Identifying and Mitigating the Antecedents of Supply Chain Disruptions - 3 Essays

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Dedication

Dedicated to my parents, Bernd and Karin Habermann

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Chapter 1
Introduction

This dissertation work is motivated by the increasing interest of practitioners and academics in the topics of supply chain disruptions and supply chain complexity. In the dissertation we examine a possible connection between complexities and disruptions based on data collected with a survey instrument. In this chapter, we begin the study by providing evidence of the increased importance of supply chain disruptions and supply chain complexity, formulate the general research questions for the dissertation, present the chosen research design for the empirical investigation, illustrate the data collection methods used for the remainder of the dissertation, and end with a brief overview of the contents of the remaining chapters.

1.1. Research Background

Globalization facilitated by information technology has changed the nature of work (Sinha and Van de Ven, 2005); work in today's economy is increasingly performed in geographically dispersed and loosely connected networks of firms, shifting the attention of practitioners and academics from individual firms to supply chains. Managing supply chains effectively and efficiently is frequently heralded as a critical source of advantage in an increasingly competitive business environment (Lee, 2002; Fisher, 1997).

At the same time, breakdowns in supply chains are cited as one of the main threats to firm profitability both in terms of revenue loss and customer dissatisfaction, according to a recent report published in *The Economist* (Anonymous, 2005). For instance, Ericsson attributed a loss of over $400 million to a disruption in its supply chain from a fire at Phillips' New Mexico chip-making plant (Latour, 2001). Similarly, the Aberdeen Group estimates that, on average, company recovery costs from supply chain disruptions range from six to seven figures (Enslow, 2004). This illustrates the negative potential of disruptions for a firm's bottom line.

There is further evidence indicating that a large proportion of firms have actually experienced disruptions in their supply chains. A recent study by Accenture (2006) revealed that, among 151 US based companies, 73% had experienced severe supply chain disruptions in the past year, and 36% of those had taken more than one month to recover. A study by the Aberdeen Group (Sadlovska et al., 2008) even reports that 99% of surveyed companies reported disruptions, with 5% suffering financial losses. These numbers are compelling illustrations of the importance of disruptions to supply chain operations, but firms show a lack of preparedness to manage these disruptions effectively. Mitroff and Alpaslan (2003) estimate that only between 5 and 25% of Fortune 500 companies are prepared to handle disruptions.

Despite the keen interest among practicing managers, most of the evidence related to supply chain disruptions is anecdotal or conceptual (Sheffi, 2005; Chapman et al., 2002; Chopra and Sodhi, 2004). The Operations Research literature has predominantly considered disruptions as exogenous variables and their examines their impact on various operational decisions, such as production lot sizing (Groenevelt et al., 1992), inventory levels (Moinzadeh and Aggarwal, 1997; Arreola-Risa and DeCroix, 1998), and scheduling (Qi et al., 2006). Few empirical studies have examined supply chain disruptions extensively; a notable exception includes Hendricks and Singhal's work (2005a, 2005b) which studies the impact of disruptions on operational and financial performance. This leaves an apparent need for further research on the antecedents of supply chain disruptions and potential mitigation techniques in order to develop practical recommendations for practicing managers and to build the academic knowledge base on the topic.

A primary obstacle to the knowledge accumulation regarding supply chain disruptions is the divergent usage of terminology in this emerging area of research. Disruption related literature is replete with terms like blips, glitches, failures, accidents, disasters, uncertainties, and risks (Anonymous, 2005; Hendricks and Singhal, 2005; Tucker, 2004; Mason-Jones and Towill, 1998; Juettner, 2005; Zsidisin et al., 2004; Zsidisin and Ellram, 2003). Moreover, the research has not only used a variety of terms, but also covered a variety of disruption types. Previous research often aggregated all sorts of problems (quality defects, late shipments, machine breakdowns, accidents, etc.) under the concept of disruptions, lacking a concise and differentiated definition of the disruption construct. The empirical testing of relationships based on vague and varying concepts leads to research that studies slightly different aspects of the same underlying phenomenon and prevents the effective accumulation of knowledge (Meredith, 1993). Thus, a concise and detailed definition of disruptions and their characteristics is needed as a prerequisite for empirical research on antecedents and successful disruption management strategies. Consequently, the first research questions for this dissertation work are aimed at defining supply chain disruptions concisely, which then provides the basis for the construction of measures to empirically assess disruptions.

> *Research Questions Part 1: "What are supply chain disruptions? How can we concisely define supply chain disruptions? What are the critical dimensions for empirically measuring supply chain disruptions?"*

These questions lay the foundation for the second part of the dissertation: the empirical examination of supply chain complexity as an antecedent of supply chain disruptions. Recent publications argue that four fundamental changes in the way business is conducted have increased the complexity of the supply chains (Deloitte Consulting, 2007; Choi and Krause, 2006). First, work is no longer conducted within the boundaries of individual firms, but by loosely connected firms in supply chains. A survey of more than 200 large manufacturers and distributors by Deloitte Consulting (1999) states that "no longer will companies compete against companies, but total supply chains will compete against other supply chains." Academic studies share the growing recognition that individual businesses no longer compete as stand-alone entities (Christopher, 2000; Boyaci and Gallego, 2004; Spekman et al., 1998; Best, 1990), but based on capabilities assembled across supply networks (Rice and Hoppe, 2001). The downside of this trend is the difficulty in identifying and locating vulnerabilities in a network extended across individual companies. Longer paths in supply chains increase the chances of disruptions (Kleindorfer and Saad, 2005), and supply chains are only as resilient as their weakest link (Sheffi, 2005).

Second, the increased pace of change in the business environment, displayed by shorter product life cycles and increased product variety, results in fragmented and less predictable customer demand patterns. The explosion of product varieties impacts manufacturing processes and supplier relationships and creates more complex structures within supply chains (Randall and Ulrich, 2001; Novak and Eppinger, 2001; Fisher and Ittner, 1999). These changes create more opportunities for disruptions and a smaller margin for error (Kleindorfer and Saad, 2005).

Third, increased global competition has contributed to a focus on efficiency improvement programs such as lean production methods, just-in-time delivery, and process reengineering within supply chain management. Organizations strive for greater speed and cost effectiveness in their supply chains to gain competitive advantages in the hypercompetitive marketplace (Lee, 2004). Most efficiency approaches advocate lower inventory levels to reduce the holding costs associated with finished goods, raw materials, and work in process (Hall, 1983; Moinzadeh and Aggarwal, 1997). These leaner supply chains are more vulnerable to potential disruptions, though, because reduced inventory levels reduce the supply chain's buffering capability and make it more dependent on uninterrupted material in- and outflows. Reduced system reliability and more frequent disruptions are the hidden costs of efficiency gains (Lee, 2004).

Finally, trends like outsourcing and offshoring contribute to the expanding geographic length/span of supply chains. Organizations are increasingly moving operations to international locations with cheaper cost structures. Today, many companies are dispersed across the globe with locations in multiple countries. A study by

Deloitte Consulting (2003) found that 80% of manufacturers surveyed either purchase or plan to purchase components or materials produced in other countries within the next three years. Moreover, 56% of manufacturers make products in other countries, and 48% engineer products outside their home country. Beyond the common risks associated with outsourcing and offshoring (Aron and Singh, 2005), global networks can make it more difficult to detect supply chain disruptions (Sheffi, 2005). The longer paths of global networks increase the chances of disruptions significantly, and longer lead times make quick recovery attempts difficult (Kleindorfer and Saad, 2005).

While much attention has been paid to how these changes have led to efficiency and speed gains, the downside of increased complexity has been predominantly neglected (Kilgore, 2004; Radjou, 2002: Lee, 2004; Kleindorfer and Saad, 2005; Chopra and Sodhi, 2004). Only recently have practitioners and academics begun to consider the downsides of this added complexity on performance (Hoole, 2006; Bozarth et al., 2008). In this dissertation, we contribute to this growing body of literature, focusing on the impact of increased supply chain complexity on disruptions. In general, the behavior of complex systems is described as difficult to predict, ambiguous, and unstable (Casti, 1994; Perrow, 1967), which makes complex systems theoretically more susceptible to disruptions (Choi and Krause, 2006). Hence, the research questions for the second portion of the dissertation revolve around the connection between complexity and disruptions.

> *Research Questions Part 2: "What are the antecedents of supply chain disruptions; more specifically, does supply chain complexity lead to supply chain disruptions? If so, what aspects of complexity are relevant drivers of disruptions?"*

After our examination of the antecedents of supply chain disruptions, the focus shifts toward methods to mitigate the impact of complexity on disruptions. Complexity has been linked with increased information processing requirements, e.g., from the environment (Dess and Beard, 1984; Duncan, 1974; Jurkovich, 1974), from technology (Woodward, 1965), from the organizational structure (Daft, 1992), and from tasks (Wood, 1986). Research shows that information processing requirements need to be matched by adequate information processing capabilities to avoid any negative performance impacts (Galbraith, 1973, 1977; Flynn and Flynn, 1999; Bensaou and Venkatraman, 1995). Similarly, we argue that the increased information processing requirements imposed by supply chain complexity need to be matched with greater information processing capabilities to avoid disruptions.

This logic is reflected in research on High Reliability Theory (HRT), which highlights the importance of information processing in order to achieve outstanding safety records (Roberts, 1993). Furthermore, research on Complex Systems Theory (CST) examines ways in which organizations maneuver rugged "complexity landscapes" focusing on organizational search activities through information processing (Levinthal, 1997; Sigglekow, 2001; McKelvey, 1997; Rivkin, 2000). Overall, the research shows strong evidence that increased complexity levels can be mitigated through increased information processing capabilities. In chapter 4 3, we empirically examine the impact of information processing as a mitigation technique for supply chain complexities and its relationship with disruptions.

Research Question Part 3: "Does information processing in the supply chain mitigate the impact of complexity on disruptions?"

1.2. Research Design

In this section, we describe the data used in the dissertation to evaluate the research questions. The data were obtained using an online survey instrument over the period of one year from Summer 2007 to Summer 2008. Within this time period we conducted several stages of the data collection, which are described in detail below.

1.2.1. Unit of Analysis

Our research questions aim at identifying the antecedents of supply chain disruptions. For the scope of this study we chose a focal firm's perspective of its supply chain for a major product line as the unit of analysis for two reasons: (1) financial markets consider the firm as the most important entity when it comes to risk evaluation and management. Hence, the assessment of disruption risk from a single, focal firm's perspective is best suited to capture this insight, which has also been applied by Hendricks and Singhal (2005) in their studies. (2) We limit the study to a major product line to avoid problems arising from supply chain variations across product lines within a single firm. Individual product lines have supply chains with characteristics that differ from other product line supply chains in the same firm. Hence, we chose a single product line as the unit of analysis to avoid any possible confusion for the respondents, and receive a less convoluted perspective of the supply chain.

1.2.2. Data Collection

To avoid overly homogenous or heterogeneous samples, we selected the population of manufacturing firms in North America (SIC Codes 21-39) for the study. This sampling frame ensures a sufficient level of variance of supply chain complexity and disruption levels across firms. Previous research has shown that supply chain risk management techniques are very similar within industries (Zsidisin et al., 2005) indicating potential problems for single industry studies in this topic area because of the low variability. The selection of manufacturing firms is justified by our focus of disruptions in the material flow within the supply chain.

The data collection effort consisted of three main stages: 1) A variety of pre-tests, 2) a pilot study, and 3) the main data collection. All stages were, in their entirety, administered online.

1.2.2.1. Pre-Test

The pre-tests were intended to ensure the content validity of the constructs. Content validity refers to the adequacy with which the content has been sampled (Nunnally, 1978). Content validity is assured through the construction of instruments using sensible methods and the grounding of the measurement instruments in the literature. A common method to assess content validity is the evaluation of the measurement instruments through content experts. Four academic and eight managerial respondents was chosen to review the items. An online adaptation of the think-aloud procedure (Duncker, 1945) for the refinement of measurement items was employed, as the use of verbalizations as indicators of cognition is a decades-old data collection technique. Research has demonstrated that using think-aloud data can lead to better designed products. Shriver (1984, 1991), for example, used think-aloud data to improve readability of written documents. Likewise, Camburn et al. (2000) and Nolan and Chandler (1996) conducted think-aloud experiments during the pilot stages of survey development and used data to improve the readability and accessibility of surveys. Think-aloud methods are used along with other assessment evaluation techniques (sensitivity reviews, statistical analysis of results, etc.) to provide otherwise untapped information about test design. The surveys provided the respondents with comment space for each of the measurement items, in which they were able to comment on the phrasing, clarity, and content of the particular item. The comments were used to adjust the wording of the question to a commonly used lingo that is easily understandable by management professionals.

After the pre-tests we conducted two waves of larger scale pilot studies to assess the psychometric properties of the developed measurement instruments. The administration of the data collection followed the general outline for survey design advocated by Dillman (2000) and used in Operations Management research (Koufteros et al., 1998; Nahm et al., 2003). The first wave of the pilot study used members of “Supply chain practitioners,” a Yahoo! user group of supply chain professionals. Approximately 250 members were contacted by email, resulting in the response of 57 individuals, or a response rate of 23%. The second wave of the pilot study was conducted using members of the Council of Supply Chain Professionals (CSCMP) which were selected based on their hierarchical position within the organization and in areas with high exposure to their firms supply chain activities. One hundred eleven responses, corresponding to a response rate of 11% were used to assess initial reliability and to conduct exploratory data analysis. The pilot sample in this study is larger than in comparative studies that conducted a pilot study for their research studies, increasing the power of the exploratory analysis conducted with the pilot data (Shah and Ward, 2007; Koufteros et al., 1998; Nahm et al., 2003).

The data from the pre-tests and pilot studies were not used in the large scale study, as the premise for them was only the identification of measurement dimensions, improvement of readability, and the establishment of content validity.

1.2.2.2. Main Data Collection

The main data analysis was conducted over 6 weeks in the Summer of 2008. The respondents belong to one of two organizations of operations management practitioners. APICS (Advancing Productivity, Innovation, and Competitive Success) is a network of accomplished industry professionals that has been active since 1957 with regard to training programs, certifications and conferences in the area of Operations Management. SCL (Supply Chain and Logistics Association) was formed in 1967 by practitioners interested in supply chain related topics. The contact lists for the survey were composed of individuals that matched three criteria: 1) person worked for manufacturing firm, 2) person had high- or mid-level position within organizations, 3) person was exposed to supply chain related activities in the organizations. The survey was administered through the organizations, which limited the contact to an initial contact and one reminder email. This is a deviation from the Dillman (2000) approach which recommends an announcement, initial contact, and two to three reminders.

The response rates for the different stages of the data collection can be found in Table 1-1. The response rates are below the recommended rule of thumb baseline of 20% for empirical studies (Malhotra and Grover, 1998), but other studies subscribe to the idea that there is no generally accepted minimum response rate (Fowler, 1993). The response rates match recent results of large scale studies, i.e., Shah and Ward (2007) reported a response rate of 13.5%, Nahm et al. (2003) of 7.47%, Li et al. (2005) of 6.3%, and Poppo and Zenger (1998) of around 5%. The response rate for SCL was especially low when compared to the other data collection efforts. We believe that is mainly due to the fact that the organization sends two e-mail newsletters per week to its members, which desensitizes them to emails sent through the organization. In general, we observed better response rates for the cases where we sent the emails (Yahoo! Group, CSCMP) than in the cases the external organization sent the email. This tendency could be a potential indicator that members or large professional organizations have become unresponsive to emails from the organization.

Table 1-1: Response rates for different stages of data collection

Stage	1	2	3a	3b
	Pilot-Test			
Organization	Yahoo	CSCMP	SCL	APICS
Sample Size	57	110	62	151
Response Rate	23%	10%	1.5-2%	7.6%

The respondents exhibit long-term experience within their respective organizations and industries. 61.2% of respondents have more than ten years of experience within their industry, while more than 75% of respondents have at least five years of work experience in the industry. 5.47% of respondents have less than two years of work experience in their industry. In terms of work experience with their current employer, 89% of respondents have more than two years of experience within the firm, while 60% have more than five years of experience. More than 83% of the respondents have more than two years of experience in their current position, and around 45% have more than five years experience. The respondents experience level is an indication of their knowledge regarding their industry and firm, and their ability to accurately answer questions regarding their supply chain operations and its competitive standing within the industry.

Table 1-2: Experience of respondents

	<1 year	1-2 years	2-5 years	5-10 years	>10 years
Time in industry	1.37%	4.10%	19.17%	15.06%	60.27%
Time in firm	4.10%	6.84%	28.76%	23.28%	36.98%
Time in current position	5.47%	12.32%	36.98%	28.76%	16.43%

The experience is reflected in the confidence with which the respondents were able to answer the questions in the survey instrument. Almost 75% of the respondents described themselves as confident, or very confident, in answering the question in the survey.

Table 1-3: Confidence level of respondents

Question	1	2	3	4	5
How confident were you in answering the questionnaire	0	3.5%	22.81%	63.16%	10.5%

1=Not confident; 5=Very Confident

1.2.2.3. Non-response Bias

Non-response bias was evaluated by testing for significant differences between early respondents and late respondents, with late respondents being considered a surrogate for non-respondents (Armstrong and Overton, 1977). The underlying assumption of the assessment is that late respondents are more similar to non-respondents. Thus, a comparison between late respondents and early respondents is considered indicative about a potential presence of non-response bias. Using this method, responses of the first 30 received surveys were compared to responses of the last 30 received surveys. We performed a series of t-tests to assess any significant differences between the groups using critical measurement items for this study and demographic variables (Filion, 1976). Results of the test indicate no significant difference between the early and late respondents at the .10 significance level. This result implies that there is no detectable non-response bias based on this test.

1.2.2.4. Sample Differences

The two samples from the data collection were evaluated regarding significant differences using t-test on critical measurement items. We did not detect any significant difference at the 0.10 significance level. Hence, we combined the two samples for the subsequent data analysis. A dummy variable indicating the sample association is included in all subsequent analysis to continuously check for any sample differences.

1.2.2.5. Coverage Bias

Coverage bias refers to differences between the sample and the underlying population of the study. In general, the population of this study includes all manufacturing firms in North America, more specifically, all manufacturing firms that are members of the two professional associations used for the data collection in this study. However, we were unable to obtain any information regarding the population characteristics from the professional associations and we resorted to compare the SIC categorization of the sample firms to the population of US firms. The data for the population were obtained from the economic census[1] conducted in five year intervals by the US Census Bureau. Table 1-4 shows the %age of respondents in each of the manufacturing relevant SIC codes (20-39) for the sample and the entire population of firms. The sample shows a strong bias toward Food and Kindred Products (SIC code = 20), Chemicals (SIC code =28), Electronics and other Electronic Equipments (SIC code=36); Transportation Equipment (SIC code =37), as well as Measuring, Analyzing, and Controlling Instruments (SIC code = 38). We believe that the bias is driven by the higher interest of the respondents in the topic of supply chain complexity and disruptions

[1] The 2002 census data were used because the 2007 data haven't been fully released yet. The 2007 data will be released starting December 2008 through late 2011. (Link: http://www.census.gov/econ/census07/)

Table 1-4: Coverage bias comparison to Census[2]

SIC Code	US - Census	Sample
20 – Food and Kindred Products	5.5%	14.4%
21 – Tobacco Products	0.0%	0.0%
22 – Textile Mill Products	1.6%	0.0%
23 – Apparel	6.2%	1.0%
24 – Lumber and Wood Products	9.7%	0.0%
25 – Furniture and Fixtures	3.2%	3.1%
26 – Paper and allied products	1.7%	3.1%
27 – Printing and Publishing	16.5%	1.0%
28 – Chemicals	3.3%	24.7%
29 – Petroleum	0.6%	0.0%
30 – Rubber and Misc. Plastics	4.5%	1.0%
31 – Leather products	0.5%	0.0%
32 – Stone, Clay, Glass, and Concrete Products	4.3%	0.0%
33 – Primary Metal Industries	1.7%	0.0%
34 _ Fabricated Metal Products	10.1%	6.2%
35 – Industrial and Commercial Machinery	14.9%	7.2%
36 – Electronic and other Electronic Equipments	4.5%	15.5%
37 – Transportation Equipments	3.3%	8.2%
38 – Measuring Analyzing, and Controlling Instruments	3.1%	9.3%
39 – Misc. Manufacturing Industries	4.8%	2.1%

within these industries. This heightened interest in supply chain problems within these industries might have resulted in higher membership levels in the supply chain oriented professional organizations we used for the data collections. However, due to the lack of

2 $\chi^2_{K-1} = \sum_{i=1}^{K} \frac{(O_i - E_i)^2}{E_i} = 468.62$

The obtained value will be distributed as a chi square with df=K-1, where K is the number of categories (SIC codes). We can use the chi-square distribution to calculate the associated p-value to decide whether to retain the null hypothesis that our sample distribution of SIC codes is the same as the population distribution of SIC codes. The test shows that we can reject the null hypothesis at the 0.001 level of confidence.

information about the demographics of the members we cannot validate this theory. The bias of the sample needs to be taken into account when interpreting the results of the analysis, as they are not fully reflective of the whole population of firms.

1.3.2.6. Common Method Bias

Common method bias 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 (Malhotra et al., 2006). The influence of common method bias is less likely in studies where respondents are asked to express their opinion about more impersonal contexts, like in this study on supply chain complexity and disruptions (Malhotra et al., 2006). It has been pointed out in the literature that common method bias only marginally inflates correlations between variables and that structural relationships remain generally significant even after controlling for common method bias (Malhotra et al., 2006).

Nevertheless, we focused on reducing the potential impact of common method bias by using different scale formats and anchors for the independent and dependent variables. Further, we simplified the formulation of items, using multi-item scales, and reducing social desirability by emphasizing the system design as the driver of disruptions compared to human errors. Further, to detect common method bias on the study, we used Harmon's one factor test to assesses common method bias through factor analysis. If the factor analysis using all relevant measurement items results in a single factor, Harmon's test assumes the existence of common method bias (Shah and Ward, 2007; Podaskoff and Organ, 1986; Miceli et al. 1991). A factor analysis without rotation with all 20 items yielded 5 factors with an eigenvalue in excess of one. This result suggests that common method bias does not seem to be problematic in this study, but it does not provide conclusive evidence.

1.2.2.7. Missing Values

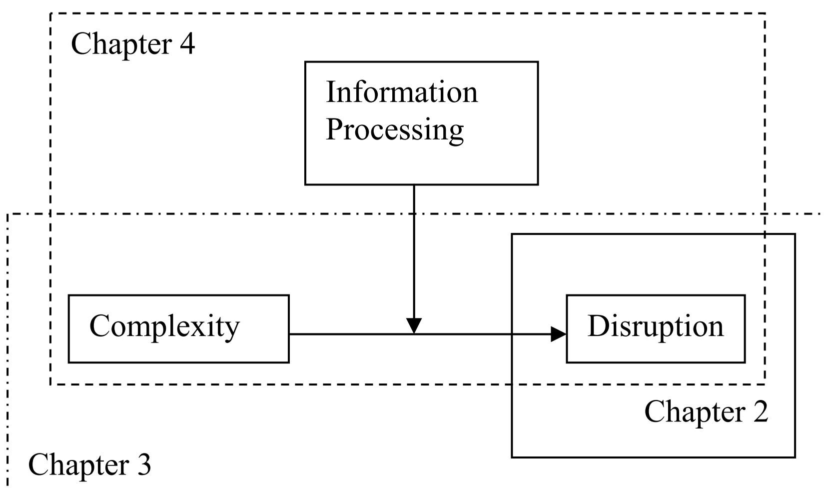
We conducted a missing value analysis, as approximately 5% of values were missing across variables. There are three different types of missing values: 1) Missing completely at random (MCAR), 2) Missing at random (MAR), and 3) Not missing at random (NMAR). MCAR refers to data where the pattern of missing values does not depend on any other variable in the data set. MCAR is a very stringent condition that is required for case deletion and occurs very rarely in data collection (Rubin, 1976). Little's MCAR chi-square test was performed using SPSS 17 on all variables of interest (dependent and independent) in this study. The significant chi-square test result suggests that the values are not missing completely at random.

