. R. Krause. 2006. The supply base and its complexity: Implications for transaction costs, risks, responsiveness, and innovation. Journal of Operations Management, 24 (5), 637-652.

Choi, T. M. (2020). Innovative "Bring-Service-Near-Your-Home" Operations under Corona-Virus (COVID-19/SARS-CoV-2) Outbreak: Can Logistics Become the Messiah? Transportation Research Part E: Logistics and Transportation Review, 140, 101961.

Chopra, S., M. S. Sodhi. 2004. Managing risk to avoid supply chain breakdown. Sloan Management Review, 46 (1), 53-62.

Chow, C. 1960. Test of equality between sets of coefficients in two linear regressions. Econometrica, 28 (3), 591-605.

Christopher, M., H. Lee. 2004. Mitigating supply chain risk through improved confidence. International Journal of Physical Distribution & Logistics Management, 32 (5), 388-396.

Craighead, C. W., J. Blackhurst, M. J. Rungtusanatham, R. B. Handfield. 2007. The severity of supply chain disruptions: Design characteristics and mitigation capabilities. Decision Sciences, 38 (1), 131-156.

Cyert, R. M., J. G. March. 1963. A behavioral theory of the firm. Englewood Cliffs, NJ: Prentice-Hall.

Daft, R. L., R. H. Lengel. 1984. Information richness: A new approach to manager information processing and organization design. In B. M. Staw (Ed.), Research in Organizational Behavior. Greewich, CN: JAI Press.

Das, S. R., M. P. Joshi. 2007. Process innovativeness in technology services organizations: Roles of differentiation strategy, operational autonomy, and risk-taking propensity. Journal of Operations Management, 25, 643-660.

Deloitte Consulting. 2007. Supply Chain's Last Straw: A vicious cycle of risk.

Ellis, S. C., R. M. Henry, J. Shockley. 2010. Buyer perceptions of supply disruption risk: A behavioral view and empirical assessment. Journal of Operations Management, 28 (1), 34-46.

Escrig-Tena, A. B., J. C. Bou-Llusar. 2005. A model for evaluating organizational competencies: An application in the context of a quality management initiative. Decision Sciences, 36 (2), 221-257.

Etienne, E.C. 1987. Choosing optimal buffering strategies for dealing with uncertainty in MRP. Journal of Operations Management. 7(1). 107-120.

Freeland, J. R., 1991. A survey of just-in-time purchasing practices in the United States. Production and Inventory Management Journal, 32 (2), 43–49.

Gao, L. L., E. P. Robinson. 1994. An arborescent network formulation of dual accent based procedure for the two stage multi-item dynamic demand lot-size problem. Decision Sciences, 25 (1), 103–121.

Griffith, D.A., Lee, H.S., Yeo, C.S., and Clantone, R. Marketing process adaptation: Antecedent factors and new product implications in export markets. International Marketing Review. 31(3), 308-334.

Hair, J. F., W. C. Black, B. J. Babin, R. E. Anderson, R. L. Tatham. 1998. Multivariate data analysis. Upper Saddle River, New Jersey. Pearson-Prentice Hall.

Hambrick, D., D. Lei. 1985. Toward an empirical prioritization of contingency variables for business strategy. Academy of Management Journal. 28, 63-788.