MAR means that data are missing that are conditional on some other predictor or control variable observed in the data set, but not on the dependent variable (Schafer, 1997). The separate variance t-test was performed to investigate whether values are missing at random. The test selects variables with more than 5% of missing values. For each quantitative variable, pairs of groups are formed by indicator variable (missing vs. present values) and are tested for group-mean differences. Alternatively, a logistic regression for each variable grouped into missing and non-missing as the dependent variable with all other variables as predictors can be run. The tests suggest that values are missing at random. Based on the missing value analysis, we consider the values are missing at random. We used deletion, mean replacement, and EM imputation (which uses the Expectation-Maximisation algorithm to predict the missing values) to treat the missing values. We conducted the subsequent analysis with all three alternative methods for treating missing values, but didn't find any significant deviations in results.

1.3. Organization of the Dissertation

The dissertation consists of three main chapters. Each chapter builds on the previous chapter and adds another aspect of the overall framework, as illustrated in Figure 1-1. The content and goals for each chapter are discussed briefly below.

Figure 1- 1: Organization of Dissertation



Chapter 2 provides an overview of previous definitions of disruptions and develops a new and concise definition of supply chain disruptions. Based on the definition we develop measurement instruments for supply chain disruptions that are used in primary data collection efforts.

In Chapter 3 we examine the relationship between supply chain complexity and supply chain disruptions. We lay the foundation for the link between complexity and disruptions through the examination of organizational theories (specifically Normal Accident Theory and Complex Systems Theory). The discussion of the theoretical lenses results in the identification of four critical complexity dimensions for the supply chain setting: detail complexity, dynamic complexity, interdependence, and coupling. We discuss each of the dimensions and its relevance to the supply chain context in detail. Measures for the four complexity dimensions are developed and verified using reliability and validity assessments. A hierarchical regression approach is used to empirically examine the link between the complexity dimensions and disruptions.

Chapter 4 focuses on the empirical examination of information processing capabilities on the relationship between supply chain complexity and supply chain disruptions. We base the empirical investigation on prior conceptual work that provides a sound theoretical foundation for the link between complexity and disruptions. The use of Normal Accident Theory (Perrow, 1999), High Reliability Theory (Roberts, 1993) and Complex Systems Theory (Kauffman, 1993) provides the theoretical basis for the conceptual framework.

The dissertation concludes in Chapter 5 with a review of the insights that have been gained based on the empirical assessment of complexity as an antecedent for disruptions, and the evaluation of possible mitigation techniques. Implication for practice and theory are discussed.

Chapter 2
Supply Chain Disruptions – Definition and Measurement

In this chapter we review the literature on supply chain disruptions regarding previously used definitions and conceptualizations of the construct. We present a new, concise, and narrow definition of the disruption construct. Based on the definition we develop, and validate, empirical measures for supply chain disruptions that can be used in survey instruments.

2.0 Introduction

Globalization facilitated by information technology has changed the nature of work (Sinha and Van de Ven, 2005); work in today's economy is increasingly performed in geographically dispersed and loosely connected networks of firms shifting the attention of practitioners and academics to the supply chain phenomenon. Managing supply chains effectively and efficiently is frequently heralded as a critical source of advantage in an increasingly competitive business environment (Lee, 2002; Fisher, 1997). At the same time, breakdowns in supply chains are cited as one of the main threats to firm profitability both in terms of revenue loss and customer dissatisfaction, according to a recent report published in Economist (Anonymous, 2005). For instance, Ericsson attributed a loss of over $400 million to a disruption in its supply chain from a fire at Phillips' New Mexico chip-making plant (Latour, 2001). Similarly, the Aberdeen Group estimates that on an average, company recovery costs from supply chain disruptions range from six to seven figures (Enslow, 2004). A recent disruption study by Accenture (2006) revealed that, among 151 US-based companies, 73 % experienced severe supply chain disruptions in the past year, and 36 % of the firms experienced at least one disruption that took more than one month to resolve. The Aberdeen Group (Sadlovska, 2008) reports that an astounding 99 % of surveyed companies reported disruptions, with 58 % suffering financial losses. These numbers are compelling illustrations of the importance of disruptions to supply chain operations, but despite this immense interest among practicing managers, most of the evidence related to supply chain disruptions remains anecdotal or conceptual in nature (Sheffi, 2005; Chapman et al., 2002; Chopra and Sodhi, 2004). Few academic studies have empirically examined supply chain disruptions extensively; a notable exception includes Hendricks and Singhal (2005a, 2005b) who studied the impact of disruptions on operational and financial performance. Their study showed that companies suffering from disruptions experience significantly lower stock returns relative to industry benchmarks over a three year time period. In contrast, empirical studies on the antecedents of disruptions, or even possible mitigation techniques, are still lacking in the body of knowledge on supply chain disruptions.

A primary obstacle to further knowledge accumulation in research is the divergent usage of terms related to disruption (Achinstein, 1968; Schultz, 1971). Disruption related literature is replete with terms like “blips” (Anonymous, 2005), glitches (Hendricks and Singhal, 2005), accidents (Perrow, 1998), operational failures (Tucker, 2004), interfailure-time distributions (Tomlin, 2006), supply uncertainty (Fisher, 1997; Lee,

2002) and supply chain risk (Mason-Jones and Towill, 1998; Juettner, 2005; Zsidisin, Ellram, Carter, & Cavinato, 2004; Zsidisin and Elram 2003).

In addition to using a variety of terms, the existing literature includes a wide range of "types of disruptions," creating a further barrier to progress in disruption research. A significant portion of disruption research focuses on so called "Acts of God" and other low probability/low frequency events with high impact. Among the most well known examples in supply chain literature are: (1) the fire at a Phillips microchip plant in New Mexico and its impact on Nokia and Ericsson (Chopra and Sodhi, 2004; Zsidisin et al., 2005; Rice and Caniato, 2003), (2) the fire at a major supplier of brake-fluid valves for Toyota (Chapman et al., 2002, Chopra and Sodhi, 2004, Zsidisin et al, 2005), (3) the Kobe earthquake and its impact on the semi-conductor industry (Chopra and Sodhi, 2004; Chapman et al., 2002; Martha and Subbakrishna, 2002), (4) the California dockworker strike and subsequent port shutdowns (Chopra and Sodhi, 2004), (5) the consequences of Hurricane Mitch on Dole and Chiquita (Martha and Subbakrishna, 2002), and (6) the insolvency of Land Rover's critical supplier UPF Thompson (Chapman et al., 2002). Sheffi (2005) provides further anecdotal evidence of these and other major disruptions.

Researchers have also studied high probability/high frequency events such as part shortages, production problems, equipment breakdowns, and other operational constraints (Hendricks and Singhal, 2003; Groenevelt et al., 1992; Jonsson, 200; Moinzadeh and Aggarwal, 1997). It is apparent that these two "types" of disruptions, small operational disruptions and large scale disasters, are vastly different from each other, and require different research and management approaches.

The multiplicity of descriptions and terms used with respect to disruptions, confounded by ambiguous boundaries regarding the types of disruptions, contribute to the lack of empirical research in this area. Empirical research is especially susceptible to biases from inexact and imprecise concepts that lead to a collection of studies that examine different aspects of the same underlying construct (Meredith, 1993). To advance empirical research in this area, the differences in terminology and scope of the disruption construct need to be resolved and clarified. Hence, the objectives for this paper are threefold: 1) development of a conceptual definition of the disruption constructs, 2) identification of characteristic aspects of disruptions, and 3) development of a measurement instrument that can be used in future studies.

2.1. Past Research on Disruptions

The research on supply chain disruptions is a sub-category of supply chain risk research. In the supply chain context, risk has been previously defined as variations in outcomes or performance (Zsidisin et al., 2005; Zsidisin et al., 2003; Juettner et al., 2003). Zsidisin et al. (2005) state that *"Risk is the product of two separate elements: uncertainty and impact. In this context uncertainty refers to the unpredictability of environmental or organizational variables that affect corporate performance, or to the inadequacy of information about these variables."* The impact captures the negative outcome that is associated with risk in a managerial context (in contrast to financial or mathematical situations where up-side variations are also considered risk), and is reflected by a negative impact on any performance measure. Disruptions are one reason for a negative impact on performance (Zsidisin et al., 2005; Chopra and Sodhi, 2004), while others include price fluctuations, exchange rate fluctuations, and technical obsolescence, to mention a few. Hence, disruptions are a sub-group of the reasons for negative performance effects studied in risk research. The focus of this study is limited to actual disruptions and not the more general framework of supply chain risk.

In contrast to the large scale disruptions described in section 2.0, research in operations management has predominantly focused on disruptions from everyday business operations, like machine break downs and incoming quality problems leading to production system shutdown. These are high probability/high frequency events. While each event may have low impact on performance, the cumulative effect due to their recurring nature may be significant. Our literature review was focused more generally on the high probability/high frequency events, as they are more indicative of a system's susceptibility to disruptions compared to "acts of god." In conducting the review, we found that a large part of this literature is analytical in nature and focuses on the impact of disruptions on operational decision variables such as production lot sizing (Groenevelt et al., 1992), inventory (Moinzadeh and Aggarwal, 1997; Arreola-Risa and DeCroix, 1998), scheduling (Qi et al., 2006), production and inventory system (Abboud, 2001; Xia et al. 2004) and performance in queueing models (Neuts and Lucantoni, 1979; Chen and Yao, 1992).

More specifically, research in the early 1990's embedded supply disruptions in classical inventory models to capture the possibility that suppliers experience disruptions when firms want to place orders. Supply disruptions were included in models based on economic order quantity (Berk and Arreola-Risa 1994; Parlar and Berkin, 1991), the (R,Q) model (Gupta, 1996; Parlar, 1997), the (s,S) model (Arreola-Risa and DeCroix, 1998), and the newsvendor model (Dada et al., 2007). The models incorporate disruptions as the inability to fill orders, from a supply or demand perspective, and its impact on inventory, lead times, and facility locations. In such models, the supplier is either fully operational or completely inoperable, which results in the supplier delivering an order in full and on time when the supplier is operational, and delivering nothing at all when the supplier is inoperational. This supply process is characterized through the use of distributions, more specifically, an interfailure time distribution that captures the frequency of disruptions and a repair time distribution that captures the duration of the disruptions (time to make supplier fully operational after disruption). Similarly, the literature on queuing models incorporates disruptions as server failures to evaluate the performance of such systems. White and Christie (1958) were one of the first to find a steady state solution for a M/G/1 queue with server failures. Most research on queuing systems with unreliable servers is focused on one server systems. Multi-server studies have been limited to systems with Poisson arrival processes and exponential service times (Yang and Alfa, 2009). Generally speaking, the modeling literature uses probability distributions to capture disruptions within their models. (See Table 2-1a for the review of this literature.)

A literature review on disruptions in empirical and conceptual studies indicates apparent problems with transferring the concept from the modeling literature by exhibiting a lack of consistency in the usage of the term (see Table 2-1b). Many studies refrain from providing a specific definition of disruptions and conceptualize disruptions as manifestations of a variety of negative events, such as transportation delays, port stoppages, accidents, natural disasters, poor communication, etc. (Blackhurst et al., 2005; Wu et al., 2007; Chapman et al., 2002. Mitroff and Alpaslan, 2003; Tang, 2006). A handful of studies attempt to provide more specific definitions of disruptions in the context of conceptual and empirical studies. Svensson (2000) focuses on the deviations in the supply of components and materials from normal, expected or planned schedules and activities, all of which are associated with negative outcomes for the focal manufacturer. Correspondingly, Lewis' (2003) operational risk conceptualization revolves around operational events and their negative consequences as internal and external losses. Tucker (2004) defines disruptions as operational failures in the supply of necessary materials and information for work processes. In a similar vein, Jonsson (2000) looks at operational disruptions as errors in production that occur as stoppages, speed losses, or quality problems. These disruptions lead to production losses and other indirect costs that affect the performance of the organization, with regard to cost, throughput times, quality, and customer service. Craighead et al. (2008) describe disruptions as unplanned and unanticipated events that disrupt the normal flow of goods and materials within the supply chain and examine the spread of disruptions using a multi-method (case study, semi-structured interviews, and focus groups) empirical approach.

Hendricks and Singhal (2005) conceptualize disruptions as supply chain glitches and define the concept as "a firm's inability to match demand and supply." Their approach follows Fisher's (1997) and Lee's (2002) conceptualizations of supply and demand uncertainties that might lead to mismatches in the material flows in the supply chain. In contrast, Kleindorfer and Saad (2005) focus on disruptions that stem from supply shortages and include disruptions that arise from unforeseen discontinuities in supply, human centered issues from strikes or fraud, natural hazards, terrorism, and political instability. Kleindorfer and Saad's (2005) risk conceptualization of disruptions follows a more general approach from the supply chain risk literature (Mason-Jones and Towill, 1998; Juettner, 2005; Zsidisin et al., 2004; Zsidisin, and Elram, 2003) by focusing on the identification of general disruption risk sources.

The literature review highlights that there is a lack of clarity surrounding the use of "disruption" resulting in an absence of a universal definition in the operations and supply chain management literature. A prerequisite for progress in research are finely granularized and well-formed definitions (Osigweh, 1989). Concisely defined constructs are imperative for subsequent empirical research. Consequently, developing a concise definition is necessary before disruption research can progress further to identifying its antecedents and techniques to mitigate its negative effect on performance.

2.2. Reconceptualizing "Disruption"

The original connotation of the word disruption comes from the Latin word "disrumpere," which means "to break apart." The Webster dictionary describes disruption as an "interruption in the normal course of a flow." In the current study, we define disruptions as *"an unplanned stoppage of the material, information, or monetary flow*

Table 2- 1a: Selected literature review highlighting different conceptualizations of "disruption"

Author	Type of Study[a]	Data Source (Duration)[b]	Unit of analysis	Term	Definition	Operationalization of Disruption Construct	Dependent Variable	Findings
Hendricks & Singhal (2003)	E	S (1989-2000)	Dyad	Glitches	Mismatch between supply and demand	Newspaper articles announcing production or shipping delays;	Stock price	Glitches abnormally decrease shareholder wealth of 10.28%
Hendricks & Singhal (2005)	E	S (1989-2000)	Dyad	Glitches	Mismatch between supply and demand	Newspaper articles announcing production or shipping delays;	Operating income return on sales return on assets	On average, glitches reduce performance operating income: 107%, ROS: 114%, ROA: 93%
Kleindorfer & Saad (2005)	E	S (1995-2000)	Chemical plants	Risk	Risk arising from disruptions to normal activities	Facilities report accidental releases of covered chemicals or processes that resulted in deaths, injuries, significant property damage, evacuations, sheltering in place or environmental damages.	Frequency and severity of disruptions	Identifies facility characteristics, regulations, financial structure, and socio-demographic region are drivers of disruptions.
Jonsson (2000)	E	P	Plant	Disruption	Error-free production with minimum of stoppage, speed loss, and quality defects	Maintenance as prevention technique for disruptions.	Performance	Preventive and company-wide integrated maintenance are important for companies with high breakdowns and stoppage costs.

a: E – Empirical; M-Modeling; C-Case Study;   b: P-Primary Data, S-Secondary Data

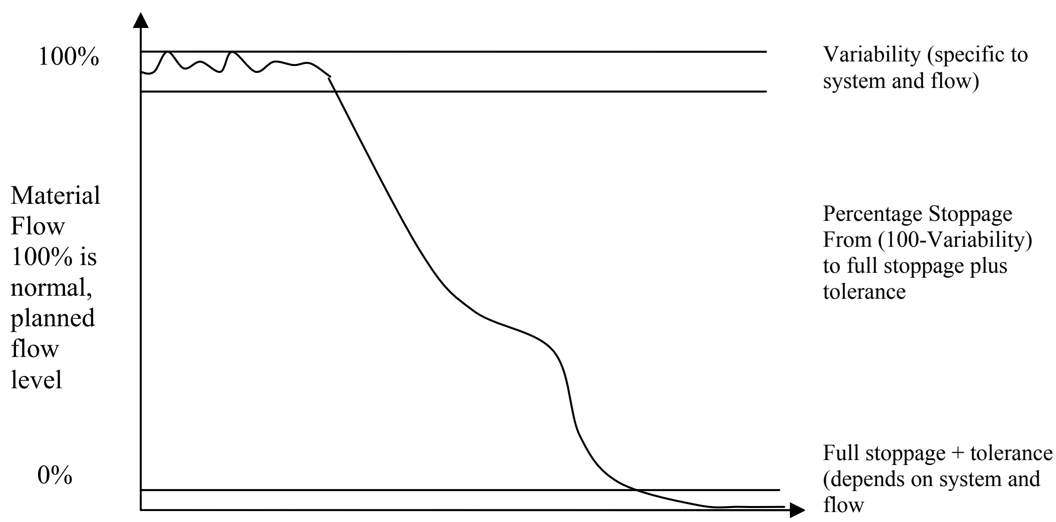
Table 2- 2b: Selected literature review highlighting different conceptualizations of "disruption"

Author	Type of Study	Data Source	Unit of Analysis	Term	Definition	Operationalization of Disruption Construct	Dependent Variable	Findings
Tucker (2004)	E	P	Individual failure (n=194)	Operational failure	Disruptions/errors/ absence of materials, information, equipment necessary for task completion	Problems: inability to execute a task due to something missing, or presence of a obstruction. System error: executing an unnecessary or incorrect task	Interruption; delay; loss; cost	Disruptions lead to higher delays, loss and cost.
Svensson (2000)	C	P	Dyadic	Vulnerability /Disturbance s	Deviations from normal, expected, or planned schedules or activities, all of which have negative effects or consequences.	Quantity and quality disturbances from logistic assurance document files at Volvo	None	Creates categorization scheme for disturbances based on sources and categories.
Tomlin, (2006)	M	N/A	Dyadic	Disruption Risk	Inability of supplier to deliver an order	Unreliable supplier's failure and repair transitions are modeled using a discrete time Morkov process.	Sourcing Strategy	Supplier's % uptime and nature of disruptions are key determinants of optimal sourcing strategy.
Arreola-Risa, A. and DeCroix, G.A.(1998)	M	N/A	Dyadic	Disruption	Unavailability of supply	Interarrival time of supply disruptions is exponentially distributed with the parameters $1/\lambda$ (average time between disruptions) and $1/\mu$ (average duration of disruptions)	Optimal inventory strategy regarding order-up-to level	Adjustment of order-up-to level dependent on severity of disruptions

within the supply chain." This definition captures the broad theme underlying the extant literature and points to three key aspects. Disruptions are *unplanned* as opposed to planned interruptions (during preventive maintenance, for example), actual (*stoppages*) as opposed to productivity losses, and occur in the *material, information, or monetary* flow. This definition is much narrower than the approach offered by Sheffi (2005) as it limits the disruption concept to stoppages in the flow as a consequence of adverse events, compared to dips in any performance metric. It incorporates the main themes of OM disruption research, and the usage of flows makes it ideally suitable for analysis within a supply chain. The usage of unplanned stoppages reflects insights from the uncertainty literature as it captures the mismatches of supply and demand. A stoppage in the material flow is an implicit mismatch of supply and demand within the material flow.

A full stoppage represents a 100% reduction in the material flow. However, partial stoppages of the material flow below 100% can cause significant performance impacts to the operation of the supply chain and need to be considered in the definition. We suggest that a differentiated sub-categorization of the supply chain disruption concept with regard to the extent of the stoppage is needed to fully capture the concept: (1) a full stoppage, 100% reduction, of the material flow is considered a disruption in its purest form (to reflect the Latin origin of the word "to break apart"), (2) a significant %age reduction in the material flow less than 100% constitutes the second category, and (3) normal fluctuations in the material flow are the third category and considered the natural variability of the flow. The three supply chain disruption categories are illustrated in Figure 2-2 and capture the different extent of the flow stoppages that constitute the overall supply chain disruption phenomenon. However, the distinction between the three categories presented in this section is highly context specific.

Figure 2 - 1: Extent of disruption



The definition of disruptions as flow stoppages presents a more specific conceptualization of supply chain disruptions when compared with the previous literature. Our approach does not focus on the types or causes of disruptions, but rather centers around the supply chain relevant aspect of flow stoppages. This conceptualization allows for a more differentiated perspective that separates the causing event (fire, earthquake, etc.) from the disruptions and is better suited for the later analysis of antecedents and mitigations techniques. The conceptual definition of disruptions can be further granularized by examining key characteristics that describe a disruption. These characteristics are based on insights from the literature we reviewed and allow for a comprehensive classification of supply chain disruptions. We discuss each of these briefly below.

2.3. Characteristics of Disruptions

2.3.1. Level of Analysis

The level of analysis determines the hierarchical level at which the disruption occurs. Disruptions can occur at different levels of analysis, i.e., machine, production system, or whole supply chain. Generally speaking, research has progressed from the study of disruptions at lower levels of analysis to more complex, aggregated and higher levels of analysis.

OM literature on disruptions focuses mainly on individual machines or system elements (see Table 2-2). This level of analysis is reflected in modeling work using queuing theory with single stations/nodes and other models focused on the impact of disruptions on individual production/inventory systems. At a higher level of analysis the literature focuses on chains of individual stations or systems. At the highest level of analysis of disruption analysis is the whole supply chain. Disruptions at lower levels of analysis can escalate and affect higher levels of analysis, i.e., machine breakdowns escalate to plant shutdowns, which have unexpected effects on the whole supply chain (the plant fire at Phillips and its impact on global supply chains of Nokia and Ericsson is a real life example of such an escalation from a low level of analysis to a higher level.)

2.3.2. Location relative to focal firm

The location of disruption identifies the supply chain link from the focal firm's perspective where the flow stoppage occurs. The supply chain from the focal firm's perspective consists of the supply base, production base (of the focal firm) and the customer base. Hence, many studies have focused on dyadic relationships from the focal firm's perspective, looking at either the supply side or customer side (see Table 2-2). The location of the flow stoppage provides critical information for the analysis and mitigation of disruptions. Organizational responsibilities in supply chains are frequently organized around the relative location in the supply chain. The procurement department handles the upstream supply base, the operations and production department is responsible for the internal production process, while the marketing and sales department works closely with the customer base. Hence, it is relevant to identify the ultimate location of a disruption in relation to the firm to effectively manage the disruption and avoid its occurrence in the future.

2.3.3. Frequency and Duration

Disruptions differ with regard to their specific characteristics such as frequency and duration. The majority of work in the area of disruptions utilized the frequency and duration of disruptions (see Table 2-3). The frequency of disruption is measured by the failure rate distribution, and the duration is assessed by the repair rate distribution in modeling work (i.e., Hopp and Spearman, 2001). The failure rate and repair rate

Table 2- 3: Level of analysis and location relative to focal firm

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Supply Chain		X	X	X											
Dyadic	Supply Side						X						X	X	X
	Customer Side											X	X		
Multiple Stations/Nodes/Machines, System Element					X			X		X					
Single-Station/Node/Machine/System Elements						X			X		X				

(1) Blackhurst et al. 2004, (2) Wu et al.2005, (3) Craighead et al.,2008, (4) Kleindorfer and Saad, 2005, (5) Hopp and Spearman, 1991, (6) Tomlin, 2006, (7) Moinzadeh and Aggarval, 1997, (8) Qi et al., 2006, (9) Neuts and Lucantoni, 1979, (10) Groenevelt et al., 1992, (11) Xi et al., 2004, (12) Hednricks and Singhal, 2005, (13) Arreola-Risa, A. and DeCroix, G.A.,1998, (14) Svensson (2000)

distributions are used to characterize disruptions and the systems overall disruption risk. Information about the type of distribution and its first two moments (mean and variance) capture the disruption's statistical properties. Exponential and Weibull distributions are frequently used to model failure rate distributions and empirical studies confirm this approach (Vineyard et al., 1999). A supply chain with frequent disruption exhibits a higher risk level compared to a supply chains with less frequent disruptions. Furthermore, long lasting disruptions are an indication of the magnitude of the disruptions and the problems with resolving the problem (Sheffi, 2005). Both aspects together provide a detailed disruption profile for any given supply chain.

2.3.4. Spread and impact of disruptions

The spread of the disruptions captures the number of nodes in a system affected by the disruptive event. The spread of the disruption through the supply chain captures the severity of the disruption (Craighead et al.,2008). A more severe disruption has more far reaching impact on the supply chain by spreading to several nodes resulting in more significant performance impacts.

The negative outcomes of disruptions are captured in the operational and financial performance (Hendricks and Singhal, 2005). The negative impact of the disruptions is a critical aspect, as described in the supply chain risk literature (supply chain risk = uncertainty + negative impact). It is necessary to capture the negative impact of disruptions to establish their relevance for the supply chain. Research shows that disruptions significantly affect performance measures. Hendricks and Singhal (2005) observed that firms suffered average abnormal stock returns of -40% in a span of three

Table 2- 4: Characteristics of disruptions

Term	Definition	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Frequency	Time between disruptions/ Disruptions per time unit				X	X	X	X	X	X	X	X	X	X	X
Duration	Time to resolve disruption					X	X	X	X	X	X	X	X	X	
Spread	Spread to other firms/elements in supply chain	X	X	X											
Impact	Impact on performance of firm					X	X	X	X	X	X	X	X	X	

(1) Blackhurst et al. 2004, (2) Wu et al.2005, (3) Craighead et al.,2008, (4) Kleindorfer and Saad, 2005, (5) Hopp and Spearman, 1991, (6) Tomlin, 2006, (7) Moinzadeh and Aggarval, 1997, (8) Qi et al., 2006, (9) Neuts and Lucantoni, 1979, (10) Groenevelt et al., 1992, (11) Xi et al., 2004, (12) Hednricks and Singhal, 2005, (13) Arreola-Risa, A. and DeCroix, G.A.,1998, (14) Svensson (2000)

years after the announcement of a disruption. Similarly, disruptions negatively affect the operating income, return on sales, and return on assets at the focal firm (Hendricks and Singhal, 2005). The same firms reported lower sales growth, higher growth in cost, and higher growth in inventory. Similarly, the modeling literature has evaluated the negative performance impact of disruptions on queueing models (Hopp and Spearman, 1991; Neuts and Lucantoni, 1979) and inventory models (Moinzadeh and Aggarwal, 1997; Arreola-Risa and DeCroix, 1998).

2.3.5. Summarizing "disruption"

The disruption definition derived in this section is specific enough to differentiate disruptions from other related concepts, but general enough for later extensions to other contexts or flows. After the literature review we define disruptions as *"an unplanned stoppage of the material flow within the supply chain."* This definition captures the broad theme underlying the extant literature and can be extended to other flows (information, monetary) in the supply chain at a later stage. Disruptions are *unplanned* as opposed to planned interruptions (during preventive maintenance, for example), and actual *stoppages* as opposed to productivity losses. This definition incorporates the main themes of OM disruption research, and its use of flows makes it ideally suitable for the analysis within a supply chain.

The contextual characteristics are critical for framing any research efforts on disruptions. The level of analysis, extent of disruptions, and its location are characteristics that are useful to specify the context of future studies on disruptions. The context of studies influences subsequent research design and analysis, and plays a critical role in differentiating and integrating insights from previous studies on the topic that were conducted in different contexts, e.g., disruptions at the machine level. The frequency, duration, spread and impact of disruption are the necessary characteristics to describe a disruption. The frequency and duration are classic characteristics used for decades to capture disruptions in the modeling literature. The spread of disruptions is relevant for multi-stage models like supply chains to capture the severity of the disruptions. The impact of the disruption captures the relevance of the disruptions for the supply chain. A material flow stoppage that does not exhibit a negative impact (or only a very small impact) on performance cannot be considered a disruption.

2.4. Measurement Design

2.4.1. Relevant Characteristics for Measurement

The development of reliable and valid measures for the construct is the aim of this study and lays the foundation for future research. We limit the study of disruptions to the supply chain level of analysis and limit this study to disruptions in the supply base. The supply base was identified by practitioners as the location with the highest risk for disruptions. However, the developed measures can later be extended to measure disruptions in the production and customer base. We define disruptions as unplanned stoppages in the material flow that are significant within the context of the respondents. Based on the literature review conducted for the definition of disruptions we consider four characteristics as critical dimensions for the accurate measurement of disruptions. Frequency and duration were identified as the key descriptive characteristics of disruptions. Furthermore, we include measures for the spread of disruptions from the supply base. Disruptions originating in the supply base may stay limited to the supply base, spread to the production base or spread to the customer base. We also assess the overall relevance of the disruptions for the supply chains with an impact measure. This is done to ensure that the disruptions measured are actually relevant to the competitiveness of the company, and not smaller events that are of no impact to the firm. Overall, these four dimensions are being tested to measure disruptions in the supply base (see Appendix 2-1). The frequency of the disruption is capture through the question “How frequently have disruptions (for any reason) originated in your supply base during the last three months?” The duration of tan average disruption is assessed through the time it takes to resolve the disruption, or more specifically “How quickly were the supply base disruptions usually resolved during the last three months?” The competitive impact of disruptions is assessed by asking “How much did these disruptions affect your competitiveness during the last three months?”The spread of disruptions is assessed by asking two separate questions, i.e., “How often did disruptions originating in the supply base spread to your production base during the last three months?” and “How often did disruptions originating in the supply base spread to your customer base during the last three months?”

2.4.3. Data Collection

The data for this study were collected through a web based survey. To avoid an overly homogenous sample the population of interest was defined as all manufacturing firms in North America (SIC Codes 21-39). The general sample approach ensures the inclusion of a large enough variety of different disruption levels for the analysis, as previous research showed that supply chain risk management techniques are very similar within industries (Zsidisin et al., 2005). The study was limited to manufacturing firms as the focus is on disruptions to the material flow.

An initial online based draft of the survey instrument was pre-tested with the help of four academic researchers and seven practitioners. Furthermore, we deployed an online adaptation of the think-aloud procedure (Duncker, 1945) for the refinement of measurement items. The use of verbalizations as indicators of cognition is a decades-old data collection technique. All participants were considered experts in the area and had the relevant knowledge pertaining this study to assess the content validity and clarity of the questions. The survey instrument was revised based on the provided comments, and special care given to practitioner relevant wording of the questions.

Following the revision to the initial draft, another round of pre-testing was carried out by sending the web-based instrument to members of "SCP-Supply Chain Practitioners," a Yahoo! user group of supply chain professionals. Approximately 250 members were contacted by email, resulting in the response of 57 individuals, or a response rate of 23%. During this round of pre-testing specific aspects of the survey taking process were examined, i.e., non-response to certain questions, survey drop outs, time taken to answer survey instrument. Following the pre-tests, a large scale pilot study was conducted using members of the Council of Supply Chain Professionals (CSCMP), that were selected based on their job title and expertise regarding supply chain management. Only managers in supply chain relevant areas were selected to participate in the survey. The administration of the data collection followed the general outline for survey design advocated by Dillman (2000) and used in Operations Management research (Koufteros et al., 1998; Nahm, 2003). One hundred eleven responses, corresponding to a response rate of 11% were used to assess initial reliability and to conduct exploratory data analysis. The pilot sample in this study is larger than in comparative studies that conducted a pilot study for their research studies (Shah and Ward, 2007; Koufteros et al., 1998; Nahm et al., 2003). As a result of the pre-tests and pilot study, the finalized survey was approximately 50% shorter than the previous versions used. Specifically, questions were limited to the supply and production base of the focal firm, resulting in a significant reduction of questions.

The data from the pilot study were not used in the large scale study, as the idea for the pilot study was only the identification of dimensional structure, improvement of readability and establishment of content validity.

2.4.4. Main Data Collection

The main data analysis was conducted over 6 weeks in the summer of 2008. The respondents belong to two organizations of operations management practitioners. APICS (Advancing Productivity, Innovation, and Competitive Success) is a network of accomplished industry professionals that has been active since 1957 with regard to training, certifications and conferences in the area of Operations Management. SCL (Supply Chain and Logistics Association) was formed in 1967 by practitioners interested in supply chain related topics. The contact lists for the survey were composed of individuals who matched three criteria: 1) respondent worked for manufacturing firm, 2) respondent had high- or mid-level position within organizations, 3) respondent was exposed to supply chain related activities in the organizations.

A total of 151 responses were gathered from APICS, resulting in a response rate of 7.6%. Eleven responses were missing a substantial amount of data on the items used in this study, therefore only 140 responses were used for the analysis. The SCL data collection resulted in a total of 62 responses of around 1.5-2%. An exact response rate could not be estimated as the organization only provided a “guesstimate” of the current status of their email list. Thirteen responses were missing substantial amounts of data, therefore only 49 responses were used in the analysis.

In contrast to the pre-test and pilot study, the surveys were administered through the professional organizations. In the case of APICS the contact to the members was limited to an initial contact and one reminder email, while SCL limited the contacts to only the initial contact. This is a deviation from the Dillman (2000) approach which recommends an announcement, initial contact, and two to three reminders, which contributes to the lower response rates for the study. However, the response rates match recent results of large scale studies, i.e., Shah and Ward (2007) reported a response rate of 13.5%, Nahm et al. (2003) of 7.47%, Li et al. (2005) of 6.3%, Simons et al. (1999) of 6%, and Poppo and Zenger (1998) of around 5%.

2.4.5. Disruptions as Events

We consider disruptions as events that occur in a supply chain. An event is a change in the state of a system manifested by the change in its variables within some observation period in a relevant state space (Blossfeld et al., 1989). In the case of the disruption, the change of variables reflects the stoppage of the material flow and transforms the system from a functioning state to a disrupted state. The data collection using a survey instrument in a cross-sectional study allows for the assessment of the mean and variance of disruptions in a supply chain, rather than detailed profiles of individual disruptive events.

We argue that a disruption, the stoppage of the material flow, is a severe and memorable event in the professional life of a supply chain professional. Such disruptions are usually associated with increased stress and work levels that remain vivid in the individual's memory. The analysis of such events requires a time period sufficiently long to observe representative samples of the events. However, descriptions of historical events become increasingly unreliable over time due to loss of memory (Gregson, 1975), and the tendency to rationalize and distort accounts of past events in light of more recent experiences (Van de Ven and Ferry, 1980). The usage of a time span of around three to six months has previously been identified as appropriate to recognize normal patterns of events, and short enough to avoid the time related distortions (Van de Ven and Ferry, 1980).

We selected three months as the appropriate time anchor for respondents to remember the facts about disruptions (i.e., frequency, duration, spread, impact of disruption over past three months) and to capture a representative sample of the disruption activities in the supply chain. Similar approaches have been used in the measurement of life events in the area of psychological research. Most of these studies are based on the insights that these life events require adaptation on the part of the individual and are stressful. The measures in these studies range from major life events, such as divorce, relocation, etc. (see Thoits, 1983, for a review) to smaller events of the daily life such as social interactions, vacations etc. (Lazarus, 1984; Pearlin, 1983; Lewinsohn and Talkington, 1979; Monroe, 1983; Stone and Neale, 1982, 1984; McLean, 1976).

2.5. Measure Assessment

The developed measures for supply chain disruptions were further examined and validated using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Therefore, the data set was split randomly in half to create calibration and validation sets. This approach was used to further increase the reliability and validity of the measurement instruments.

2.5.1. Exploratory Factor Analysis

An exploratory factor analysis using principle components extraction and various rotations was used to discover any underlying structure in the complexity and disruption item set. The rotations are performed to increase the interpretability of the underlying factor structure. The exploratory factor analysis reveals the underlying factor structure of the constructs, and aids in the development of scales to reduce the number of variables for any subsequent analysis (Hair et al., 1998).

The exploratory factor analysis is evaluated regarding significant cross-loadings of items, low extracted communalities, number of extracted factors, and variance explained. We only extracted factors with eigenvalues exceeding a value of one, as they are generally considered significant factors (Hair et al. 1998). The analysis resulted in the creation of two underlying factors for disruptions. Items were inspected regarding significant loadings, with loadings greater than .60 representing practical significance considering the sample size of the split data set (Hair et al. 1998 – page 112). Items with insignificant loadings, or significant loadings on several factors, are usually eliminated in the process.

The EFA of the disruption construct shows that the measure for disruption duration does not load with the other disruption measures. The CITC is below the recommended level of 0.40, indicating that the measure does not correlate well with the other measures. The EFA shows that the measure loads as the only variable on a second

Table 2- 5: EFA for disruption

	CITC	Factor 1	Factor 2
Disruption Frequency	0.612	**0.841**	-0.045
Disruption Duration	0.191	0.074	**0.978**
Disruption Impact	0.750	**0.832**	0.275
Disruption Spread 1	0.637	**0.872**	-0.054
Disruption Spread 2	0.696	**0.804**	0.250

factor. We decided to keep the duration measure separate based on the EFA results. The EFA provides a first insight in the concept of disruptions, as it appears that duration is different from the other disruption dimensions. For the rest of the study we are using a four items scale for disruptions consisting of frequency, impact, spread 1 and spread 2. Multi-item scales have been the norm, but recent work in Marketing argues that single item scales are acceptable for analysis as well (Bergkvist and Rossiter, 2007).

2.5.2. Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was used to assess the overall model fit and validity of each multi-item scale. CFA evaluates an a priori developed model in which the observed variables are linked to their constructs according to the insights gained in the EFA. The CFA was conducted using the validation sample of the study using AMOS 16 utilizing the maximum likelihood method.

It has been recommended to report a variety of fit indices for the assessment of the overall fit of the measurement model from different perspectives (Shah and Goldstein, 2005). We assess the overall model fit using absolute, incremental, and parsimonious measures. These fit indices provide different insights into how well the model matches the observed data (Hu and Bentler, 1995). The absolute fit measures (RMSEA, RMR) assess how well an a priori model matches the sample data. Incremental fit measures (CFI, GFI, IFI) assess the incremental fit of the model compared to a null or worst case model. Parsimonious fit measures (Normed χ^2) assess the parsimony by evaluating the fit against the number of estimated coefficients needed for the fit. All of the fit measures need to be evaluated to assess the overall fit of the model.

The fit measures for the disruption scale (Table 2-5) all match the respective cut-off points indicating acceptable fit. In addition to examining the fit statistics, we also examined the standardized residuals, as small residuals are indicative of good fit. It is recommended that no more than 10% of the absolute values of the standardized residuals are greater than 2.5 (Hu and Bentler, 1995). None of the residuals for disruptions exceeded the threshold. Furthermore, all the factor loadings are greater than 0.50 ($p<0.01$) and all modification indices are below 10 (Shah and Ward, 2007).

Table 2- 6: CFA for disruption

Statistic	Disruption	Cut off values
χ^2	4.274	NA
Df	2	NA
P-value	0.118	NA
χ^2 /DF	2.137	$\leq$3.0
GFI	.979	$\geq$.90
CFI	.984	$\geq$.90
IFI	.985	$\geq$.90
RMR	.025	$\leq$.10
RMSEA	.092	$\leq$.10

Content validity is the adequacy with which a specific construct (or content domain) has been sampled during the data collection (Nunnally, 1978; Flynn et al., 1990). To ensure content validity the instrument needs to contain a representative collection of items and the instrument construction used sensible methods. We achieved content validity through the grounding of the constructs in the literature and the review by experts (practitioners and academics). Furthermore, we used several pre-tests rounds to evaluate the new measurement items and their psychometric properties.

Construct validity is the assessment of the degree to which a scale measures the intended construct. The convergence and divergence of the scale items is a way to assess and establish construct validity and is addressed in section 2.5.3.

2.5.3. Convergent Validity

Anderson and Gerbing (1988) propose that significant item loadings on the respective constructs are evidence for convergent validity. A within factor analysis is used to show that all measurement items load on one common factor to establish convergent validity.

Eigenvalues in excess of 1.00 and factor loadings above .40 are considered acceptable evidence of convergent validity through factor analysis (Hair et al. 1995). For the disruption scale the loadings range from 0.745 to 0.826 and the variance explained (R-squared) from 0.555 to 0.682. The loadings can be seen in Table 2-7.

Table 2- 7: Factor loadings and R-Square for disruption

	Loadings	R-Square
Frequency	0.745	0.555
Impact	0.798	0.636
Spread 1	0.772	0.595
Spread 2	0.826	0.682

2.5.4. Discriminant Validity

Discriminant validity assesses the degree to which measurement items from different constructs are unique and distinct from each other. Measurement items that exhibit satisfactory discriminant validity should only measure the construct they are intended to measure, and show no (or little) loadings on other constructs.

Discriminant validity can be assessed with a three-step procedures: 1) a model with two constructs and their respective measurement items is run in CFA where the covariance between the constructs is fixed to one; 2) a second model is run with the same two constructs and measurement items, but this time the covariance between the constructs is free to vary; 3) χ^2 differences between the two models is tested for significance. Constraining the covariance between the two constructs is equivalent to assuming they are the same construct, and not unique. If both constructs are unique the difference between the fixed and the free model needs to be significant.

The χ^2 difference is being tested with one degree of freedom because the free model is nested in the fixed model. A significant difference between the models indicates that the constructs and their measures are unique and necessary to explain the data structure (Bagozzi and Phillips, 1982; Bagozzi et al., 1991). We test the disruption scale with the individual duration measure and the free model fit the data structure better than the fixed model at the .01 level – indicating strong evidence for discriminant validity of the construct.

2.5.5. Unidimensionality

Unidimensionality is a necessary condition to establish reliability and validity. Unidimensional items only capture one construct, and do not exhibit significant cross-loadings onto other constructs. Unidimensionality can be concluded if the overall fit of the measurement model during the CFA is appropriate. Another approach for unidimensionality checking has been proposed by Joreskog and Sorbom (1997), which requires the construction of a measurement model for each individual construct. A goodness of fit index (GFI) of 0.90 or higher for such a single constructs model indicates appropriate confidence in the unidimensionality of the constructs. The GFI index for the construct is above 0.90, indicating evidence of unidimensionality.

2.5.6. Reliability

Reliability can be broadly defined as the degree to which the scales are free from error and, therefore, yield consistent measurements (Flynn et al., 1990). Cronbach's alpha is a measure of the internal consistency of the measurement construct and often used to assess reliability. Cronbach's alpha is calculated for the disruption construct. Scales are considered internally consistent with a Cronbach's value exceeding 0.60, which is the cut-off point for newly developed scales (Nunnally, 1978), while 0.70 is a more conservative value for established scales (Hair et al., 1998). The disruption scale exhibits values for Cronbach's alpha exceeding the conservative value, loads on a single factor, and explain above 50% of the variance. An alternative way to measure the reliability for measures of one construct is the composite reliability (Escrig-Tena and Bou-Llusar, 2005), calculated as follows:

$$Composite\ Reliability = \frac{(\sum Standardized\ Loadings)^2}{(\sum Standardized\ Loadings)^2 + (\sum measurement\ error)}$$

The value for the composite reliability is 0.866, exceeding the 0.70 threshold. Furthermore, we calculated the average variance extracted (AVE) (Fornell and Larcker, 1981) to assess reliability as follows:

$$AVE = \frac{(\sum Standardized\ Loadings^2)}{(\sum Standardized\ Loadings^2) + (\sum measurement\ error)}$$

The AVE is 0.618, exceeding the threshold value of 0.50 (Shah and Ward, 2007). All measures indicate good construct reliability. The reliability evaluation is conducted at this point, because the validity and unidimensionality of the constructs is a necessary condition for the establishment of construct reliability (Koufteros, 1999).

2.6. Discussion and Limitations

In this paper we set out to develop a conceptually concise definition of disruptions, provide an overview of relevant characteristics to describe disruptions, and develop measurement instruments for disruptions that can be used in future studies. We review the literature on supply chain disruptions and develop a fine-grained definition of disruptions. The precise classification of disruptions is a prerequisite for disruption analysis and the identification of countermeasures. Our approach combines insights from previous studies in a variety of literature streams and provides the groundwork for future research. The development of precise constructs in research is the prerequisite for cumulative knowledge generation (Achinstein, 1968; Schultz, 1971).

We select the frequency, duration, spread and impact as key dimensions for the disruption scale. The measurement scale was developed and tested using EFA and CFA procedures. We show that the disruption scale is a two-dimensional construct. The duration of disruptions is different from the other tested disruption dimensions. Our operationalized measure is, to our knowledge, the first attempt at measuring supply chain disruptions using scales developed for a survey instrument. It is a comprehensive measure that reflects the disruption construct broadly by including several of the relevant characteristics.

The empirical development of our operational measures suggests that they are reliable and meet established criteria for assessing validity. The developed and validated measurement instrument is useful for researchers who are interested in conducting survey research related to supply chain disruptions. The measures allow researchers to assess the level of disruptions in supply chains and to test relationships between disruptions and possible antecedents, or performance outcomes. The framework for disruptions builds a foundation for research and should help facilitate researchers to agree on a definition. It is necessary to come to an agreement on both a conceptual definition and an operational measure to advance the research on supply chain disruptions. Additionally, the measurement instrument provides a tool for managers to assess the level of disruptions in their specific supply chains. For instance, the scales developed here may be used by managers to evaluate different parts of their supply chain regarding its levels of disruptions. The business community requires guidance and advice regarding the management, or avoidance of disruptions, which the academic community can only provide if it agrees on the terminology and measurement of the disruption construct.

Any empirical study has inherent limitation based on its research design. This study is no exception. The use of a single informant for collecting information about a focal firm limits this study. Multiple informants provide the possibility for increased reliability to the study's findings, through inter-rater reliability assessments. However, multiple respondents are often only a possibility when data are collected within a single firm or a limited set of firms. In this study, the conceptual framework necessitates data collection that allows for collection of a large number of firms to provide a heterogeneous sample for the assessments of different disruption levels. Therefore, we approached professional management associations for data collection, and accepted the limitation of a single respondent design in favor of greater heterogeneity in the sample.

A second limitation of the study is the use of focal firm's perspective. Supply chain research favors the use of supplier-buyer dyads for research designs. The focal firm perspective omits any analysis from the supplier's perspective of the reported disruption levels from 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 heterogeneity and sample size priority over a dyadic approach. Another limitation of our study concerns the generalizability of our results. The statistical results obtained from CFA provide compelling evidence to the factor structure within the tested data set. However, the factor structure needs to be reexamined in future research to check for its general validity across data sets. We used a split sample approach with a calibration and validation set for increases rigor, but only a newly collected data set can truly validate the discovered factor structure. Despite these limitations, the development of the disruption scale contributes to the supply chain disruption research. In particular, we hope that the measurement scales developed here will provide a foundation for furthering the research and understanding on supply chain disruptions in a more consistent manner.

Appendix 2 - 1: Measurement Items in Survey

Disruption
Origin of disruption

Refers to the initial location of the disruption in the supply chain. Disruptions in the supply base negatively affect your firm's ability to procure the required quantity of inputs.
This section contains questions related to **disruptions originating in the supply base.**

Frequency

How frequently have **disruptions (for any reason) originated** in your **supply base** during the last three months? (7-Continously; 1=Never)

How quickly were the **supply base disruptions usually resolved** during the last three months? (7=Very Slow; 1=Very fast)

How much did these disruptions **affect your competitiveness** during the last three months? (5=Very significantly; 1=Not at all)

Spread of disruption

Refers to the extent to which disruptions affect other parts of the supply chain. For example, an input material shortage from the supply base may reduce your production output.

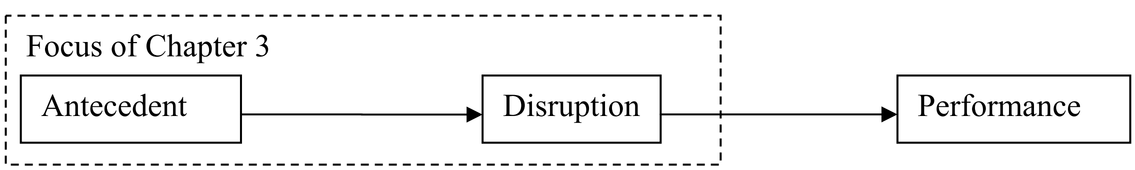
How often did disruptions originating in the supply base **spread** to your **production base** during the last three months? (7=Always; 1=Not Once)

How often did disruptions originating in the supply base **spread** to your **customer base** during the last three months? (7=Always; 1=Not Once)

Chapter 3
Supply Chain Complexity as an Antecedent of Supply Chain Disruptions

This chapter focuses on the identification of possible antecedents of supply chain disruptions (see Figure 3-1). Disruptions are defined in the previous chapter as unplanned stoppages to the material flow from the supply base of the focal firm. We identified frequency, duration, impact, and spread as critical dimensions of disruptions. Frequency captures how often disruptions occur during a specified time period, duration relates to the time it takes to resolve the disruption, impact captures the severity of the negative consequences, and spread captures the possible escalation of the disruption from the supply base to downstream parts of the supply chain. In this chapter, we suggest and examine supply chain complexity as a driver of supply chain disruptions. For this purpose, we examine the literature to provide a sound theoretical foundation for the link between complexity and disruption, identify the relevant complexity dimensions in the supply chain context, develop four hypotheses based on a conceptual model, and empirically examine the relationship between complexity and disruptions based on data collected with a survey instrument.