Handfield, R. B., E. L. Nichols. 1999. Introduction to supply chain management. Englewood Cliffs, NJ: Prentice-Hall.
Heide, J. B., G. John. 1988. The role of dependence balancing in safeguarding transaction specific assets in conventional channels. Journal of Marketing, 52 (1), 20-35.
Hendricks, K., V. Singhal. 2005. An empirical analysis of the effect of supply chain disruptions
on long-term stock price performance. Production and Operations Management, 14(1) ,35-52.
Hendricks, K., V. Singhal, R. Zhang. 2009. The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. Journal of Operations Managerment, 27, 233-246.
Hopp, W.J., Spearman, M.L., 2004. To pull or not to pull: what is the question? Manufacturing & Service Operations Management 6 (2),133–148.
Hu, L.-T, P. Bentler. 1995. Evaluating model fit. In R. H. Hoyle (Ed.), Structural Equation Modeling. Concepts, Issues, and Applications. London: Sage. 76-99.
Huber, G. P. 1991. Organizational learning: The contributing processes and the literatures. Organization Science, 2 (1), 88-115.
Hult, G. T. M., D. J. Ketchen Jr., S. F. Slater. 2004. Information processing, knowledge development, and strategic supply chain performance. Academy of Management Journal, 47 (2), 241-253.
Isenberg, D. J. 1984. How senior managers think. Harvard Business Review, 62 (6), 81-90.
Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. International Journal of Production Research, 58(10), 2904-2915.
Jablin, F. M., L. W. Porter, K. H. Roberts. 1987. Handbook of organizational communication: an interdisciplinary perspectives. Thousand Oaks, CA: Sage Publications.
Jonsson, P. 2000. Towards an holistic understanding of disruptions in operations management. Journal of Operations Management, 18 (6), 701-718.
Joreskog, K. G., D. Sorbom. 1997. LISREL 8: User’s reference guide. Chicago, IL: Scientific Software.
Juettner, U., H. Peck, M. Christopher. 2003. Supply chain risk management: Outlining an Agenda for future research. International Journal of Business Logistics: Research and Applications, 6 (4), 197-210.
Kauffman, S. A. 1993. The origins of order: Self-organization and selection in evolution. Oxford, U.K.: Oxford University Press.
Kauffman, S. A., S. Levin. 1987. Toward a general theory of adaptive walks on rugged landscapes. Journal of Theoretical Biology, 128 (1), 11-45.
Kleindorfer, P. R., G. H. Saad. 2005. Managing disruption risks in supply chains. Production and Operations Management, 14 (1), 53-68.
Kristal, M.M., Huang, X., Roth, A.V., 2010. The effect of an ambidextrous supply chain
strategy on combinative competitive capabilities and business performance. Journal of Operations Management 28, 415–429
Lee, H. L., S. Whang. 2000. Information sharing in a supply chain. International Journal of Manufacturing Technology and Management, 1 (1), 79-93.
Levinthal, D. A. 1997. Adaptation on rugged landscapes. Management Science, 43 (7), 934-950.
Levinthal, D. A., M. Warglien. 1999. Landscape design: Designing for local action in complex worlds. Organization Science, 10 (3), 342-357.
Li, S., S. Subba Rao, T. S. Ragu-Nathan, B. Ragu-Nathan. 2005. Development and validation of a measurement instrument for studying supply chain management practices. Journal of Operations Management, 23 (6), 618-641.
Loch, C. H., M. E. Solt, E. M. Bailey. 2008. Diagnosing unforeseeable uncertainty in a new venture. Journal of Product Innovation Management, 25 (1), 28-46.
March, J. G., H. A. Simon. 1958. Organizations. New York: Wiley.
Mason-Jones, R., D. R. Towill. 1998. Shrinking the supply chain uncertainty cycle. The Control Journal of the Institute of Operations Management, 24 (7), 17-22.
McKelvey, B. 1999. Avoiding complexity catastrophe in coevolutionary pockets: Strategies for rugged landscapes. Organization Science, 10 (3), 294-321.
Mendelson, H., R. P. Pillai. 1998. Clockspeed and informational response: Evidence from the information technology industry. Information Systems Research, 9 (4), 415-433.
Miller, K. 1992. A framework for integrated risk management in international business. Journal of International Business Studies, 23 (2), 311-331.
Miller, R., D. R. Lessard. 2000. The strategic management of large engineering projects. Cambridge, MA: The MIT Press.
Mohr, J., R. Spekman. 1994. Characteristics of partnership success: Partnership attributes, communication behavior, and conflict resolution techniques. Strategic Management Journal, 15 (2), 135-152.

Nahm, A. Y., M. A. Vonderembse, X. A. Koufteros. 2003. The impact of organizational structure on time based manufacturing and plant performance. Journal of Operations Management, 21 (3), 281-306.

Nunnally, J. C. 1978. Psychometric theory (2nd ed.). New York: McGraw-Hill.

Perrow, C. 1984. Normal accidents: Living with high risk technologies. New York: Basic Books.

Perrow, C. 1999. Organizing to reduce the vulnerabilities of complexity. Journal of Contingencies and Crisis Management, 7 (3), 150-155.

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2019). Ensuring supply chain resilience: Development and implementation of an assessment tool. Journal of Business Logistics, 40(1), 1-21.

Petersen, K. 1999. The effect of information quality on supply chain performance and inter-organizational information system perspective. Unpublished Dissertation. Michigan State University, MI.

Powell, B. 2011. The global supply chain: So very fragile. Fortune. December 12, 2011.

Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2020). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Annals of Operations Research.