Figure 3- 1: Focus of Chapter 3



Research Questions Chapter 3: "What are the antecedents of supply chain disruptions, more specifically does supply chain complexity lead to supply chain disruptions? If so, what aspects of complexity are relevant drivers of disruptions?"

3.0 Introduction

Disruptions to supply chains have become a critical issue for many firms and the costs associated with disruptions frequently make headlines in the supply chain related press (e.g., Latour, 2001; Enslow, 2004). A survey of more than six hundred financial executives found that twenty-five % of the executives considered supply chain disruptions as the greatest threat to their firm's profitability and revenue growth (Smyrlis, 2006). Despite the growing awareness about the negative consequences of disruptions, theory-driven, empirical research highlighting the causes for the increased threat of disruptions remains scarce (Hendricks and Singhal, 2009).

The search for the antecedents of disruptions begins by identifying relevant supply chain risks and classifying potential disruption sources on the basis of their location in relation to the focal firm (see Table 3-1). Shrivastava et al. (1988) simply distinguish between internal and external sources for disruptions[3] from the perspective of a firm. Miller's (1992) classification differentiates sources of disruptions into the general environment, the industry environment, or the firm specific internal environment. Juettner et al. (2003) adapt Miller's categorization to better fit the supply chain setting and transformed the three levels into environmental risk sources, network-related risk sources and organizational risk sources. Environmental risk sources arise from

[3] The various literature streams discussed in this section use inconsistent terminology for the disruption construct. However, all are referring to unplanned events that have a negative impact, whether these events are called disruptions, accidents, failures or anything else. In this section we do not distinguish between these terms, as the focus is on the review of classifications for the categorizations of sources that lead to the unplanned events. We refer to these events as disruptions in this study to avoid confusion, although the original might have used a different term (the original terminology is used in the tables).

interactions of the supply chain with the general environment at the macroeconomic level (i.e., socio-political risk, natural disasters etc.). Network-related risks arise from the interaction between organizations within the supply chain, while organizational risks lie within the boundaries of the individual organizations.

Table 3- 1: Classifications of sources of disruption risk

Author	Type of Study	Dependent Variable	Sources/Categories
Tucker, 2004	E	Operational failures	Failures can arise from nurse's own work activity, the nursing unit's activities, or groups outside the nursing unit.
Shrivastava et al., 1988	C	Accidents	Accidents can be caused by internal or external sources from the organization. The internal cause are a complex set of human, organizational, and technological factors. The external causes are regulatory, infrastructural, and preparedness factors.
Miller, 1992	C	Risk	The risk facing an organization can be classified into three levels of analysis as the general environment, industry, and firm specific.
Juettner et al., 2003	C	Risk	Supply chain risk sources can be divided into general environment, network-related, and organization specific.
Brown, 2000	E	Accidents	Accidents are caused by interactive effects by social systems, technical systems, and operator cognitions.
Deming, 1986	C	Accidents	Accidents attributed to operator error frequently have their true roots in the system design.
Perrow, 1984	C	Accidents	Accidents inevitable occur in complex interactive systems.
Reason, 1990	C	Accidents	Human factor is most critical contributing variable in accidents.

E=Empirical Paper; C=Conceptual Paper

Another way to describe disruption risk focuses on the causal event that leads to the disruption instead of the source location in relation to the firm. Such classifications look at human error, system error, or human-system interactions as causes for disruptions.

Human error as a cause of disruptions is a widely used perspective, and presumes that failure in human cognition and behavior are critical factors that lead to disruptions (Reason, 1990). This perspective has been previously used in the literature on work safety (Bigos et al., 1992), but also as an explanation for catastrophic accidents like the Challenger Space Shuttle accident (Vaughan, 1996).

However, the quality movement in operations management made the case that disruptions attributed to "operator error" frequently occur due to poor system design (Deming, 1986; Norman, 1988). Deming (Latzko and Saunders, 1995) noted that poor system design and process management are the root causes of simple quality errors as well as majors disasters. Deming's red-bead experiment is frequently used to illustrate the varying impact of human and system factors on quality performance.

A third perspective combines the social and technical system to derive the central premise that the system influences the occurrence of disruptions via people that operate the system. The proponents of this view emphasize the role of organizational climate as a social system variable, as well as technical attributes of the system and their influence on human behavior as a critical cause of disruptions (DeJoy, 1986; 1994; 1996). Brown et al. (2000) used human-system interactions to frame a socio-technical model of safe employee behavior in the steel industry.

The classification approaches highlight changes in the environment, human behavior, and system design as potential factors that contribute to a systems susceptibility to disruptions. We examined the literature on supply chain risk and disruptions for

Table 3- 2a: Drivers of disruptions in supply chain related literature

Author	Type of Study	Dependent Variable	Drivers of Disruptions/Risk
Wu et al., 2007	M	Supply chain disruptions	The size, complexity, and dynamic nature of supply chains contributed to increases in disruptions.
Kleindorfer and Saad,. (2005)	E	Disruption Risk	Extreme leanness and efficiency increase vulnerability due their tradeoff with robustness and reliability.
Craighead et al., 2008	E	Disruption severity	Supply chain design as driver of disruption severity in form of supply chain density and complexity.
Hendricks and Singhal, 2009	E	Glitches	Organizational slack reduces the impact of glitches on performance, geographical diversification increases the impact, and vertical relatedness reduces the impact.
Jonsson, 2000	E	Disruption	Lack of maintenance is reason for disruptions.
Lewis, 2003	E	Operational risk	Categorizes risk by sources based on Hayes and Wheelwright decision areas: Capacity and facilities, process technology, supply chain management, new product development, workforce and organization, control systems.
Choi and Krause, 2006)	C	Disruption risk	Supply base complexity drives disruption risk.
Chopra and Sodhi, 2004	C	Supply chain breakdown	Provide examples of drivers for different risk categories in supply chain, i.e., natural disasters, labor disputes, supplier bankruptcy, war and terrorism, and dependency on single source of supply as drivers of disruption risk.
Hoole, 2006	C	Failures and profitability	Cites PRTM study which states that supply chain complexity threatens to undermine operations and eats away profits. “Complexity makes supply chains inflexible and inefficient, hampers on-time delivery and creates problems for product quality. The more complex the supply chain, the greater the possibility it will fail in one or more of its functions.”
Christopher et al., 2002	C	Supply chain vulnerability	“The greater the uncertainties in supply and demand, globalization of the market, shorter and shorter product and technology life cycles, and the increased use of manufacturing, distribution and logistics partners resulting in complex international supply network relationships, have led to higher exposure to risks in the supply chain.”
Christopher and Lee, 2004	C	Supply chain risk	Complexity and uncertainty within a supply chain result in over-reactions, unnecessary interventions, second guessing, mistrust, and distorted information throughout the supply chain.
Kilgore, 2004	C	Supply chain risk	Increased exposure of supply chains to risk because of pursuit of cost minimization strategies.

M=Modeling Paper; E=Empirical Paper; C=Conceptual Paper

Table 3- 3b: Drivers of disruptions in supply chain related literature

Author	Type of Study	Dependent Variable	Drivers of Disruptions/Risk
Smyrlis, 2006	C	Supply chain risk	Extended supply chain is more complex from outsourcing and more susceptible to disruptions.
Stauffer, 2003	C	Supply chain risk	Focus on cost efficiency and lean operations lead to higher supply chain risk.
Tang, 2006	C	Supply chain disruptions	In an attempt to improve the financial performance in supply chains, executives implemented initiatives to increase revenue, reduce cost, and reduce assets. "However, these initiatives have created longer and more complex global supply chains, which are more vulnerable to business disruptions in a turbulent world."
Bartholomew, 2006	C	Supply chain risk	Leaner supply chains, with less buffer and more inventories being held in other countries create systems that are less able to absorb any possible shocks that might occur. This new design creates a greater potential for the effect of disruptions in the supply chain to be amplified.
Hillman, 2006	C	Supply chain risk	Increasing globalization with lean operations and increasing uncertainty in commodity markets lead to higher supply chain risk levels.
Juettner, 2003	C	Supply chain risk	Supply chains that include hundreds of firms over several tiers increase supply chain complexity and supply chain risk. Authors identify several factors that changed over past decade which have increased risk levels: 1) focus on efficiency rather than effectiveness, 2) globalization, 3) focused factories and centralized distribution, 4) outsourcing, and 5) reduction of supply base.

M=Modeling Paper; E=Empirical Paper; C=Conceptual Paper

evidence regarding critical changes to any of the three potential factors associated with the rise in supply chain disruptions. Rapid technological change, deregulation, and globalization have intensified competition and required managers to change and align their supply chain strategies accordingly (D'Aveni, 1994; Hamel and Prahalad, 1994; Brown and Eisenhardt, 1998). Work tasks are broken apart and distributed over several firms in the supply chain, allowing for more specialization but requiring high levels of coordination (Bartlett and Goshal, 1989; VandeVen and Sinha, 2006; Drucker, 1988; Sanchez and Mahoney, 1996; Hitt, 1999).

In order to identify specific aspects of how changes in the environment impacted supply chain design, we conducted an extensive literature review (see Table 3-2). Our review shows a convergence toward increases in the competitive environment leading to a higher focus on efficiency as the main causes of increasing supply chain disruptions. Several authors point to the increased competitive pressure and resulting cost minimization strategies as a driver of disruptions (Kilgore, 2004; Tang, 2006). More specifically, authors claim that the cost minimization strategies created leaner supply chains, with fewer buffers, that reach around the globe (Kleindorfer and Saad, 2005; Stauffer, 2003; Bartholomew, 2006; Hillman, 2006; Juettner et al., 2003).

Kleindorfer and Saad (2005) point to the inherent trade-off between leanness and efficiency with robustness and reliability. Lee (2002) shares this sentiment and points to the high costs associated with efficiency in case things do go wrong. These changes in supply chain operations have altered the design of supply chains and made supply chains more complex. Tang (2006) states, “These initiatives have created longer and more complex global supply chains, which are more vulnerable to business disruptions in a turbulent world.” Bartholomew (2006) concurs that, “This new design creates a greater potential for the effect of disruptions in the supply chain to be amplified.” Craighead et al. (2008) used structured interviews in their study that clearly illustrates that practitioners share this idea and believe that complexity is a key factor in explaining disruptions.

An increasing number of studies propose complexity as the main driver of supply chain disruptions (Choi and Krause, 2006; Hoole, 2006; Christopher and Lee, 2004; Wu et al., 2007; Juettner et al., 2003). Increases in supply chain complexity as a driver could be classified as a network-related risk source according to Juettner et al. (2003) or as a change in the system as a source according to Brown et al. (2000). Disruptions might arise from other sources identified in the classification schemes, but the anecdotal evidence from academics and practitioners alike points to supply chain complexity as the prime suspect for our investigation of supply chain disruption antecedents.

In the following sections we discuss the connection between complexity and disruptions from a theoretical point of view. The goals are to define supply chains as complex systems, to identify complexity dimensions of relevance for supply chains, and provide a theoretical lens to support our assertion that complexity leads to disruptions in supply chains. Finally, we empirically examine the relationship between complexity and disruptions

3.1. Complexity and Disruptions in Supply Chains

3.1.1. Supply Chains as Complex Systems

Conceptualizing supply chains as complex systems is not a novel idea in the literature (Choi et al., 2001; Choi and 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). The supply chain as a system includes all companies that participate in the value adding process to provide the end-consumer with a product (or service). This includes companies that are directly or indirectly involved in the value adding process (Choi et al., 2001). 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 and Krause, 2006). One of the earliest conceptualizations of supply chain complexity is the supply chain complexity triangle by Wilding (1998), which was comprised of deterministic chaos, parallel interactions and amplification. Choi et al. (2001) recognized supply chains as complex adaptive systems with extensive interconnectedness, while Vachon and Klassen (2002) used a multi-dimensional definition of supply chain complexity to show its impact on delivery performance. More recently, authors have investigated other aspects of supply chain complexity, and have applied complex systems theory to supply chain management (Surana et al., 2005; Pathak et al., 2007; Bozarth et al., 2008). This work lays the foundation for describing supply chains as complex systems and allows for the application of complex systems related theories in supply chain settings.

3.1.2. Complex Systems and Disruptions

Most proponents of complex systems theory argue that perturbation to any element in the system affects other interconnected elements in the system (Ashby, 1960), and a change to a system element necessitates the simultaneous adjustment of all other interconnected elements (Nadler et al., 1994). The behavior of complex systems is difficult to predict, and makes the systems less knowable, more ambiguous (Perrow, 1967), and less stable (Casti, 1994).

Normal accident theory (NAT) provides a qualitative lens to examine the organizational performance of complex systems. Under NAT, accidents are considered "normal" and thus unavoidable in complex systems. Perrow (1984) points to the frequency of interactions and the extent of coupling (slack) between the system elements as critical factors impacting normal accidents and suggests that the size and interconnectedness of complex systems make the failure-free management of such systems an inherently impossible task.

NAT has been applied to a variety of cases and fields of study. In his initial work, Perrow (1984) used NAT to explain accidents in nuclear power plants, petrochemical plants, airway traffic, shipping, earthbound systems (i.e., damns, quakes, mines, etc.), as well as, space travel, weapons systems and DNA research. More specifically, NAT was used in the investigations of the Columbia space shuttle disaster (Weick and Sutcliffe, 2001), the Union Carbide plant at Bhopal, India (Shrivastava et al., 1988), and the Three Mile Island accident in the USA (Perrow, 1984). Besides the use of NAT to explain major industrial accidents, it has found applications in many other fields that investigate system failures. Ellis (1998) used NAT to capture a disruption to the service of the Hong Kong Mass Transit Rail System. Mascini (1998) shows empirical support for the concepts of NAT in a study of 208 near-accidents in an industrial plant. Ivory and Alderman (2005) used NAT to explain failures in project management. Wolf (2001) tested NAT in the oil processing industry. He characterized interactive complexity based on the number of unit processed, number of nodes that connect the processes, number of process parameters at each node, and the number of possible states of each parameter.

The findings of the study are in support of NAT and show that more complex refineries experience more frequent accidents.

The conceptualization of complexity in NAT is consistent with the fitness landscape model in complex systems theory. Different configurations of the system elements are associated with specific performance peaks in the landscape model. The number of performance peaks increases with the system's complexity level and creates more rugged landscapes. The interactions among system elements make it difficult to identify and reach the highest peak, or global optima, in rugged landscapes (Sinha and Van De Ven, 2005; Levinthal and Warglien, 1999). Adjustments to any element impact all other elements and make the isolated optimization of elements impossible. NAT explains the performance differences between the peaks with the occurrence of "normal" accidents due to the non-optimal system configuration. Kauffman (1993) states that:

> *"As systems with many parts increase both the number of these parts and the richness of interactions among the parts, it is typical that the number of conflicting design constraints among the parts increases rapidly. The conflicting constraints imply that optimization can attain only ever poorer compromises." (pp.53-54)*

Based on the literature review, we identify complexity in the supply chain as one of the key drivers of supply chain disruptions. Below, we identify characteristics of complexity that are most applicable to supply chains.

3.2. What Constitutes a Complex System?

Simon (1962) notes that complex systems consist of a large number of parts that interact in non-simple ways. Any complex system is composed of interrelated hierarchic subsystems until an elementary subsystem level is reached, that is not further decomposable. Size, interdependence, and hierarchical subsystems are widely accepted attributes of complex systems in a variety of scientific fields, such as biology, chemistry, physics, and social sciences (Simon, 1962). Organizational theory augments this view of complex systems by including the heterogeneity of the system elements (LaPorte, 1975). LaPorte's conceptualization states, "The degree of complexity of organized social systems is a function of the number of system components, the relative differentiation, or variety of these components, and the degree of interdependence among these components" (LaPorte, 1975, p.6). Kauffman's (1993) fitness landscapes conceptualization of complex adaptive systems (CAS) incorporates all previously presented complexity attributes. CAS is the most influential model in a recent stream of complex system studies. CAS's main premises are based on evolutionary biology and have been applied to studies about organizational adaptation (Levinthal, 1997; Sigglekow, 2001; McKelvey, 1997; Rivkin, 2000). Kauffman (1993) models CAS with two structural variables, N, the number of attributes or elements, and K, the number of elements of N with which a given element interacts. This NK model characterizes the fitness landscape, a mapping of all the possible decision choices of the organization with regard to its elements and their interactions onto the organization's fitness (performance).

The parameter P captures the fraction of attributes with the same value (in Kauffman's Boolean function it is 0 or 1). The deviation of P above 0.5 measures the internal homogeneity of the system (Boisot and Child, 1999). High internal homogeneity

Table 3- 4: Complexity conceptualizations in different literature streams

Definitions in Different Literature Streams					
Complex System in General	**1**	**2**	**3**	**4**	**Authors**
Large **number** of element**s** that **interact** in non-simple way	X		X		Simon, 1962
Number of parts, **interactions**, **nonlinearity**	X	X	X		Yates, 1978
System with **connectivity** and **differentiation** between elements		X	X	X	Klir, 1985
Number of elements, their **interrelatedness,** and **heterogeneity**	X	X	X	X	Kauffmann, 1993
Size and **coupling** of elements	X			X	Perrow, 1984
System that is **difficult** to understand					Flood and Carson, 1988
Organizational Theory					
Number of components within organization that are distinct	X	X			Blau and Schoenherr, 1971
Number of activities/systems across organizational levels (departments) or geographic locations.	X				Daft, 1983
Number of system components**,** relative **differentiation, and** degree of **interdependence.**	X	X	X		LaPorte, 1975
Number of elements**,** lack of clarity about **cause and effect**	X	X			Senge, 1990
Number of elements that need to be considered simultaneously	X		X		Scott, 1992
Information Technology and Information Processing					
Level of information processing needs					Galbraith, 1977
Number of information cues	X				Wood, 1986
Diversity and rate of change of information		X			Campbell, 1988
Supply Chain and Operations Management					
Number of suppliers, **interactions**, and **heterogeneity**	X	X	X		Choi and Krause, 2006
Number of parts and **unpredictability of change**	X	X			Bozarth et al., 2009
Number of components, degree of **novelty**, and **interaction**	X		X		Novak and Eppinger, 2001
Number of constraints in system	X				Eglese, Mercer, and Sohrabi, 2005

1= Detail Complexity; 2= Dynamic Complexity; 3=Interdependence; 4=Coupling corresponds to a high degree of structural stability and lower levels of information requirements. The literature review identifies four essential characteristics to capture the nature of complex systems – 1) the number of elements 2) the heterogeneity of the elements, 3) the interdependencies of elements within systems, and 4) the coupling between elements. Each of these dimensions is discussed in more detail below.

3.2.1. Number of Elements and Differentiation

The number of system elements is a well-established attribute of complex systems in the literature (Simon, 1962). In an organizational context this attribute relates to the concept of structural complexity (Daft, 1992). For instance, organizations with more departments, hierarchical levels, and geographic locations exhibit higher structural complexity than organizations with fewer departments, hierarchical levels, and geographic locations.

The underlying concepts of structural complexity are the number of elements and the degree of differentiation between these elements (Blau and Schoenherr, 1971; Price and Mueller, 1986). Detail complexity frequently refers to the aspect of structural complexity related to the number of elements, while dynamic complexity captures the heterogeneity of the system (Senge, 1990). The number of tiers and the number of suppliers, customers, and production locations at each tier indicate the level of structural complexity in supply chains.

A large number of suppliers forms a more complex supply base compared to a supply base with fewer suppliers (Choi and Krause, 2006; Handfield and Nichols, 1999).

Detail complexity increases the information processing requirements, because more elements need to be monitored and managed (Wood, 1986). The greater number of suppliers in the supply base increases coordination costs significantly in the supply chain (Handfield and Nichols, 1999) because more information flows, physical flows and relationships must be managed (Bozarth et al., 2008).

The excessive information processing and coordination requirements place more stress on the system management. The sheer size of the supply chain increases the uncertainty about optimal system configurations and leads to suboptimal choices with more disruptions. The uncertainty and increased information processing need therefore, increase the likelihood for disruptions.

H1: Supply chains with higher levels of detail complexity are more susceptible to disruptions compared to supply chains with lower levels of detail complexity.

Dynamic complexity describes systems where cause and effect relations between the elements are subtle and not obvious (Senge, 1990). This complexity type relates to the heterogeneity of system elements (Daft and Lengel, 1984). Different business practices, technologies, communication styles, and differences in organization culture capture the differentiation, or heterogeneity, within supply chain systems (Choi and Krause, 2006). Global supply chains exhibit increased levels of dynamic complexity because of the magnifying effect of long distances and different national cultures on the heterogeneity between supply chain members. Distances and cultural differences hinder the full understanding of cause and effect relationships within the system.

Equivocality, or ambiguity, is a concept related to the analyzability of cause and effect relationships in organizational theory (Thompson, 1967; Tung, 1979; Daft and Lengel, 1986). Dynamic complexity requires decision makers to constantly evaluate the cause and effect relationships between elements and to frequently adapt the means-end hierarchy. Hence, a system that exhibits detail complexity consists of many elements but might posses simple and predictable behavior. A system with dynamic complexity might have a simpler structure, but the behavior is unpredictable (Senge, 1990, p.71).

Planning and analysis methods are not well suited to deal with dynamic complexity, when actions have different effects in the short run versus the long run and locally versus globally (Senge, 1990). A dynamically complex system is low in stability and structure and posses higher cognitive processing requirements for decision makers (Boisot and Child, 1999). The lack of knowledge about cause and effect relationships in the system makes its optimization impossible. The sub-optimal configuration causes low supply chain stability and increases the occurrence of disruptions within the system.

H2: Supply chains with higher levels of dynamic complexity are more susceptible to disruptions compared to supply chains with lower levels of dynamic complexity.

Detail and dynamic complexity as aspects of structural complexity describe the basic system characteristics and provide the foundation for the relational complexity constructs. The number of possible interactions increases with the number of elements, or dynamic complexity, in the system. Four elements have twenty four possible interconnections, while five elements have one-hundred and twenty potential interconnections. Greater dynamic complexity, or heterogeneity, of the system increases the probability that diverse elements are interdependent, which makes their management more difficult due to the increased information processing needs.

3.2.2. Interdependence Within Systems

Interdependence of the workflow captures the extent to which work stations, or workers, need to cooperate and work interactively to complete their respective tasks (Thompson, 1967). This intra-organizational interdependence concept was successfully tested in an inter-organizational context (Borys and Jemison, 1989; Gulati and Singh, 1998). The exchange of resources to deal with contingencies explains the existence of interdependencies between supply chain partners (Hickson et al., 1971; Pfeffer and Salancik, 1978). The degree to which the success of any entity depends on its supply chain partners captures the interdependence construct in supply chains (Stock et al., 2000; Lejeune and Yakova, 2005).

The scope and direction are the critical attributes of the interdependence construct (Fiske, 1990). The interdependence relationship between two supply chain entities can be shallow or deep and uni- or bi-directional, which results in four possible combinations (Sheppard and Sherman, 1998). The number of exchanged resources, the extent of their exchange, and the exchange frequency capture the scope of the interdependence relationship (McCann and Ferry, 1979). A deeper dependency relationship exhibits more frequent exchanges of critical items or information in large numbers. The direction of the dependency indicates if the relationship is uni- or bi-directional. This interdependence conceptualization is able to capture Thompson's (1967) pooled, sequential, and reciprocal interdependence categorization.

Interdependence of system elements increases the coordination needs and uncertainty levels (Galbraith, 1973; Thompson, 1967; Daft and Lengel, 1984). Interdependence increases uncertainty because actions of individual system elements require adjustments of other system elements. Frequent alterations of system elements are necessary when interdependence is high (Van de Ven and Delbecq. , 1976). Low interdependence, on the other hand, gives elements greater autonomy, stability and certainty (Daft and Lengel, 1984). Hence, interdependencies of the system elements are often referred to as relationship complexity (Boisot and Child, 1999). Many supply chain interdependencies are not known to focal firms (Choi and Krause, 2006) and lead to more difficult to analyze system configurations (Wu and Choi, 2005). The increased levels of uncertainty and required levels of coordination lead to higher disruption probabilities in the system.

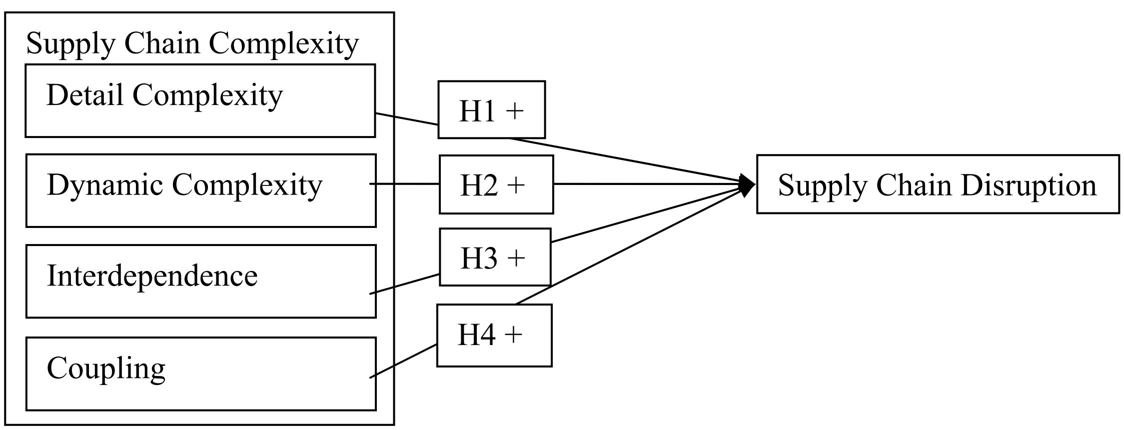
H3: Supply chains with higher levels of interdependence are more susceptible to disruptions compared to supply chains with lower levels of interdependence.

Coupling in supply chains is a function of slack between the system elements. The higher the slack between two elements the more loosely coupled they are – low levels of slack result in tightly coupled systems. Actual and potential resources as slack allow an organization to prevent disruptions to its workflow (Bourgeois, 1981). Slack provides the organization with a larger margin of error and buffers system elements from influences that could disrupt its processes (Cyert and March, 1963; Pondy, 1967; Thompson, 1967). Slack takes the form of cash, people, inventory, capacity, and so forth (Sharfman et al., 1988).

NAT considers coupling a critical antecedent for system accidents. The extent of coupling between the system elements is referred to as “tightly” or “loosely.” In a tightly coupled system the state of one element immediately affects the state of other elements (Perrow, 1984). Tight coupling requires management to find solutions and remedies for disruptions within a short time frame before they spread through the supply chain and result in larger scale disruptions. Loosely coupled systems seal off, and prevent the spread of, disruptions (Weick, 1976) because the slack makes them less sensitivity to disruptions (Perrow, 1984). Any system without slack built into it to absorb shocks will experience disruptions at some time (Bourgeois, 1981).

H4: Supply chains with tighter coupling are more susceptible to disruptions compared to supply chains with looser coupling.

Figure 3- 2: Conceptual model



Dynamic complexity, detail complexity, interdependence and coupling are characteristics of complex supply chains. Each characteristic individually increases the disruption risk - together they provide a comprehensive complexity measure to assess the total supply chain disruption risk. We argue that supply chains with higher complexity levels incur more frequent disruptions of larger scale and longer duration (see Figure 3-2).

3.3. Data Collection

3.3.1. Pre-Tests

We identified an developed and initial list of items from the literature to represent the four identified dimensions of complexity. The items were examined through two stages to ensure high research design quality. An initial online based draft of the survey instrument was pre-tested with the help of four academic researchers and seven practitioners. We deployed an online adaptation of the think-aloud procedure (Duncker, 1945) for the refinement of measurement items. The use of verbalizations as indicators of cognition is a decades-old data collection technique. All participants were considered experts in the area and had the relevant knowledge pertaining this study to assess the content validity and clarity of the questions. The survey instrument was revised based on the provided comments, and special care given to practitioner relevant wording of the questions.

Following the revision to the initial draft, another round of pre-testing was carried out by sending the web-based instrument to members of “SCP-Supply Chain Practitioners,” a Yahoo! user group of supply chain professionals. Approximately 250 members were contacted by email, resulting in the response of 57 individuals, or a response rate of 23%. During this round of pre-testing specific aspects of the survey taking process were examined, i.e., non-response to certain questions, survey drop outs, time taken to answer survey instrument.

3.3.2. Pilot Study

To avoid an overly homogenous sample the population of interest was defined as all manufacturing firms in North America (SIC Codes 21-39). The general sample approach ensures the inclusion of a large enough variety of different disruption levels for the analysis, as previous research showed that supply chain risk management techniques are very similar within industries (Zsidisin et al., 2005). The study was limited to manufacturing firms as the focus is on disruptions to the material flow. Following the pre-tests, a large scale pilot study was conducted using members of the Council of Supply Chain Professionals (CSCMP), that were selected based on their job title and expertise regarding supply chain management. Only high level management in supply chain relevant areas were selected to participate in the survey. The administration of the data collection followed the general outline for survey design advocated by Dillman (2000) and used in Operations Management research (Koufteros et al., 1998; Nahm, 2003). One hundred eleven responses, corresponding to a response rate of 11% were used to assess initial reliability and to conduct exploratory data analysis. The pilot sample in this study is larger than in comparative studies that conducted a pilot study for their research studies (Shah and Ward, 2007; Koufteros et al., 1998; Nahm et al., 2003). As a result of the pre-tests and pilot study, the finalized survey was approximately 50% shorter than the previous versions used. Specifically, questions were limited to the supply and production base of the focal firm, resulting in a significant reduction of questions.

3.3.3. Main Data Collection

The main data collection was conducted over six weeks in the summer of 2008. The respondents belong to two organizations of operations management practitioners. APICS (Advancing Productivity, Innovation, and Competitive Success) is a network of accomplished industry professionals that has been active since 1957 with regard to training, certifications and conferences in the area of Operations Management. SCL (Supply Chain and Logistics Association) was formed in 1967 by practitioners interested in supply chain related topics. The contact lists for the survey were composed of individuals that matched three criteria: 1) respondent worked for manufacturing firm, 2) respondent had high- or mid-level position within organizations, 3) respondent was exposed to supply chain related activities in the organizations.

A total of 151 responses were gathered from APICS, resulting in a response rate of 7.6%. Eleven responses were missing a substantial amount of data on the items used in this study, therefore only 140 responses were used for the analysis. The SCL data collection resulted in a total of 62 responses of around 1.5-2%. An exact response rate could not be estimated as the organization only provided a "guesstimate" of the current status of their email list. Thirteen responses were missing substantial amounts of data, therefore only 49 responses were used in the analysis. However, the response rates match recent results of large scale studies, i.e., Shah and Ward (2007) reported a response rate of 13.5%, Nahm et al. (2003) of 7.47%, Li et al. (2005) of 6.3%, Simons et al. (1999) of 6%, and Poppo and Zenger (1998) of around 5%.

Coverage bias was assessed by comparing the responding firms to the population of North American firms. Results indicate that our sample is slightly biased toward certain industries (see Chapter 1 for more detail on all data assessments), which limits the generalizability of our results. We assessed potential difference between the samples from the two associations using t-test comparisons on critical items. No significant differences between the samples were found and for the remaining analysis we combined the two samples. However, during all steps of the analysis we retained a dummy variable controlling for the sample. Non-response bias was assessed through comparison of early and late respondents. The test resulted in no significant difference between the two respondent groups, indicating the absence of any non-response bias. Common method bias is present when correlations between measurement items are explained by the use of common methods, rather than by the existence of any true relationship between the items. Harmon's one factor test was conducted and resulted in no apparent existence of common method bias.

Only the data from the large scale data collection phase are used for the empirical analysis in this chapter.

3.4. Measurement Design

Measurement is the process of assigning numbers or labels to variables of units in order to represent their conceptual properties (Singleton and Straits, 2005; p.76). The development of measures begins by reducing the level of abstraction to recast the theoretical constructs into observable variables, and select indicators to measure these variables in reliable (i.e., replicable) and valid (i.e., capture their intended meaning) ways. The next sections proceed with the description of the measurement design process for the dependent and independent variables.

3.4.1. Dependent Variable

Disruption is measured using 7-point Likert scales measuring the frequency, duration, impact, and spread of disruptions (see Appendix 3-1). Frequency and Duration have previously been described as the critical attributes to assess system reliability. The impact measures the significance of disruptions for the competitiveness of the company; it is not a direct performance measure, but rather a measure of the severity of the disruptions. The spread of disruptions through the supply chain is measured using two items assessing the spread from disruption originating in the supply base to the production base with one measure, and the spread from the supply base to the customer base with one measure. The measures show that frequency, impact and the two spread measures load significantly on one factor, while duration remains separately. The constructs were found to be valid and reliable measurement scales.

3.4.2. Independent Variables

Detail Complexity: Detail complexity is a function of the number of elements in complex systems. In the supply chain detail complexity represents the number of firms, more specifically the number of suppliers and the number of tiers in the supply chain. Complexity was measured using 5-point Likert scales (1= Strongly Disagree, 5= Strongly Agree) capturing the size of the supply base in relation to other firms in the industry, e.g., "*The overall size of our supply base larger than that of our competitors*." (see Appendix 3-1 for all items) A comparative measure is used because the size of the supply chain varies significantly across industries and it is the comparative size that matters the most.

Dynamic Complexity: In general, dynamic complexity assesses differences between system elements. In the supply chain it refers to the heterogeneity of firms in the supply chain with respect to critical attributes. The main attributes of difference in the supply chain are technical capabilities, operational techniques, and organizational culture, as conceptually outlined by Choi and Krause (2006). The dynamic complexity measures use 5-point Likert scales to assess the differences between suppliers and the focal firm regarding the three identified attributes, e.g., *"Our suppliers have technical capabilities that are very similar to ours."*

Interdependence: Interdependence assesses the dependence of a firm on its trading partners. The reasons for the dependence may vary but the firm's inability to replace a partner has been considered an indication of a firms dependence on its partners (Heide and John, 1988). Hence, replaceability of trading partners in supply chains has frequently been used to assess the dependence relationships empirically (Buchanan, 1992: Heide, 1994; Heide and John, 1988; Kumar et al., 1995). Five-point Likert scales (1= Strongly Disagree, 5= Strongly Agree) are used to assess the replaceability of the supplier in the focal firm's supply base, e.g.*"Our production process can easily use components from different suppliers."*

Coupling: Coupling is a function of slack between system elements. The more slack between two elements the more loosely coupled they are – low levels of slack result in tightly coupled systems. The coupling measures use 5-point Likert scales (1= Small Extent; 5=Great Extent) assessing the extent to which specific means are used to decouple the focal firm from the supply base. The measures use safety stock, safety lead times, and capacity as the main drivers of slack to assess coupling in the supply chain. The more extensively the three techniques are used, the more decoupled is the focal firm from its supply base, e.g., *"How extensively is safety stock used to decouple your production process from the supply base?"*

3.4.3. Control Variables

Every system is composed of many sub-systems, each of which may contain their own sub-systems, giving them a hierarchical structure. Consequently, system complexity is also a function of constituent sub-system complexity. For instance, source, make, and deliver represent sub-systems of the overall supply chain, while a supplier is a sub-system of the source system, and an individual plant is a sub-system of the supplier. The influence of other systems, or sub-systems, has also been captured in Kauffman's NK model of complex systems (Kauffman, 1993). The introduction of the parameter C refers to the number of elements that are linked across systems to elements from other complexity landscapes. This model distinguishes between interactions among subsystems, and interactions within subsystems. In general, there are more interactions within a system than across systems (Simon, 1962).

Thus, supply chain complexity is related to complexities at lower and higher system levels, which we need to control for during the analysis of the linkage between supply chain complexity and disruptions. The lower levels of the supply chain system are represented by controls for the firm, the manufacturing process, and the product. The firm is being controlled for by the use of a revenue scale assessing what %age of the overall revenue is contributed by the product line used in for this study. This measure assesses the overall importance of the product line and the diversification of the firm (Hendricks et al., 2009). The production process represents another lower system level in the supply chain with relevance for our research question. The type of process used for the production of the product lines (i.e., line flow, large or small batch, job-shop, or project) is captured with a single measurement item. The product, its components, and its configurations represent another lower system level within the supply chain. The more components a product consists of, and the more configurations of the product exist, the more complex the product becomes. Hence, we use simple measurement items for the number of components used to manufacture the product and the number of available configurations to control for the product level of the complex system. The supply chain is also influenced by the complexity of higher system levels, specifically by the industry in which the focal firm operates. We utilize two Likert type measurement items to assess the competitiveness and degree of regulation as control variables for the industry.

3.5. Measure Assessment

The developed measures for supply chain complexity are examined and validated using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The EFA approach is used to uncover the underlying structure of the measurement items. We use the CFA to confirm the data structure and to assess convergent validity, discriminant validity, and unidimensionality. The data set was split randomly in half to create a calibration (n=95) and validation (n=94) set. This approach was used to further increase the reliability and validity of the measurement instruments.

3.5.1. Exploratory Factor Analysis

An exploratory factor analysis using principle components extraction and various rotations was used to determine the underlying measurement structure in the complexity item set. Rotations of the factor solution increase the interpretability of the underlying factor structure. The exploratory factor analysis aids the development of scales to reduce the number of variables for the subsequent regression analysis (Hair et al., 1998). The reduction of variables to composite scales is beneficial for the statistical power in the regression analysis. The Bartlett test of sphericity for the complexity measures was significant indicating that the data are suited for a factor analysis. The Bartlett test is a statistical examination of the presence of correlations among the variables, which is a pre-requisite for the successful conduct of a factor analysis.

The rotated results of the exploratory factor analysis (see Table 3-4) are evaluated regarding significant cross-loadings of items, low extracted communalities, number of extracted factors, and variance explained. Only factors with eigenvalues exceeding a value of one were extracted in the factor analysis, as they are generally considered significant (Hair et al. 1998). The analysis resulted in the identfication of four underlying factors for complexity, which matches our theoretically derived dimensions to capture complexity in supply chains.

Table 3- 5: EFA for complexity

	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

Components extracted using principle components extraction with Varimax rotations

Items were inspected regarding significant loadings, with loadings greater than .60 representing practical significance considering the sample size of n=95 for the split data set (Hair et al. 1998 – page 112). Items with insignificant loadings, or significant loadings on several factors, should be eliminated in the process at the discretion of the researcher. The remaining items with cross-loadings in excess of 0.30 (Detail Complexity 2 and Coupling 1) are retained in the analysis due to the fact that a loading of 0.30 is not significant in a small sample (Hair et al., 1998). Furthermore, the communalities are assessed to examine the variance extracted for each variable. In the process of the EFA procedure we eliminated three variables that showed significant cross-loadings, and/or insufficient extracted variance, or did not match our theoretically developed framework.

3.5.2. Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was used to assess the overall model fit for the complexity scales (see Chapter 2 for fit of disruption scale) and validity of each multi-item scale. The CFA was conducted using the validation sample of the study using AMOS 16 utilizing the maximum likelihood method based on the insights gathered in the EFA. The CFA evaluates an a priori developed model in which the observed variables are linked to their constructs according to its fit with the data. The researcher should examine a variety of fit indices for the assessment of the overall fit of the measurement model from different perspectives (Shah and Goldstein, 2005). Absolute, incremental, and parsimonious measures were used to assess the overall model fit with the underlying data structure (see Table 3-5). The fit indices provide different insights into how well the model matches the observed data (Hu and Bentler, 1995). The absolute fit measures (RMSEA, RMR) assess how well the a priori model matches the sample data. Incremental fit measures (CFI, GFI, IFI) assess the incremental fit of the model compared to null or worst case model. Parsimonious fit measures (Normed χ^2) assess the parsimony by evaluating the fit against the number of estimated coefficients needed for the fit. All of the fit measures need to be evaluated to assess the overall fit of the model.

The fit measures for the disruption scale all match the respective cut-off points indicating acceptable fit (see Chapter 2). The fit measures for the complexity measures are all very close to the cut off points (close to 0.90), while the others match their criteria. This also indicates relatively good fit of the complexity scales, as fit measures are designed to specify the degree of fit to the data, and are not intended as hypothesis tests with the binary outcome (fit/no-fit) (Marsh et al. 2004). Four recent papers have essentially shown that the notion of a single threshold-value for the fit indices does not apply (Beauducel and Wittmann, 2005; Fan and Sivo, 2005; Marsh et al., 2004; Yuan, 2005). Hence, we conclude that the complexity scales show acceptable levels of fit.

In addition to examining the fit statistics, we also examined the standardized residuals, as small residuals are indicative of good fit. It is recommended that no more

Table 3- 6: CFA for complexity

Statistic	Complexity	Cut off values
χ^2	79.278	NA
Df	49	NA
P-Value	0.000	MA
χ^2 /DF	1.618	≤3.0
GFI	.870	≥.90
CFI	.888	≥.90
IFI	.894	≥.90
RMR	.086	≤.10
RMSEA	.088	≤.10

than 10% of the absolute values of the standardized residuals are greater than 2.5 (Hu and Bentler, 1995). Two residuals, or 3.03% (2 out of 66) marginally exceed the value of 2.5 (largest residual is 2.7) for the complexity scale, which is indicative of an acceptable fit (no residual exceeds the threshold for disruption scale). Furthermore, all the factor loadings are greater than 0.50 ($p<0.01$) and all modification indices are below 10 (Shah and Ward, 2007). The normality assessment based on the skewness and kurtosis of the factor model shows that none of the variables exceeds the 2.58 threshold, which is indicative of acceptable levels of normality. The multivariate normality test is below 1 and points to multivariate normality (see Table 3-6).

Content validity is the adequacy with which a specific construct (or content domain) has been sampled during the data collection (Nunnally, 1978; Flynn et al., 1990).

Table 3- 7: Normality of variables

Variable	min	max	skew	critical ratio	kurtosis	critical ratio
DetC1	-1.807	2.233	.184	.661	-.973	-1.742
DetC2	-2.000	1.450	.297	1.065	-.814	-1.458
DetC3	-1.894	1.991	.326	1.166	-.385	-.690
Interd1	-1.635	2.415	.414	1.484	.015	.027
Interd2	-2.185	1.906	.005	.017	-.735	-1.316
Interd3	-1.283	2.014	.387	1.386	-.350	-.628
Coupl1	-2.055	1.428	-.199	-.712	-1.172	-2.099
Coupl2	-1.664	1.217	-.676	-2.423	-.438	-.785
Coupl3	-1.901	1.597	-.030	-.106	-1.103	-1.977
DynC1	-1.752	2.009	.538	1.929	-.305	-.547
DynC2	-1.829	1.492	.314	1.124	-.442	-.793
DynC3	-1.941	2.040	.051	.183	.014	.024
Multivariate					3.717	.890

To ensure content validity the instrument needs to contain a representative collection of items and the instrument construction use sensible methods. We achieve content validity through the grounding of the constructs in the literature and the review by experts (practitioners and academics, as described in Chapter 1). Furthermore, we used several pre-test rounds to evaluate the new measurement items and their psychometric properties.

Construct validity is the assessment of the degree to which a scale measures the intended construct. The convergence and divergence of the scale items is a way to assess and establish construct validity.

3.5.3. Convergent Validity

Anderson and Gerbing (1988) propose that significant item loadings on the respective constructs are evidence for convergent validity. The loadings for the items on the complexity dimensions range from 0.605 to 0.997 and are significant at the .001 level. The variance explained by each variable ranges from 0.366 to 0.994 with the average amount of variance explained exceeding 0.50 overall. The loadings can be seen in the Table 3-7.

3.5.4. Discriminant Validity

Discriminant validity is used to assess the degree to which measurement items from different constructs are unique and distinct from each other. Measurement items that exhibit satisfactory discriminant validity should only measure the construct they are intended to measure, and show no (or little) loadings on other constructs. Discriminant validity can be assessed with a three-step procedure: 1) a model with two constructs and their respective measurement items is run in CFA where the covariance between the constructs is fixed to one; 2) a second model is run with the same two constructs and measurement items, but this time the covariance between the constructs is free to vary; 3) χ^2 difference between the two models is tested. Constraining the covariance between the two constructs is equivalent to assuming they are the same construct, and not unique. If

Table 3- 8: Loadings for complexity

	Loadings	R-square
DetC1	0.740	0.548
DetC2	0.847	0.717
DetC3	0.755	0.570
Interd1	0.687	0.472
Interd2	0.897	0.805
Interd3	0.652	0.425
Coupl1	0.655	0.429
Coupl2	0.605	0.366
Coupl3	0.880	0.774
DynC1	0.705	0.497
DynC2	0.997	0.994
DynC3	0.704	0.496

both constructs are unique the difference between the fixed and the free model needs to be significant. The χ^2 difference is being tested with one degree of freedom, because the free model is nested in the fixed model. A significant difference between the models indicates that the constructs and their measures are unique and necessary to explain the data structure (Bagozzi and Phillips, 1982; Bagozzi et al., 1991). The proposed factor structure for complexity of four unique constructs requires the conducting of six pair-wise comparisons. The results in Table 3-8 show that all pair-wise tests show that the free model fits the data structure better than the fixed model at the .001 level – indicating strong evidence for discriminant validity of the constructs.

3.5.5. Unidimensionality

Unidimensionality is a necessary condition to establish reliability and validity. Unidimensional items capture only one construct, and do not exhibit significant cross-

Table 3- 9: Discriminant validity χ^2 difference test for complexity

Pairs		Free	Fixed	Diff	P-Value
		χ^2 Values			
Coupling	Dynamic Complexity	21.031	98.737	77.706	0.001
	Interdependence	32.492	157.754	125.262	0.001
	Detail Complexity	34.433	107.89	73.457	0.001
Interdependence	Dynamic Complexity	21.123	152.135	131.012	0.001
	Detail Complexity	39.497	188.344	148.847	0.001
Detail Complexity	Dynamic Complexity	26.419	163.857	137.438	0.001

loadings onto other constructs. Unidimensionality can be concluded if the overall fit of the measurement model during the CFA is appropriate (Shah and Ward, 2007). Another approach for unidimensionality checking has been proposed by Joreskog and Sorbom (1989), which requires the construction of a measurement model for each individual construct. A goodness of fit index (GFI) of 0.90 or higher for such a single constructs model indicates appropriate confidence in the unidimensionality of the constructs. The GFI indices for all the constructs are above 0.90, indicating strong evidence of unidimensionality.

Table 3- 10: Unidimensionality for complexity

Construct	GFI
Interdependence	0.940
Coupling	0.916
Detail Complexity	0.938
Dynamic Complexity	0.912
Disruption	0.979

3.5.6. Reliability

Reliability can be broadly defined as the degree to which the scales are free from error and, therefore, yield consistent measurements (Flynn et al., 1990) (see Table 3-10 for all reliability scores). Cronbach's alpha is a measure of the internal consistency of the measurement construct and often used to assess reliability. Cronbach's alpha is calculated for each complexity construct and the disruption construct. Scales are considered internally consistent with a Cronbach's value exceeding 0.60, which is the cut-off point for newly developed scales (Nunnally, 1978), while 0.70 is a more conservative value for established scales (Hair et al., 1998). All the complexity and disruption constructs exhibit values for Cronbach's alpha exceeding the conservative value, load on a single factor, and explain above 50% of the variance.

An alternative way to measure the reliability of measurement scales of one construct is composite reliability (Escrig-Tena and Bou-Llusar, 2005). The formula for composite reliability can be found in section 2.4.6. The value for the composite reliability for all dimensions is exceeding the commonly used 0.70 threshold (Shah and Ward, 2007). Furthermore, we calculated the average variance extracted (AVE) (Fornell and Larcker, 1981). The AVE is exceeding the commonly used threshold value of 0.50 (Shah and Ward, 2007). All measures indicate good construct reliability. The reliability evaluation is conducted at this point, because the validity and unidimensionality of the constructs is a necessary condition for the establishment of construct reliability (Koufteros, 1999).