Rajma, J. A. 1997. Complexity, Tight–Coupling and Reliability: Connecting Normal Accidents Theory and High Reliability Theory. Journal of Contingencies & Crisis Management, 5 (1), 15.

Roberts, K. H. 1990. Some characteristics of high reliability organizations. Organization Science, 1 (2), 160-177.

Roberts, K. H. 1993. New challenges to understanding organizations. New York, NY: Macmillan Publishing.

Roberts, K. H., R. G. Bea. 2001. When systems fail. Organizational Dynamics, 29 (3), 179-191.

Rochlin, G. I., T. R. LaPorte, K. Roberts. 1987. The self designing high reliability organization: Aircraft carrier flight operations at sea. Naval War College Review, 40 (4), 76-95.

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research, 57(7), 2117-2135.

Sage, A. P. 1981. Designs for optimal information filters. In Nystrom, P.C. and Starbuck, W.H. (Eds.), Handbook of Org. Design, Vol.1. London: Oxford University Press. 105-121.

Salvador, F.; Chanrasekaran, A.; Sohail, T. 2014.Product configuration, ambidexterity and firm performance in the context of industrial equipment manufacturing. Journal of Operations Management, 32 (1), 138-153.

Senge, P. M. 1990. The fifth discipline: the art and practice of the learning organization. New York: Doubleday Dell Publishing.

Shah, R., S. Goldstein. 2005. Use of structural equation modeling in operations management research: Looking back and forward. Journal of Operations Management, 24 (2) 148-169.

Siggelkow, N. 2001. Change in the presence of fit: The rise, the fall, and the renaissance of Liz Claiborne. Academy of Management Journal, 44 (4), 838-857.

Smyrlis, L. 2006. Risky business: there has been a significant increase in external risk during the past five years and supply chain is the major concern, new survey shows. Canadian Transportation and Logistics, 109 (6).

Stauffer, D. 2003. Risk: The weak link in your supply chain. Harvard Management Update. March.

Tang, C. S. 2006. Robust strategies for mitigating supply chain disruptions. International Journal of Business Logistics: Research and Applications, 9 (1), 33-45.

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: definition, review and theoretical foundations for further study. International Journal of Production Research, 53(18), 5592-5623.

Venkatraman, N. 1989. The concept of fit in strategy research toward verbal and statistical correspondence. Academy of Management Review, 14 (3), 423-444.

Wang, Y., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98-110.

Weick, K. E., K. M. Sutcliffe. 2001. Manging the unexpected: Assuring high performance in an age of complexity. San Francisco: Jossey-Bass.

Whipple, J. M., R. Frankel, P. J. Daugherty. 2002. Information support for alliances: Performance implications. Journal of Business Logistics, 23 (2), 67-82.

Zajac, E., M. Bazerman. 1991. Blind spots in industry and competitor analysis: Implications of interfirm (mis)perceptions for strategic decisions. Academy of Management Review, 16, 37-56.

Zhou, H., W. C. Benton. 2007. Supply chain practice and information sharing. Journal of Operations Management. 25, 1348-1365.

Appendix A: Measurement Items (*Items in Italics were dropped during EFA*)

Please indicate **whether you agree or disagree with the following statements** about your supply base. (5 = Strongly Agree; 1 = Strongly Disagree)

Detail Complexity Supply Base
DetC1: Our supply base consists of too many suppliers compared to our competitors
DetC2: Our supply base is very deep (has many tiers) compared to our competitors
DetC3: The overall size of our supply base is larger than that of its competitors

Interdependence / Replaceability
Interd.1: Our production process can easily use components from new/different suppliers
Interd.2: There are minimal costs associated with switching to different suppliers
Interd.3: There are many competitive suppliers for our components

Dynamic Complexity
DynC1: Our suppliers have technical capabilities that are very similar to ours
DynC2: Our suppliers use operational techniques that are very similar to ours
DynC3: Our suppliers have business cultures that are very similar to ours

Coupling
How extensively are the following operational techniques used to **decouple your production process** from the supply base
Coupl1: Safety lead times
Coupl2: Excess capacity
Coupl3: Safety stock

Disruption
This section contains questions related to **disruptions originating in the supply base.**

Frequency
Freq1: How frequently have **disruptions (for any reason) originated** in your **supply base** during the last three months? (7-Continously; 1=Never)
Freq2: How quickly were the **supply base disruptions usually resolved** during the last three months? (7=Very Slow; 1=Very fast)