Table 3- 11: Reliability for complexity

	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
Disruption	0.865	0.866	0.618

3.6. Regression Analysis

We use a hierarchical regression analysis with ordinary least squares (OLS) procedure to test the proposed hypotheses. The equation below (Figure 3-3) represents the regression model:

Figure 3- 3: Regression function[4]

$$\left. \mathit{Disruption} = \right\} \text{Dependent Variable}$$

$$\left. \begin{array}{l} \beta_0 + \beta_1 * \mathit{Dummy} + \beta_2 * \mathit{Comp.} + \beta_3 * \mathit{Regul.} + \beta_4 * \mathit{Vol.} \\ + \beta_5 * \mathit{Prod} + \beta_6 * \mathit{Config.} + \beta_7 * \mathit{Compon.} + \beta_8 * \mathit{Reve.} \\ + \beta_9 * \mathit{Empl.} + \beta_{10} * \mathit{Process} \end{array} \right\} \text{Control Variables}$$

$$\left. + \beta_{11} * \mathit{DetailC.} + \beta_{12} * \mathit{DynamC.} + \beta_{13} * \mathit{Interdep.} + \beta_{14} * \mathit{Coupl} \right\} \text{Predictor Variables}$$

[4] Explanation of abbreviations in formula: Dummy=Variables for the two data sets; Comp=Competitiveness of industry; Regul.=Regulation of industry; Vol=Volume of products sold; Config=Configurations of product available; Reve.= Revenue share of product line; Process=Type of process used for production; DetailC.=Detail Complexity; DynamC.=Dynamic Complexity; Interdep.=Interdependence; Coupl.=Coupling

The hierarchical regression model is used to test the incremental effect of supply chain complexity on supply chain disruptions. This technique was selected to assess the incremental effects of the supply chain complexity measures after controlling for the effects from other system levels, e.g., industry, product, process, etc. We conducted six sets of regression analyses, one for the disruption scale developed in Chapter 2 and one for each individual measurement item (frequency, duration, impact, spread 1 and 2) of supply chain disruptions.

First, we entered a dummy variable to control for the two combined data sets from APICS and SCL and all other control variables as predictors into the regression model. This model establishes a baseline and serves as a control model against which we access the incremental effect of supply chain complexity on disruptions. Second, the factor scores for the four complexity dimensions are entered into the regression model to examine their incremental effects. We also conducted the analysis using the additive scores for the complexity dimensions based on the measurement items, with almost identical results.

The hierarchical regression analysis is evaluated regarding the overall significance of the R-square change when the complexity dimensions are entered, and the individual significance levels for the β's of the individual complexity dimensions. The analysis is first run with the disruption scale as the dependent variable and then with disruption duration as the dependent variable to capture two factor structure results of the scale development process in Chapter 2. The results of the analysis can be found in Table 3-11. We will discuss the results in the following paragraphs by dependent variable.

Disruption Scale: The model with the disruption scale as a dependent variable exhibits an overall R-Square of 0.150 for the full model. The change in R-square after entering the four complexity dimensions is 0.043, which is associated with an overall significant F ratio at the $p<0.10$ level. Detail complexity and coupling have significant β values, while dynamic complexity and interdependence have β values that are not significantly different from zero at the tested alpha level. Both β's, for detail complexity and coupling, are positive. The β for detail complexity is significantly different from zero at the $p<0.10$ level, while the β for coupling is significantly different from zero at the $p<0.05$ level. These results confirm hypotheses 1 and 4, while we can reject hypotheses 2 and 3.

Duration Measure: The model with the duration measure as the dependent variable exhibits an overall R-Square of 0.194. The change in R-square for the four complexity dimensions is 0.140, which is has a significant F ratio at the $p<0.01$ level. Similar to the prior model, detail complexity and coupling have significant β values, while dynamic complexity and interdependence have β values that are not significantly different from zero at the tested alpha level. Detail complexity has a positive β value, while coupling has a negative β value. Both β's are significantly different from zero at the $p<0.01$ level. The negative β values for coupling implies that tighter coupled supply chains experience shorter lasting disruptions, compared to more loosely coupled supply chains. The results of the regression analysis confirm hypothesis 1 and reject hypotheses

Table 3- 12: Regression results

	Disruption		Duration		Frequency		Impact		Spread 1		Spread 2	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Dummy Country	.038	-.009	-.151*	-.114	.113	.078	.007	-.035	.068	.037	-.055	-.105
Competitiv.	-.154†	-.240*	.009	.069	-.122	-.139	-.115	-.209	-.204*	-.254*	-.076	-.197*
Regulation	.120	.124	.074	.143†	.096	.102	.034	.053	.137†	.125	.135†	.134†
Volume	.054	.059	.053	.041	-.051	-.063	.105	.113	.066	.070	.055	.072
Product Config.n	.166†	.186*	-.060	-.073	.032	.023	.170*	.199	.161†	.172*	.186*	.219*
Comp.	.172†	.185*	.112	.026	.190*	.188*	.223**	.228	.084	.111	.074	.089
Revenue	.151	.208	.097	.034	.152	.204	.160	.202	.026	.068	.163	.218
Employee	-.008	-.063	-.124	-.083	-.047	-.101	.042	.003	.017	-.017	-.039	-.098
Process	-.140†	-.150†	-.057	-.056	-.111	-.102	-.151*	-.167	-.137†	-.140†	-.066	-.089
Detail Complexity		.134†		.281**		.140*		.194**		.012		.098
Dynamic Complexity		.029		-.046		.137*		.096		.017		.112
Interdep.		-.097		.054		.071		.144*		.084		.023
Coupling		.183*		-.192**		.192*		.111		.127		.182*
										.		
R-Square	.107	.150	.054	.194	.102	.142	.131	.196**	.086	.107	.076	.125*.
R-Square Change	.107**	.043†	.054	.140**	.102*	.040†	.131**	.065.	.086†	.021	.076	.049

† p<.10; * p<.05; ** p<.01;

2 and 3. Hypothesis 4 is rejected, as we hypothesized a positive connection between coupling and duration. However, the relationship between the dependent and independent variable is significant. The negative link between coupling and disruptions may be explained through the literature on lean management. Studies find that tightly coupled manufacturing systems that employ lean thinking principles, show higher levels of worker motivation and productivity (Schultz et al., 1998).

Furthermore, it can be argued that in a tightly coupled, or lean, supply chain, small disruptions become apparent sooner and appropriate actions can be taken. This also explains why coupling seems to impact the disruption construct positively and the disruption duration negatively. Tightly coupled systems experience more frequent disruptions that spread easier, while they usually last shorter.

After the analysis of the two main dimensions of disruptions – the disruptions scale and disruption duration, we ran the analysis on the individual variables of the disruption scale. This analytical step allows us to explain more of the variance of the individual measurement items compared to the aggregated measurement scale. The analysis provides more information about which complexity dimensions drive the frequency of disruptions and their spread in the supply chain, and increases the value of the findings for practice.

Frequency Measure: The model with the disruption scale as a dependent variable shows an overall R-Square of 0.142, while the R-square change after entering the four complexity dimensions is 0.040. This change is associated with an overall significant F ratio at the $p<0.10$ level. Detail complexity, dynamic complexity and coupling have significant β values, while interdependence has a β value that does not significantly deviate from zero. All three significant β's are positive, indicating a positive relationship with the response variable. The β for detail complexity is significantly different from zeroat the $p<0.10$ level, the β for dynamic complexity is significantly different from zero at the $p<0.10$ level, while the β for coupling is significantly different from zero at the $p<0.05$ level. These results confirm hypotheses 1, 2 and 4, while we can reject hypothesis 3.

Impact Measure: The model with the impact measure as a dependent variable exhibits an overall R-Square of 0.196. The change in R-square after entering the four complexity dimensions is 0.065, which is associated with an overall significant F ratio at the $p<0.01$ level. Detail complexity and interdependence have significant β values, while detail complexity and coupling have β values that are not significantly different from zero at the tested alpha level. All significant β's are positive, indicating a positive relationship with the response variable. The β for detail complexity is significantly different from zero at the $p<0.01$ level and the β for interdependence is significantly different from zero at the $p<0.05$ level. These results confirm hypotheses 1 and 3, while we can reject hypotheses 2 and 4.

Spread 1 Measure: The model with the spread 1 measure, which captures the spread of disruptions from the supply base to the productions base, as a dependent variable exhibits an overall R-Square of 0.107. The change in R-square after entering the four complexity dimensions is 0.021, which is associated with an overall non-significant F ratio. This means that the addition of the four complexity dimensions did not result in a significant increase in R-square. All four dimensions have non-significant β values, which are statistically not different from zero. These results lead to a rejection of all hypotheses for spread 1 as a dependent variable.

Spread 2 Measure: This model uses spread 2, which measures the spread from the supply base to the customer base, as a dependent variable. The model exhibits an overall R-Square of 0.125. The incremental increase in R-square for the four complexity dimensions is 0.049 with an overall significant F ratio at the $p<0.05$ level. In this model only coupling has a significant β values, while all other complexity dimensions have β values that are not significantly different from zero at the tested alpha level. The β for coupling is positive and significantly different from zero at the $p<0.05$ level. These results confirm hypothesis 4, while we can reject hypotheses 1, 2 and 3.

3.6.2. Findings

The hypotheses test results are summarized in Table 3-12. Our results suggest that the relationship between complexity and disruptions is dependent upon the operationalization of disruptions. No single aspect of complexity is significant for all measures of supply chain disruptions. Detail complexity has a positive relationship to all measures, but not the two measures of disruption spread. Coupling has a significant relationship to all variables, but not impact and spread 1. The link between coupling and duration is negative, while all other have positive β values. Interdependence has a significant relationship with only impact as a dependent variable, and is non-significant for the other dependent variables. Dynamic complexity has a significant relationship with only frequency as a dependent variable. As for the dependent variables, only spread 1 shows no significance for all four predictors. All others have at least one significant predictor (spread 2) leading up to a maximum of three significant predictors (frequency). In no case are all predictor variables significant for a dependent variable.

The results show that individual dimensions of complexity are significantly associated with disruptions. Detail complexity and coupling appear as critical dimensions associated with four of the individual dependent disruption variables. Dynamic complexity and interdependence are each reaches significant for only one disruption dimension. Overall, the tests show that supply chain complexity is very likely to be a significant driver of supply chain disruptions.

Table 3- 13: Hypotheses test results

		Dependent Variables					
		Scale	Duration	Frequency	Impact	Spread 1	Spread 2
H1	Detail Complex	(+)†	(+)**	(+)†	(+)**	ns	ns
H2	Dynamic Complex	ns	ns	(+)†	ns	ns	ns
H3	Interdependence	ns	ns	ns	(+)*	ns	ns
H4	Coupling	(+)*	(-)**	(+)*	ns	ns	(+)*

ns=not significant; † p<.10; * p<.05; ** p<.01; + pos.coeff; - neg.coeff.

3.7 Discussion and Contributions

Identifying antecedents of supply chain disruptions is of critical importance to practitioners and academics alike (Deloitte, 2003; Bozarth et al., 2008). We conduct an extensive literature review and use organizational theory to identify complexity as a key driver of supply chain disruptions. We then use previous research on complex systems to identify four dimension of complexity that are relevant in supply chains. The four dimensions are: 1) detail complexity which refers to the number of firms and tiers in the supply chain, 2) dynamic complexity, or the heterogeneity of the firms in the supply chain, 3) interdependence, or the replaceability of suppliers by the focal firm, and 4) coupling, or the amount of slack between the firms. We propose four research hypotheses linking each of the four complexity dimensions with supply chain disruptions. In this study we develop operational measures for the complexity dimensions in supply chains and assess their validity and reliability using EFA and CFA techniques. Using data from a large scale survey study we employ hierarchical regression analysis to test our research hypothesis.

In general, our data analysis shows a positive relationship between supply chain complexity and disruptions. We can say that more complex supply chains are more susceptible to disruptions. However, the results depend strongly on the dimensions of complexity and the measurement of disruptions. Overall, each of the four dimensions show predictive power regarding supply chain disruptions to different degrees, and regarding different aspects of disruptions.

The identification of detail complexity as a critical antecedent of disruption confirms the sentiment uttered by previous authors about the increased opportunities for disruptions in larger and longer supply chains (e.g., Kleindorfer and Saad, 2005; Juettner et al., 2003). Detail complexity of the supply base is associated with more chances for disruptions due to the larger number of organizations involved in the supply chain process. The increased size of the supply base requires more coordination between firms (Handfield and Nichols, 1999) because more information flows, physical flows and relationships must be managed (Bozarth et al., 2008). Such an information overload can lead to sub-optimal decision making, and hinders the quick intervention in case of a disruption. Dynamic complexity has a positive effect on the frequency of disruptions. This effect is due to dynamic complexities characteristic of not having clear cause and effect relations between the elements (Senge, 1990) before a disruption occurs. The unclear cause and effect relationship seems to be unclear before the disruption, but becomes clear at hindsight, as it does not negatively impact the recovery process.

The role of coupling needs to be addressed separately, as it is the only dimension that has a negative impact on the duration of disruptions. It is the only complexity dimension that exhibits any association with reducing disruptions, more specifically the duration of disruptions. A possible explanation of this observation can be found in the lean management literature. Schultze et al. (1998) examined the behavioral effects of tightly coupled systems in the context of just-in-time manufacturing systems with low inventory levels. They found that low-inventory systems provided specific, timely, and frequent feedback, which is information used to control systems (Wiener, 1954; Nadler, 1979). This sort of feedback is a critical aspects of the duration of disruptions, as the recovery starts when the disruption is first detected. The feedback aspect of tightly coupled systems indicates that disruptions are detected earlier and explain the negative relationship of our coupling measure with the duration of disruptions. Schultze et al. (1998) also show that tightly coupled systems show greater group cohesion, which is especially important regarding the relationships between supply chain partners that are tightly coupled. Group cohesiveness reflects the amount of effort members will allocate to the group (Goodman et al., 1987), which is critical for disruption recovery as the fire at a breaking caliber plant in Toyota's supply chain showed (Sheffi, 2005). The fire to the only plant producing breaking calibers for the Asian market put Toyota's tightly coupled supply chain at jeopardy. However, the cohesiveness of the Toyota supply chain led to a remarkable recovery effort that involved a great number of Toyota's suppliers to get production up and running in record setting pace (see Sheffi, 2005 for more detail). Hence, we conclude that tight coupling can lead to more frequently occurring disruptions due to the lower buffer deployed in such a design, but that the tight coupling is beneficial for disruption recovery through the feedback and cohesiveness mechanism.

The empirical findings from this study are important for a number of reasons. First, there is little empirical research identifying the antecedents of supply chain disruptions. The presented study supplements findings from case studies and empirically validates ideas from conceptual pieces. Second, the four tested hypotheses offer guidance for managers to systematically evaluate their supply chain for potential disruption problems. Furthermore, the insights from this study offer practitioners guidance in evaluating specific supply chain management decisions (e.g., change in sourcing strategy) in terms of their impact on the complexity of the supply chain, and in turn on the potential for disruptions in the supply chain. Third, the study represents a formal assessment of Normal Accident Theory in a supply chain context. It validates the main premise of NAT that links complex system designs to disruptions. However, in contrast to the main propositions in NAT, we found that tightly coupled supply chains might actually have some beneficial impact on aspects of supply chain disruptions.

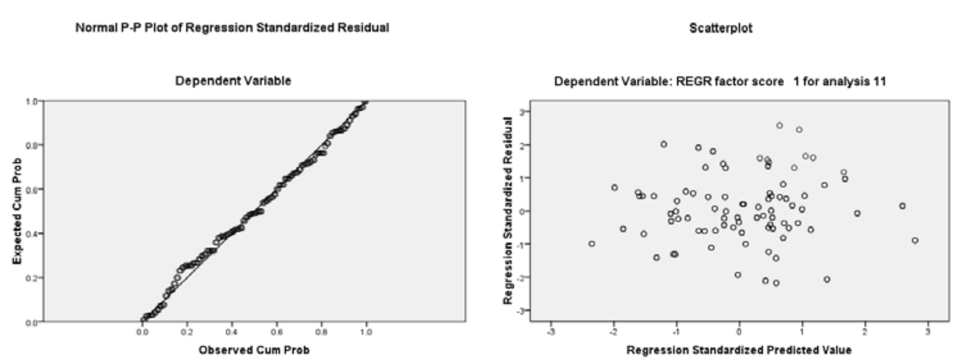
Moving forward, a few research opportunities are noteworthy. A first and logical opportunity for future research is to test and validate the four hypotheses with a longitudinal research design. Complex systems theory is dynamic by nature, and only longitudinal research can fully uncover interactions between the four complexity dimensions regarding their impact on disruptions. Research needs to evaluate the extent to which the interactions, if any, among the complexity dimensions increase or decrease the impact on disruptions. The aim of such research is to go beyond simple main effects to determine if, and to what extent, the four complexity dimensions might compensate for one another with respect to individual disruption dimensions. Such trade-offs can only be assessed by studying changes in the complexity dimensions over time, but promises to provide insights into the changing complexity landscape of supply chains and ways to better manage these transitions in the complexity structure effectively.

Appendix 3- 1: Diagnostics

The underlying assumptions of regression analysis were evaluate through several test statistics (Kutner et al., 2004; Hair et al., 1998). None of the variables showed any indication of high correlation. All variance inflation factors (VIF) are below 2 which is far below cut-off points suggested in the literature (Kutner et al., 2004 and Hair et al., 1998, suggest 10 as a cut-off, while others suggest more conservative cut-offs of 4 or 5, leading to the conclusion that multicollinearity is not a problem in our models).

The predicted Y values were plotted against the standardized residuals, which show a random scattered pattern, supporting the assumption of linearity and homoscedaticity. Furthermore, normal probability plots showed no significant deviations from normality. The Durbin-Watson coefficient, which uses the standardized residuals to assess the independence of model, is between 1.5 and 2.5, which indicates no problems. The tests indicate no violations of the underlying regression assumptions.

Figure 3- 4: PP-Normality plot and scatterplot for regression



We used several statistics to check for outliers in the model, i.e., leverage statistic, Cook's distance, Mahalabobis distance, dfFit, and DfBeta. The leverage statistic, h, is also called the hat-value. It can be used to identify cases which influence regression coefficients more than others. The leverage statistic varies from 0 (no influence on the model) to 1 (completely determines the model). A rule of thumb is that cases with leverage under 0.2 are not a problem, but if a case has leverage over 0.5, the case has undue leverage and should be examined for the possibility of measurement error or the need to model such cases separately. All the leverage values had absolute values below 0.20, indicating no influential cases according to the leverage statistic. Mahalanobis distance is another leverage value that we checked. As a rule of thumb, the maximum Mahalanobis distance should not exceed the critical chi-squared value with degrees of freedom equal to number of predictors and alpha =.001, or else outliers may be a problem in the data. For our case this value is (df=14, Chi-Square at p=.001 = 36.21). There were two values slight larger than the cut-off value. We ran the analysis with, and without the two observations. The analysis did not show any significance changes. Hence, we decided to keep the observations in the analysis.

Cook's distance measures the effect of deleting a given observation. Observations with larger D values than the rest of the data are those which have unusual influence or leverage. Fox (1991: 34) suggests as a cut-off for detecting influential cases, values of D greater than 4/(n - k - 1), where n is the number of cases and k is the number of independents. Others suggest D > 1 as the criterion to constitute a strong indication of an outlier problem, with D > 4/n the criterion to indicate a possible problem. No problems were detected. DfFit measues how much the estimate changes as a result of a particular observation being dropped from analysis. dfBeta is another statistic for assessing the influence of a case by measuring the change in b coefficients in standard errors due to adding a case to the dataset. If dfbeta > 0, the case increases the slope; if < 0, the case decreases the slope. The case may be considered an influential outlier if |dfbeta| > 2. In an alternative rule of thumb, a case may be an outlier if |dfbeta|> 2/SQRT(n).

Appendix 3- 2: Measurement Items

Please indicate **whether you agree or disagree with the following statements** about your supply base.

Detail Complexity Supply Base
(5=Strongly Agree; 1=Strongly Disagree)

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
(5=Strongly Agree; 1=Strongly Disagree)

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
(5=Strongly Agree; 1=Strongly Disagree)

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
DynC4: Our suppliers are co-located within close proximity of our production facilities
DynC5: Our suppliers are globally dispersed

Coupling
(5=Strongly Agree; 1=Strongly Disagree)

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
Coupl4:Multi-sourcing

Disruption
Origin of disruption

Refers to the initial location of the disruption in the supply chain. Disruptions in the supply base negatively affect your firm's ability to procure the required quantity of inputs.
This section contains questions related to **disruptions originating in the supply base.**

Frequency

How frequently have **disruptions (for any reason) originated** in your **supply base** during the last three months? (7-Continously; 1=Never)

How quickly were **supply base disruptions usually resolved** during the last three months? (7=Very Slow; 1=Very fast)

How much did these disruptions **affect your competitiveness** during the last three months?(5=Very significantly; 1=Not at all)

Spread of disruption

Refers to the extent to which disruptions affect other parts of the supply chain. For example, an input material shortage from the supply base may reduce your production output.

How often did disruptions originating in the supply base **spread** to your **production base** during the last three months? (7=Always; 1=Not Once)

How often did disruptions originating in the supply base **spread** to your **customer base** during the last three months? (7=Always; 1=Not Once)

Control Variables

(5=Strongly Agree; 1=Strongly Disagree)
We are in a highly competitive industry.
Our industry is highly regulated.

Approximate volume (in ‘000s) produced during the last 12 months?
(7=>5,000; 1= <500)

Approximate number of final product configurations offered to customers during last 12 months? (7=>1,000; 1=<10)

Approximate number of components/parts for most common product configuration?
(7= >1000; 1=<5)

Product line accounted for what % of total business unit’s revenue last year? (5=100%; 1=<25%)

Appendix 3- 3: Correlation Table

	Disruption	Frequency	recovery	Impact	Spread 1	Spread 2	Detail Complexity	Interdependence	Coupling	Dynamic Complexity
Disruption	***1.00***	0.76**	0.27**	0.82**	0.79**	0.87**	0.07	-0.04	0.11	0.07
Frequency	0.76**	***1.00***	0.16**	0.55**	0.59**	0.58**	0.06	-0.03	0.08	-0.11
Duration	0.27**	0.16**	***1.00***	0.35**	0.15*	0.29**	0.30**	0.11	-0.28**	-0.07
Impact	0.82**	0.55**	0.35**	***1.00***	0.60**	0.69**	0.17**	-0.08	0.04	0.06
Spread 1	0.79**	0.59**	0.15*	0.60**	***1.00***	0.54**	-0.05	-0.09	0.08	0.04
Spread 2	0.87**	0.58**	0.29**	0.69**	0.54**	***1.00***	0.05	0.00	0.13*	0.10
Detail Complexity	0.07	0.06	0.30**	0.17*	-0.05	0.05	***1.00***	0.18*	-0.22**	0.14*
Interdependence	-0.04	-0.03	0.11	-0.08	-0.09	0.00	0.18*	***1.00***	-0.05	-0.02
Coupling	0.11	0.08	-0.28**	0.04	0.08	0.13*	-0.22**	-0.05	***1.00***	0.33**
Dynamic Complexity	0.07	-0.11	-0.07	0.06	-0.04	0.10	0.14*	-0.02	0.33**	***1.00***

† p<.10; * p<.05; ** p<.01;

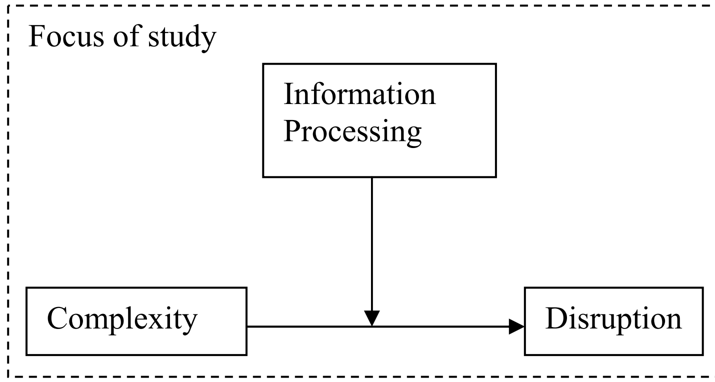
Chapter 4

Impact of Information Processing on Complexity as Antecedent of Disruptions

In the previous chapters we conceptualized supply chain disruptions as unplanned stoppages in the material flow and developed a measurement scale consisting of items assessing the frequency, impact, and spread of supply chain disruptions. Furthermore, we proposed supply chain complexity as the critical antecedent of supply chain disruptions and identified the size of the supply chain (detail complexity), the heterogeneity of the firms in the supply chain (dynamic complexity), their interdependence, and the degree of coupling as dimensions of supply chain complexity. In Chapter 3 we empirically validated the link between complexity and supply chain disruptions, creating further evidence for research regarding mitigation techniques to overcome the negative impact of complexity on the reliability of supply chains.

Chapter 4 focuses on the identification of techniques and tools that can be used to lessen the impact of complexity on supply chain disruptions. After an extensive literature review we confine our empirical analysis to the examination of information processing capabilities as a mitigating factor on the complexity/disruption relationship (see Figure 4-1). We provide the theoretical foundation for the alleviating effect of information processing based on High Reliability Theory (Roberts, 1993) and Complex Systems Theory (Kauffman, 1993). Subsequently, we identify four relevant dimensions of information processing in supply chains, and empirically examine the mitigating effect using sub-group analysis and moderated regression analysis.

Figure 4- 1: Focus of Chapter 4



Research Question Chapter 4: "What mitigates the relationship between complexity and disruptions; more specifically does information processing in the supply chain mitigate the impact of complexity on disruptions?"

4.0. Introduction

"The global business climate has changed faster in the past 10 years than it had in the preceding 1,000 years. The speed and expanse of supply chains have become too complex for mere mortals to handle." (Deloitte, 2007, p.7)

We do not share Deloitte's pessimistic outlook, but the above quote underscores the importance of investigating how supply chain managers can successfully master supply chain complexity. Recent research has highlighted the negative effect of increasing complexity on supply chain performance (Hoole, 2006; Bozarth et al., 2008), while we provide empirical evidence for the connection between supply chain complexity and supply chain disruptions (see Chapter 3). This growing evidence regarding the negative effects of supply chain complexity illustrates the need for research on effective means to counteract the negative impact of complexity on supply chains. In this chapter we identify techniques most applicable to overcome the impact of supply chain complexity on supply chain disruptions.

General disruption management approaches: Analytical approaches in the operations research literature focus predominantly on the use of inventory as a disruption mitigation technique in production/inventory models (Moinzadeh and Aggarwal, 1997; Parlar, 1997; Arreola-Risa and DeCroix, 1998). Extensions to multi-supplier models permit the consideration of sourcing mitigation in the form of re-routing order quantities between available suppliers (Parlar and Perry, 1996; Gurler and Parlar, 1997) and the inclusion of capacity flexibility between the supply sources (Tomlin, 2006). Inventory and sourcing related mitigation techniques have been labeled as buffer-oriented supply risk management tools (Zsidisin and Elram, 2003). Buffer-oriented mitigation techniques are frequently represented in the conceptual and empirical literature on supply chain disruptions. In addition to buffer-oriented options, the literature proposes strategic approaches toward disruption mitigation, such as collaboration, postponement, modularization, responsiveness, flexibility, and quality management approaches etc. (see Table 4-1). Classification approaches attempted to better structure the growing laundry list of mitigation techniques. Juettner et al. (2003) categorize the mitigation techniques based on Miller's (1992) work into avoidance, control, co-operation, and flexibility strategies. The avoidance technique refers to dropping specific products, suppliers, markets, or geographic areas if the disruptions risk levels are considered unacceptable by the focal firm. Alternatively, firms may seek to control the contingencies that lead to disruption

Table 4- 1: Mitigation techniques in disruption related literature

Author	Type of Study	Mitigation techniques	Complex Reduct..	Complex Mgmt
Blackhurst et al., 2005	E	• Visibility through real time information sharing • Capacity • Reconfiguration	X	X
Chopra and Sodhi, 2004	C	• Capacity • Inventory • More suppliers • Responsiveness • Flexibility • Demand pooling • Capability • More customer accounts	X	X
Christopher and Lee 2004	C	• Visibility • Control • Both increase confidence		X
Craighead et al., 2007	E	• Coordination of resources • Detect and disseminate pertinent information		X
Hendricks and Singhal, 2009	E	• Organizational Slack • Vertical relatedness	X	X
Jonsson, 2000	E	• Preventive Maintenance		X
Kleindorfer and Saad, 2005	E	• Diversification • Slack, backup, redundancy • Modularity of process and product designs • TQM principles • collaboration	X	X
Smyrilis, 2006	C	• Visibility • Collaboration		X
Stauffer, 2003	C	• Slack • Collaboration	X	X
Tang, 2007	C	• Postponement • Strategic Stock • Flexible supply base • Make vs. buy decisions • Economic supply initiatives • Flexible transportation • Revenue Management • Silent production • Assortment plan	X	X

E=Empirical Paper; C=Conceptual Paper

risk through vertical integration, stockpiling, buffer inventory and capacity, or finally, contractual requirements for suppliers. Co-operation aims to increase supply chain visibility and understanding through the sharing of information. Flexibility in this context includes postponement strategies and multi-sourcing strategies.

Complexity related management approaches: We conceptualize supply chains as complex systems in this study, which directly influences the choice of mitigation techniques. We propose that the mitigation techniques should be structured regarding their ability to reduce complexity or manage complexity. An avoidance strategy is frequently not a suitable option for firms because supply chain complexity is driven by market pressures which lead to necessary supply chain design changes (out-sourcing, off-shoring, product variety, geographic spread of markets, etc) in an effort to remain competitive. Thus, the avoidance of complexity is not an attractive option for firms in competitive environments.

Complexity reduction: Several mitigation techniques reduce complexity directly and change the design structure of the supply chain. Inventory and other buffer strategies, combined in the "control category" by Juettner et al. (2003), directly change the extent of coupling in the supply chain, thereby changing the complexity of the supply chain. Similarly, multi-sourcing reduce the interdependence of supply chain partners. Hence, these techniques represent simplifications of the supply chain, and system simplifications inherently reduce the system complexity (Perrow, 1999). As such, these mitigation techniques simply represent the reverse effect of the antecedents studied in Chapter 3. Hence, the focus needs to be on "true" mitigation techniques that leave the complexity structure of the supply chain unchanged. If supply chain complexity is necessary to operate in a specific competitive environment, the organization needs to adapt its supply chain strategy to the complex structure of its supply chain – the firm needs to find a fit between supply chain complexity and its supply chain management capabilities.

Complexity management: The co-operation category in Juettner et al. (2003) classification method received much attention in the conceptual literature. The techniques in the category leave supply chain complexity unchanged and represent supply chain relevant management capabilities that overcome the downsides of complexity. Blackhurst et al. (2005) emphasize that every executive interviewed during their study stressed visibility as a key issue relative to dealing with disruptions.

In the context of their study visibility is achieved through the sharing of correct information from every node in the supply chain, which according to the authors maximizes responsiveness to avoid and mitigate disruptions. Christopher and Lee (2004) also point to the value of shared information among supply chain members to improve supply chain visibility, as the supply chain becomes more responsive and performs significantly better than supply chains that do not exchange information (Mason Jones and Towill, 1997, 1998). Craighead et al. (2008) point to the coordination of resources and dissemination of pertinent information through the supply chain as the critical capabilities to recover and prevent disruptions. Kleindorfer and Saad (2005) emphasize that collaborative sharing of information is essential in identifying vulnerabilities and in preparing and executing effective crisis management.

The presented research has used multiple terms such as visibility, information sharing, coordination, and collaboration, which all refer to an organization's ability to process information. Although the primary role of firms in supply chains is usually the processing of materials, information processing is critical to their success (Bowersox et al. 1999). Information processing in the context of this study refers to the ability of the focal firm to effectively manage information flows, which includes the acquisition, distribution, and interpretation of information (Huber, 1991, Hult et al., 2004). In this chapter we empirically examine the effectiveness of information processing as a mitigation technique for the relationship between complexity and disruptions. The remainder of the chapter begins with a detailed review on the theoretical perspective regarding the management of complex systems, the identification of the relevant information processing dimensions for supply chains, and ends with an empirical examination of the proposed mitigation technique.

4.1. Managing Complexity

4.1.1. Maneuvering Complex Landscapes

The following discussion about the importance of information processing in complex supply chains is based on two related literature streams: complex systems theory (CST) and high reliability theory (HRT). CST suggests that organizations as complex systems adapt by changing organizational attributes to avoid mismatches between their strategic choices and the complex landscapes they navigate (Levinthal, 1997). At the highest level of analysis the self-adaptation of the system occurs through the emergence of new, appropriate system configurations. The emergence, or evolution, of system designs is primarily based on insights gained from research in biological systems (Kauffman, 1993) and not well suited for research in non-biological fields. As a consequence, organizational researchers have investigated the mechanisms, or enablers, of such emergence to better understand the principles and processes that are guiding the evolution of the systems. A social system does not automatically evolve as a result of external demands like a biological system might, because it consists of decision makers, rules, and processes, etc. that guide the emergence of the system.

Organizational literature on complex systems identifies local or incremental search, and global or radical search as adaptation mechanisms in complex systems. Local search aims at identifying better organizational solutions in the immediate neighborhood of the existing organizational configuration (March and Simon, 1958; Cyert and March, 1963). A better organizational configuration is defined by changes in organizational attributes that lead to higher fitness (performance) levels, which in the context of this study indicate decreased disruption levels (see Chapter 3 for more detail). In general, organizations are assumed to be able to identify these alternative organizational forms in their direct neighborhood and to modify their organizational configuration accordingly (Levinthal and Warglien, 1999). This allows a firm to "walk" (Levinthal and Warglien, 1999) over the rugged landscapes of alternative organizational configurations toward a configuration with better performance than the organization's starting point (Kauffman and Levin, 1987; Smith 1970). This local adaptation is very successful in modestly complex systems and allows organizations to find local fitness peaks.

However, in a highly complex system, with very rugged landscapes, the local search and incremental adaptation are not as effective (Siggelkow, 2001). In such cases, the organization becomes stuck on local peaks and is not able to identify superior, global peaks within the landscape (McKelvey, 1999). Only through radical adaptation is the organization able to achieve significant performance improvement. Research on organizational change has identified processes to find alternatives that are far removed from the current position (March and Simon, 1958; Nelson and Winter, 1982). To achieve such a radical change the organization must be willing to overcome its behavioral "blind spots" (Zajac and Bazerman, 1991) and integrate new perspectives.

Organizations that are able to manage complex landscapes successfully must be able to incrementally and radically adapt within their complexity landscapes. The aim is to further understand how organizations are able to search the landscapes for optimal solutions. The organization's search activities are tightly linked to its ability to manage information flows. Systems research has identified information flows as the most critical attribute connecting system elements (Sage, 1981) and further studies have examined the positive impact of information management on a firm's ability to navigate complex landscapes (Loch et al., 2008; Sommer and Loch, 2004). The ability to manage information flows effectively allows the firm to better evaluate the options available in the rugged landscape, and consequently improves its search activities. It is critical to constantly screen for new information (Isenberg, 1984), to recognize even unexpected information sources (Weick and Sutcliffe, 2001), and to actively gather information to make better adjustments (Miller and Lessard, 2000; Thomke, 1998).

Information processing capabilities as the key characteristic of firms that are able to better navigate complex landscapes and identify "fitting" configurations are reflected in HRT (High Reliability Theory) which explains how some organizations operate reliably as complex systems. HRT focuses on organizational strategies with which organizations have achieved outstanding system reliability (Roberts, 1993). These organizations operate complex systems in a highly reliable way because they are able to identify and adjust to optimal configurations. We use HRT to better understand the characteristics and mechanisms of organizations that are able to successfully maneuver rugged landscapes through local and radical adaptation.

The HRT literature identifies information processing as a critical organizational attribute that increases the reliability of complex organizations (Roberts, 1990; Roberts and Bea, 2001; Bain, 1999; Rijpma, 1997 Weick and Sutcliffe, 2001). A resilient organization has an "informed culture" in which system managers and operators have current knowledge about the human, technical, organizational, and environmental factors that determine the reliability of the system as a whole (Reason, 1997; Weick and Sutcliffe, 2001).

"If timely, candid information generated by knowledgeable people is available and disseminated, and informed culture becomes a learning culture" (Weick and Sutcliffe, 2001)

Complexity necessitates that organizational information processing increase system knowledge and decreases the chance for surprises (Rijpma, 1997). Decision makers in the system become more familiar and better understand the complex supply chain (Rochlin, LaPorte, and Roberts, 1987), which is the real leverage in most management situations (Senge, 1990).

This leads to the formulations of our first hypothesis for this study. While NAT (Normal Accident Theory) states that disruptions are inevitable in complex systems, HRT takes a contingent approach. HRT acknowledges that complexity is a possible antecedent for supply chain disruptions, but in contrast to NAT, HRT does not consider these disruptions inevitable. In organizations with high information processing capabilities the link between complexity and disruptions is small, or even non-existent.

> *H5: Information processing capabilities moderate the relationship between complexity and disruptions.*

4.2. Managing of Information Flows in Supply Chains

After identifying the critical importance of information processing in complex systems, we focus on the relevant aspects of information processing in supply chains. The effective management of information flows in supply chains improves the effectiveness of most supply chain initiatives (Chen and Chen, 1997; Lummus and Vokurka, 1999; Lee and Whang, 2000). Huber (1991) states that information processing mainly involves the acquisition and distribution of information which is reflected in Hult et al.'s (2004) integrated model of information processing in supply chains. Based on the insights from their work we identify three main aspects regarding supply chain information processing capabilities that are of interest for this study: first, the exchange of information which represents information acquisition and distribution between supply chain partners (Monczka et al., 1998; Mohr and Spekman, 1994); second, the extent of collaboration between supply chain partners as this directly relates to the amount and quality of exchanged information (Spekman et al., 1998, Moberg et al., 2002, Whipple et al., 2002); third, knowledge and experience regarding the supply chain, which drives information acquisition and distribution processes and enables decision makers to direct information to where it is most needed (Huber, 1991; Hult et al., 2004). We propose that informed supply chains differ regarding these three aspects from other supply chains. The resulting information processing capabilities of the supply chain make it more adaptable, and better able to handle complexity. In the following paragraphs we expand on these three aspects of information processing.

4.2.1. Information Exchange

The exchange of information refers to the extent to which critical and proprietary information are communicated throughout the supply chain and the quality of the exchanged information (Monczka et al., 1998; Mohr and Spekman, 1994)[5] and is often considered as a generic cure for supply chain ailments (Forrester, 1968; Lee et al., 1997). Information sharing has been advocated to reduce supply and demand uncertainties in supply chains by increasing information visibility for all supply chain partners (Lee and Whang,. 2000; Fisher, 1997; Sahin and Robinson, 2002). Having high information visibility is a key capability for any firm within a supply chain. With high visibility, many of the problems within a supply chain, such as the 'Bullwhip' effect, can be alleviated (Lee et al., 1997; Dejonckheere et al., 2004). High visibility is achievable

[5] We consider the amount and quality of the exchanged information as relevant for this construct. The amount captures the type and extent of information exchanged between the partners, while information quality assesses the accuracy, timeliness, etc. of the exchanged information.

through extensive sharing of useful and meaningful information amongst different players within the supply chain. We argue that the increased visibility of supply chains also allows for better adaptability in cases of high supply chain complexity.

Many studies have argued that information sharing leads to better coordination of physical movements within the supply chain (Clark and Scarf, 1960, Collier, 1982, Gao and Robinson, 1994, Gustin et al., 1995; Closs et al., 1997), better coordination of decision making (Whang, 1995), better price coordination (Jeuland and Shugan, 1983; Corbett and Tang, 1999), and optimal inventory holding polices (Gavirneni et al., 1999) including vendor-managed inventory approaches (Clark and Hammond, 1997; Waller et al., 1999; Yu et al., 2000). Generally, theses studies highlight the fundamental need for information sharing to gain visibility if supply chains are to improve their performance. In addition to increased visibility, information sharing has also been seen as critical for the establishment of collaborative linkages within the supply chain.

4.2.2. Collaboration of Supply Chain Partners

A number of authors suggest that close collaborative linkages enabled through information sharing are critical for the effective management of supply chains (Spekman et al., 1998, Moberg et al., 2002, Whipple et al., 2002). Mishra and Shah (2008) reviewed the body of literature on collaboration in organization theory, strategy, and operations management and conclude that collaboration is frequently used interchangeably with integration (Gulati et al., 2005; Frohlich and Westbrook, 2001; Van de Ven and Delbecq, 1976). The main premise behind all these terms is the idea that organizations in the supply chain need to ultimately be managed as one entity or one system. Research has shown that the integration and collaborations in the supply chain leads to superior performance (Anderson and Katz, 1998; Hines et al., 1998; Johnson, 1999; Frohlich and Westbrook, 2001), while problems of non-collaboration have also been documented (Lee and Billington, 1993; Hammel and Kopczak, 1993).

Research on supplier integration indicates that it improves supplier reliability (Carr and Pearson, 1999) and communication (Freeland, 1991). A number of authors have also suggested the benefits that arise from visibility that are of interest to disruption avoidance, including: (1) improved responsiveness (Armistead and Mapes, 1993, Berry et al., 1994; Patterson et al., 2004); (2) improved planning and replenishment capabilities (Armistead and Mapes, 1993, Karkkainen, 2003; Mentzer et al., 2001); (3) improved decision making (Kent and Mentzer, 2003); and (4) improved quality of products (Armistead and Mapes, 1993).

4.2.3. Knowledge and Experience Regarding Supply Chain

The insight on supply chain knowledge is built on conclusions drawn by Huber (1991) about organizational learning, adapted for the supply chain context by Hult et al. (2004). Supply chains that possess significant knowledge and experience are aware that knowledge coordination across nodes reduces duplication, waste, and redundancy (Handfield and Nichols, 1999). The more knowledge chain members possess, the greater their awareness that additional knowledge can ultimately enhance outcomes. Indeed, Bowersox et al. (1999) found that supply chains that use benchmarking have more accumulated knowledge than others and also have stronger beliefs that they need additional knowledge throughout their systems. Furthermore, knowledge and experience helps supply chains indentify where a certain piece of information will be likely to have a positive impact on outcomes and so determines which entities will receive the information (Huber, 1991). In supply chains, the presence of more experience encourages *more* information distribution. Specifically, a strategic supply chain is formed in an effort to create a rare, valuable, and inimitable source of knowledge and coordination (Grant, 1996). Supply chains require continuous information distribution in order to maintain strategic, operational, and technological integration (Hult, 2004). Previous retained learning, such as lessons from success and failure experiences, makes clear the need for information to be circulated (Bowersox et al., 1999). Thus, chains with more experience regarding information processing distribute information more effectively than those with less experience, which is invaluable when it comes to disruption prevention.

Information exchange, collaboration, and the knowledge/experience in the supply chain are aspects of the system's information processing abilities. Information exchange provides organizations with critical information that enhances their visibility of potential supply chain problems. Collaboration is an extension of information sharing. Without the most basic level of collaboration supply chain partners would not exchange information and vice versa.

Hence, information exchange and collaboration go hand in hand, and reciprocally increase information processing in the supply chain. The extent of the collaborative relationship also influences the type of information exchanged. The closer the relationship between the partners the more detailed and critical information will be exchanged.

Through the exchange of relevant information and collaboration, firms become knowledgeable and experienced regarding their supply chain. This increases their ability to identify and disseminate critical information more quickly and accurately.

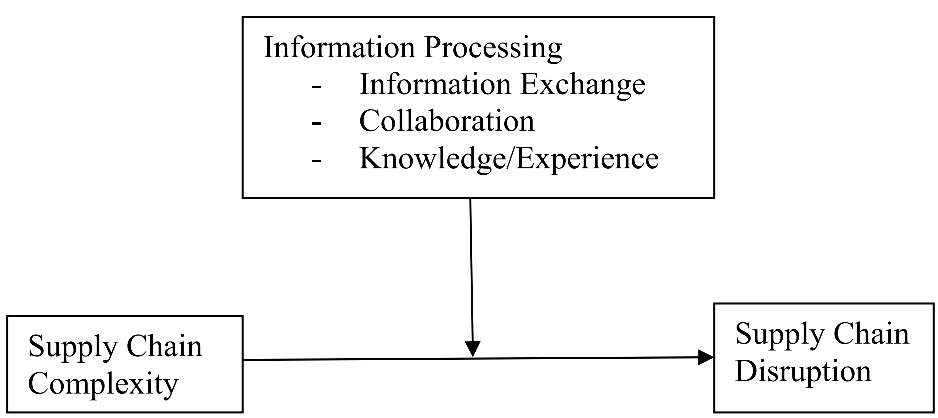
In summary, information capabilities within a supply chain are captured through information exchange, collaboration and knowledge/experience. These capabilities enable the firm to better navigate the complexity landscapes of the supply chain and identify suitable configurations. As a result, a supply chain with high levels of information capabilities should encounter lower disruption levels (see Figure 4-2).

H6: Information exchange (amount and quality) moderates the impact of complexity on disruptions.

H7: Collaboration moderates the impact of complexity on disruptions.

H8: Knowledge/Experience moderates the impact of complexity on disruptions.

Figure 4- 2: Conceptual Model



4.3. Measurement Design

The data analysis for this chapter is based on the same data set used for the previous chapters. For a more detailed description of the data collection effort the reader is referred to chapters 2 and 3.

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 EFA techniques.

The main data collection was conducted during a six week period over the summer of 2008. The respondents belonged to APICS (Advancing Productivity, Innovation, and Competitive Success) and SCL (Supply Chain and Logistics Association), and the contact lists for the survey were composed of individuals that matched three criteria: 1) respondent worked for manufacturing firm, 2) respondent had high- or mid-level position within organizations, 3) respondent was exposed to supply chain related activities in the organizations.

The data collection with APICS members totaled 151 responses, resulting in a response rate of 7.6%. A usable data set with 140 responses was the result of the data cleaning during which eleven responses with substantial missing values were eliminated. The SCL data collection had a response rate of 1.5-2%, or 62 responses. An exact response rate could not be estimated as the organization only provided a “guesstimate” of the current status of their email list. Thirteen responses were missing substantial data, therefore only 49 responses were used in the analysis. The response rates are similar to results achieved by comparable large scale studies in operations management, i.e., Nahm et al. (2003) reported a response rate of 7.47%, Li et al. (2005) of 6.3%, and Poppo and Zenger (1998) of around 5%.

No significant differences between the two samples were detected using t-tests across critical measurement items, warranting a combination of the two samples for the remaining data analysis. The data set exhibits a slight coverage bias toward certain industries in comparison with Census data (see Chapter 1). Further examination of the data set found no significant non-response bias or common method bias (see Chapter 1 for more detail on the tests).

4.3.1. Dependent and Independent Variables

We measure disruption frequency, impact, and spread. Each of the disruption items uses a seven-point Likert type scale. The complexity construct was assessed with multi-items scales for the four identified sub-dimensions: detail complexity, dynamic complexity, interdependence and coupling. The number of elements in the supply base is an indicator of its detail complexity. The measures for dynamic complexity capture the differences between the elements in the supply chain. The main indicators of dynamic complexity are differences regarding technical capabilities, operational techniques, and organizational culture, as conceptually outlined by Choi and Krause (2006). Coupling was measured using measurement items for safety stock, safety lead times, and capacity. The firm's inability to replace a partner has been considered an indication of a firm's dependence on its partners (Heide and John, 1988) and has frequently been used to assess the dependence relationships empirically (Buchanan, 1992: Heide, 1994; Heide and John, 1988; Kumar et al., 1995). Five-point Likert scales were used for all complexity measurement items.

4.3.3. Moderating Variables

Information processing capabilities are assessed using four dimensions: information amount, information quality, collaboration, and knowledge/experience. Information amount and information quality represent the assessment of the information exchange construct.

The information amount measures the extent to which critical information is communicated with suppliers. The extent of the information exchange increases the visibility throughout the supply chain. The information amount is measured using five items with a 5-point Likert scale. The questions ask the respondents to assess the extent to which information is exchanged within the supply chain, e.g., *"Please indicate to what extent sales forecasts are being shared in the supply chain."* (see Appendix 4-1).

Information quality is a key aspect of information exchange (Jablin et al., 1987) and measures the degree to which the information exchanged between entities meets the general needs of the organization (Petersen, 1999). Accuracy, timeliness, and reliability are three well established dimensions of information quality in the literature (Neumann and Segev, 1979; Mendelson and Pillai, 1998; McCormack, 1998; Petersen, 1999; Zhou and Benton, 2007). The three dimensions of information quality are assessed with 5-point

Likert scales, e.g., *"Please indicate whether you agree or disagree with the following statements about the information that is being exchanged between the focal firm and its suppliers. The information exchanged is accurate."*

Collaboration is an assessment of the relationships among the firms in the supply chain. Close relationships and collaborative linkages are critical for the effective management of supply chains and further improve the communication throughout the supply chain (Freeland, 1991). Collaboration is assessed using 5-point Likert scales and the questions assess the extent of collaboration within the organization, e.g., *"We consider our suppliers as partners."*

Supply chains with knowledge and experience are better at coordinating the information flows throughout the supply chain (Handfield and Nichols, 1999). The construct is directly adapted from the literature (Hult et al., 2004; Huber, 1991). The construct is measured using established 5-point Likert scales from Hult et al. (2004), e.g., *"We have a great deal of knowledge about the supply chain."*

4.3.4. Control Variables

Complex systems are hierarchical by nature (Kauffman, 1993). Complexities at the supply chain level are related to complexities at lower and higher system levels, which need to be controlled for in this study (see section 3.4.3 for a more detailed discussion of the control variables). The lower levels of the system are represented by controls for the firm, the manufacturing process, and the product. The firm is controlled for by the use of a revenue scale which captures its size. The process is controlled for according to it type, i.e., mass-production, batch, job-shop, etc. The product controls include the number of components and configurations for the specific product. The higher system levels are represented by the industry and we control for its competitiveness and degree of regulation (see Appendix 4-1 for items).

4.4. Measure Assessment

4.4.1. Exploratory Factor Analysis

We use the same split sample data set developed in the previous chapters with a calibration (n=95) and validation (n=94) set. An exploratory factor analysis using principle components extraction and a varimax rotation was used to empirically explore the four underlying information processing dimensions. The rotation was performed to improve the interpretability of the underlying factor structure.

Table 4- 2: EFA for information processing

	1	2	3	4
Info Amount 1	**.795**	.004	.088	.012
Info Amount 2	**.816**	-.084	.051	.127
Info Amount 3	**.798**	.249	.091	.024
Info Amount 4	**.648**	.206	.021	.057
Info Qual 1	.160	**.875**	.243	.189
Info Qual 2	.123	**.891**	.257	.009
Collab. 1	.221	.244	**.697**	.068
Collab. 2	-.116	.079	**.832**	.097
Collab. 3	.068	.151	**.879**	.174
Collab. 4	.163	.166	**.816**	.245
Knowledge 1	.069	.100	.148	**.945**
Knowledge 2	.059	.026	.190	**.940**
Knowledge 3	.086	.085	.153	**.924**

The exploratory factor analysis must be evaluated for significant cross-loadings of items, low extracted communalities, number of extracted factors, and variance explained. Eigenvalues exceeding a value of one were used as a selection criterion, as they are generally considered significant (Hair et al.,. 1998). The analysis resulted in the empirical validation of the four underlying factors for information processing, which matches our theoretically derived dimensions to capture information processing in supply chains. Items were inspected regarding significant loadings, with loadings greater than .60 representing practical significance considering the sample size of the split data set (Hair et al., 1998 – page 112). Furthermore, the communalities are assessed to examine the variance extracted for each variable. In the process of the EFA procedure we eliminated three variables that showed significant cross-loadings, and/or insufficient extracted variance, or did not match our theoretically developed framework.

4.4.2. Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was used to assess the overall fit of the measurement model for the information processing construct. CFA evaluates a measurement model in which the observed variables are linked to their constructs. The measurement model's structure reflects the insights gained in the EFA. The CFA was conducted using the validation sample using AMOS 16 utilizing the Maximum Likelihood method.

The literature recommends reporting a variety of fit indices (Shah and Goldstein, 2005) to assess the overall fit of the measurement model from different perspectives. The absolute, incremental, and parsimonious fit indices provide different insights into how well the model matches the observed data (Hu and Bentler, 1995). The fit measures for the information processing construct match the respective cut-off points indicating acceptable fit. The fit measures for the complexity measures are all very close to the cut off points (close to 0.90), while the others match their criteria. This indicates an overall good fit of the information processing scales (see Table 4-3).

In addition to examining the fit statistics, we also examined the standardized residuals, as small residuals are indicative of good fit. It is recommended that no more than 10% of the absolute values of the standardized residuals are greater than 2.5 (Hu and Bentler, 1995). None of the residuals exceeds the value of 2.5 for the information processing scales, which is indicative of a good fit (the largest residual is 2.32). Furthermore, all the factor loadings are greater than 0.50 ($p<0.01$) and all modification indices are below 10 (Shah and Ward, 2007).

Table 4- 3: CFA for information processing

Statistic	Information	Recommended Cut off values
χ^2	112.778	NA
Df	59	NA
P-Value	0.000	NA
χ^2 /DF	1.911	≤3.0
GFI	0.918	≥.90
CFI	0.96	≥.90
IFI	0.96	≥.90
RMR	0.042	≤.10
RMSEA	0.07	≤.10

Construct validity is the assessment of the degree to which a scale measures the intended construct. The convergence and divergence of the scale items is a way to assess and establish construct validity. A within factor analysis is used to show that all measurement items load on one common factor to establish convergent validity. Eigenvalues in excess of 1.00 and factor loadings above .40 are considered acceptable evidence of convergent validity through factor analysis (Hair et al., 1998).

4.4.3. Convergent Validity

Anderson and Gerbing (1988) propose that significant item loadings on the respective constructs are evidence for convergent validity. The loadings of the items for the information processing scales range from 0.542 to 0.958 and all are significant at the .001 level (see Table 4-4). The variance explained by each variable ranges from 0.294 to .917 with average amount of variance explained exceeding 0.50 overall. The loadings of the items on the factors and the variance explained (R-square) can be seen in the Table 4-4.

4.4.4. Discriminant Validity

Discriminant validity was assessed with a three-step procedure: 1) a model with two constructs and their respective measurement items is run in CFA where the covariance between the constructs is fixed to one; 2) a second model is run with the same two constructs and measurement items, but this time the covariance between the

Table 4- 4: Loadings for information processing

	Loadings	R-square
Information Amount 1	0.686	0.470
Information Amount 2	0.716	0.512
Information Amount 3	0.809	0.654
Information Amount 4	0.542	0.294
Collaboration 1	0.854	0.729
Collaboration 2	0.903	0.815
Collaboration 3	0.708	0.494
Collaboration 4	0.674	0.454
Information Quality 1	0.828	0.685
Information Quality 2	0.942	0.887
Knowledge 1	0.958	0.917
Knowledge 2	0.937	0.877
Knowledge 3	0.908	0.824

constructs is free to vary; 3) χ^2 differences between the two models is tested. Constraining the covariance between the two constructs is equivalent to assuming they are the same construct, and not unique. A significant difference between the models indicates that the constructs and their measures are unique and necessary to explain the data structure (Bagozzi and Phillips, 1982; Bagozzi et al., 1991).

The proposed information processing measures are divided into four unique constructs, which requires six pair-wise comparisons. The results in Table 4-5 show that in all pair-wise tests the free model fits the data structure better than the fixed model at the .001 level – indicating strong evidence for discriminant validity of the constructs.

Table 4- 5: Discriminant validity for information processing

Pairs		Free	Fixed	Diff	P-Value
Info Amount	Info Qual	10.399	63.3	52.9	0.001
	Collab	29.2	83.0	53.8	0.001
	Knowledge	21.9	87.9	66.0	0.001
Info Qual	Collab	11.5	45.4	33.9	0.001
	Knowledge	13.8	70.7	56.9	0.001
Collab	Knowledge	32.6	78.9	46.3	0.001

4.4.5. Unidimensionality

Unidimensionality is a necessary condition to establish reliability and validity. Unidimensional items only capture one construct, and do not exhibit significant cross-loadings onto other constructs. Unidimensionality can be concluded if the overall fit of the measurement model during the CFA is satisfactory. Another approach for checking unidimensionality has been proposed by Joreskog and Sorbom (1989), which requires the construction of a measurement model for each individual construct. A goodness of fit index (GFI) of 0.90 or higher for such a single constructs model indicates appropriate confidence in the unidimensionality of the constructs. The GFI indices for all the constructs are above 0.90, indicating that there no problems with unidimensionality are present in the study (The GFI for InfoQual cannot be calculated as the scale only consists of two measurement items).

Table 4- 6: Unidimensionality test for information processing

Construct	GFI
Info Amount	0.993
Info Qual	na
Collab	0.986
Knowledge	0.962

4.4.6. Reliability

Cronbach's alpha is calculated for each information processing construct. Scales are considered internally consistent with a Cronbach's value exceeding 0.60, which is the cut-off point for newly developed scales (Nunnally, 1978), while 0.70 is a more conservative value for established scales (Hair et al., 1998). All of the complexity and disruption constructs exhibit values for Cronbach's alpha exceeding the conservative value, load on a single factor, and explain above 50% of the variance. An alternative method for measuring the reliability of measurement scales is composite reliability (Escrig-Tena and Bou-Llusar, 2005). The value for the composite reliability for all dimensions exceeds the 0.70 threshold.

Furthermore, we calculated the average variance extracted (AVE) (Fornell and Larcker, 1981). The AVE is exceeds the threshold value of 0.50 for all dimensions, except information amount (0.483), which does not constitute a major violation and we retain all four dimensions. All measures indicate good construct reliability. The reliability evaluation is conducted at this point, because the validity and unidimensionality of the constructs is a necessary condition for the establishment of construct reliability (Koufteros, 1999).

Table 4- 7: Reliability for information processing

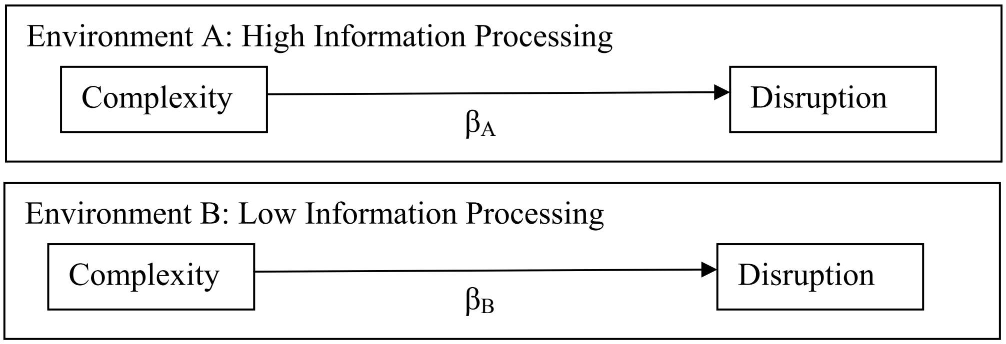
	Cronbach's Alpha	Composite Reliability	AVE
Information Amount	0.783	0.785	0.483
Information Quality	0.875	0.880	0.786
Collaboration	0.860	0.867	0.625
Knowledge	0.954	0.953	0.873

4.5. Data Analysis

Regression analysis is used to test the research hypotheses. In general, the mitigation effect of information processing capabilities has the form of a strategic fit between the antecedent and the mitigation technique. An appropriate fit leads to better performance outcome (in our case lower disruption levels), while misfits lead to worse performance outcomes. The test of the fit between the antecedent and mitigation technique can take several different versions (Venkatraman, 1989).

The literature distinguishes between moderation of "strength" or "form" of a relationship (Venkatraman, 1989). The moderation of strength states that the relationship between the antecedent and the dependent variable varies depending on the environment in which the relationship is examined. This approach is ideal for examining the first hypothesis developed for this paper, whether the relationship between complexity and disruptions differs for firms with high information processing capabilities and firms with low information processing capabilities.

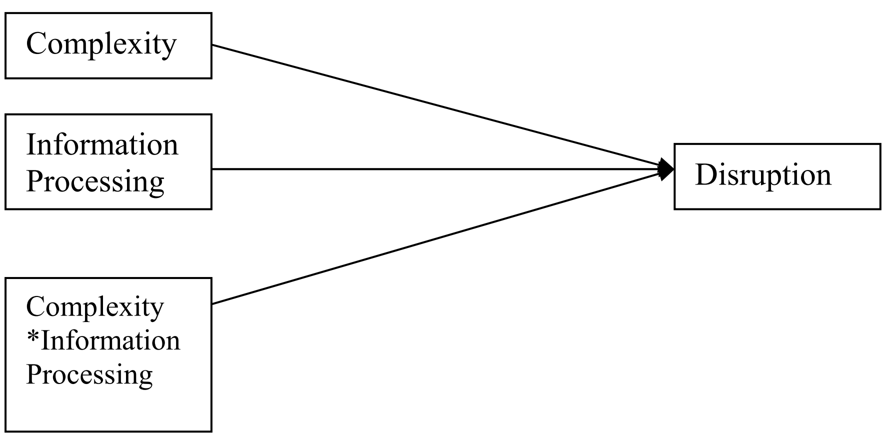
Figure 4- 3: Moderation of "strength"



$\beta_A < \beta_B$

The form moderation can be tested using interaction terms. The form moderation states that the predictor and moderator variables together affect the outcome. This interaction is tested using multiplicative terms of the two variables in the analysis. The form moderation set up can be seen in Figure 4-3.

Figure 4- 4: Moderation of "form"



4.5.1. Sub-group Analysis to Test HRT in Supply Chain

The hypothesized relationships in the conceptual framework represent an equation wherein the complexity dimensions are the predictor variables and disruptions constitute the response variable. We test whether the relationship between complexity and disruptions differs between firms with high and low information processing capabilities. The average score of the four information dimensions is used to estimate the overall information processing capabilities. The respondents are separated into two groups – one consisting of the top third on the information construct, and the second group consisting of the bottom third of respondents (Note: middle third not used). Using the top and bottom thirds of respondents ensures that the differences between the groups are emphasized (Boyer et al., 1997). A hierarchical regression model using ordinary least squares (OLS) procedure is being used to test the proposed hypotheses. The regression model can be formulated as follows:

Figure 4- 5: Regression function for sub-group analysis

$$\left.\begin{array}{l} Disruption = \end{array}\right\}\text{Dependent Variable}$$

$$\left.\begin{array}{l} \beta_0 + \beta_1 * Dummy + \beta_2 * Comp. + \beta_3 * Regul. + \beta_4 * Vol. \\ + \beta_5 * Prod + \beta_6 * Config. + \beta_7 * Compon. + \beta_8 * Reve. \\ + \beta_9 * Empl. + \beta_{10} * Process \end{array}\right\}\text{Control Variables}$$

$$\left. + \beta_{11} * DetailC. + \beta_{12} * DynamC. + \beta_{13} * Interdep. + \beta_{14} * Coupl \right\}\text{Predictor Variables}$$

The model is used to test for any positive main effect of the complexity dimensions on disruptions. This is equivalent to testing whether the coefficients for the main effects are significantly different from zero and positive. The results for the OLS regression analysis for the high and low information processing firms can be found in Table 4-8.

Table 4- 8: Results sub-group analysis

	Info. Proc. Capabilities	
	High	Low
Dummy Country	-.262	.471
Competitiveness	-.121	.101
Regulation	.176	.306*
Volume	-.284†	-.030
Product Configuration	.307	-.022
Components	.352*	.044
Employee	-.166	.749*
Process	-.250*	.343**
Detail Complexity	.021	.584**
Dynamic Complexity	.150	.531**
Interdependence	.016	.353*
Coupling	.076	.493**
R-Square Adjusted	.153	.374
R-Square Change	.013	.227**

† $p<.10$; * $p<.05$; ** $p<.01$;

It is evident that the coefficients for the complexity dimensions in the high information group are much smaller than in the low information group. Furthermore, all complexity coefficients are significant at the $p<0.01$ and $p<.05$ in the low information group, while no complexity coefficient is significant in the high information group. The change in R-square for the addition of the complexity variables is insignificant in the high information group and significant at the $p<0.01$ level for the low information group.

The Chow test was used to assess whether coefficients in the respective sub-groups are significantly different (Chow, 1960). This test is a formal assessment of the differences between the coefficients in the sub-groups and has been routinely used to analyze sub-group moderation results for significant differences (Das and Joshi, 2007; Das and Jayaram, 2003; Fynes and Voss, 2002; Hambrick and Lei, 1985).

$$F = \frac{((RSS_c - (RSS_1 + RSS_2))/k}{(RSS_1 + RSS_2)/n - 2k}$$

In the above formula c indicates the complete model consisting of the two sub-groups, and the sub-groups are noted by a subscript 1 or 2. The sample size is denoted by n, and k represents the number of variables in the model. This F-statistic has (k, n-2k) degrees of freedom and uses the residual sum of squares (RSS) to assess the difference between the coefficients. Filling in the numbers we obtain the following formula:

$$F = \frac{(116.4 - (26.068 + 61.7))/12}{(26.068 + 61.7)/128 - 2 * 12} = 2.745$$

Comparing the result to the value in the corresponding F-table indicates that F>F* at the 0.01 confidence level, which indicates that we can reject the null hypothesis, that is, we reject the hypothesis that the parameters are constant across the sub-groups. Based on the sub-group test we can deduct that all complexity dimensions have a significant impact on disruptions in the low information environment, while its impact in a high information environment is insignificant. This provides evidence for the applicability of HRT in the supply chain setting.

4.5.2. Interaction Test of Individual Dimensions

After the sub-group analysis to test the strength moderation we proceed to test the form moderation (Venkatraman, 1989) using interaction terms and MMR (multiple moderated regression). The procedure used to test moderating effects of complexity and the information processing dimensions is a hierarchical regression analysis (Cohen and Cohen, 1975; Miller and Droge, 1986; Stone and Hollenbeck, 1989; Dean and Snell, 1991; Boyer et al., 1997). This approach allows for an analysis of groups of variables in an incremental manner. The analysis is conducted stepwise – 1) the control variables are entered, 2) the main complexity dimensions are entered. 3) the moderating variable OverallInfo is entered, and 4) the interaction terms are entered. The regression model can be seen in Figure 4-6.

Figure 4- 6: Interaction regression model

$$
\begin{array}{l}
\left.\begin{array}{l} Disruption = \end{array}\right\} \text{Dependent Variable} \\[6pt]
\left.\begin{array}{l} \beta_0 + \beta_1 * Dummy + \beta_2 * Comp. + \beta_3 * Regul. + \beta_4 * Vol. \\ + \beta_5 * Prod + \beta_6 * Config. + \beta_7 * Compon. + \beta_8 * Reve. \\ + \beta_9 * Empl. + \beta_{10} * Process \end{array}\right\} \text{Control Variables} \\[6pt]
\left.\begin{array}{l} + \beta_{11} * DetC. + \beta_{12} * DynC. + \beta_{13} * Interd. + \beta_{14} * Coupl \\ + \beta_{15} * OverallInfo \end{array}\right\} \text{Main Effect Variables} \\[6pt]
\left.\begin{array}{l} + \beta_{16} * DetC * OverallInfo. + \beta_{17} * DynC * OverallInfo \\ + \beta_{18} * Interd. * OverallInfo + \beta_{19} * Coupl * OverallInfo \end{array}\right\} \text{Interaction Effect Variables}
\end{array}
$$

The results of the MMR analysis can be found in Table 4-10. In the analysis with the disruption scale none of the interaction terms is significant. Furthermore, the R-square change of the block with the interaction terms is also not significant. These results are an indication that the overall information processing capabilities of the firm do not show any significant sign of a form moderation with the disruption scale as a dependent variable.

As a next step, we used the individual measurement items from the disruption scale as dependent variables to further evaluate potential moderating relationships. While multi-item scales have been the norm in operations management research, the usage of single item measures has become accepted in other fields (Bergkvist and Rossiter, 2007). The items are very concrete and singular which helps with the use of single item indicators. The use of the individual items in the interaction analysis increases the variance each item exhibits compared to the aggregate scale. Each item has its unique variance which is reduced in an aggregated scale. The use of the individual measurement items provides a better chance to find moderating relationships regarding individual disruption dimensions that were hidden before due to the use of the aggregate scale.

The interaction of OverallInfo and coupling is significant for disruption frequency at the $p<0.10$ level, while it is significant at the $p<0.05$ for impact as the dependent variable. OverallInfo and interdependence show a significant interaction at the $p<0.10$ level for spread1 as the dependent variable.

The interaction of overallinfo and detail complexity is significant at the $p<0.10$ level for spread2 as the dependent variable. All models show that the addition of the interaction terms did not result in a significant increase of R-squared, which in combination with the rather high p-values indicates that the effect size of the interaction effects is small.

Table 4- 9: Regression Results for Interaction Analysis with Overall Information Processing

	Scale		Frequency		Impact		Spread 1		Spread 2	
	Model 1	Model 2	Model3	Model4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	.022	.045	-.157	-.134	.086	.068	-.074	-.026	.225	.255
Dummy Country	-.029	-.010	.204	.203	-.111	-.046	.096	.138	-.292	-.286
Competitiveness	-.273*	-.277*	-.127	-.179	-.250*	-.243*	-.266*	-.300*	-.204†	-.139
Regulation	.160†	.172†	.124	.145	.072	.070	.136	.163†	.164†	.158†
Volume	.128	.160	-.042	.043	.185	.140	.111	.209	.133	.105
Product Configuration	.267*	.274*	.023	.015	.294*	.330**	.216†	.214†	.291*	.280*
Components	.245*	.252*	.233*	.262*	.279**	.242*	.138	.168	.106	.110
Employee	.178	.211†	.100	.067	.265*	.365**	.060	.073	.119	.138
Process	-.160†	-.140	-.079	-.089	-.194*	-.152†	-.145	-.127	-.076	-.063
Detail Complexity	.137†	.157†	.115	.135	.207**	.225**	.010	.044	.091	.081
Dynamic Complexity	-.098	-.105	.122	.124	.081	.061	.016	-..032	.106	.064
Interdependence	.028	-.007	.057	.029	.150*	.211**	-.078	-.063	.020	.017
Coupling	.170*	.181*	.161	.212*	.094	.062	.112	.161†	.161*	.134
Overall Info	.008	-.002	-.010	-.018	.032	.043	.002	-.018	.001	-.016
Overall Info* Detail		.082		-.027		.078		.084		-.121†
Overall Info * Dyna		-.085		-.050		.017		-.028		-.099
Overall Info * Interde		-.013		-.045		.116		-.149†		-.130
Overall Info * Coupl.		-.054		-.174†		-.149*		-.129		-.037
R-square	.143	.157	.136	.157	.195	.225	.107	.148	.119	.144
R-Square change	.001	.015	.136	.020	.195	.031	.107	.041	.119	.025
R-square Adj	.078	.073	.060	.057	.123	.133	.028	.047	.041	.042
Sig. F Change	.805	.565	.050	.487	.002	.231	.189	.147	.115	.387

† p<.10; * p<.05; ** p<.01;

However, all interaction effects are negative which indicates that the interactions between the complexity dimensions and disruption have a negative relationship with the disruption variables. The direction of the effect is of a moderating relationship, as we predicted in the hypotheses development.

In the next step we decompose the overallinfo construct into its sub-dimensions to further analyze the moderating effects of the individual information dimensions. This approach allows for an analysis of groups of variables in an incremental manner. The analysis is conducted stepwise – 1) the control variables are entered, 2) the main complexity dimensions are entered. 3) the moderating variables are entered, and 4) the interaction terms are entered. The regression model can be formulated as follows, where j for the predictor goes from 1 through 4 for the four different complexity dimensions:

Figure 4- 7: Regression model for interactions

$$Disruption =$$

Dependent Variable

$$\beta_0 + \beta_1 * Dummy + \beta_2 * Comp. + \beta_3 * Regul. + \beta_4 * Vol. \\ + \beta_5 * Prod + \beta_6 * Config. + \beta_7 * Compon. + \beta_8 * Reve. \\ + \beta_9 * Empl. + \beta_{10} * Process$$

Control Variables

$$+ \beta_{11} * Pred._j$$

$$+ \beta_{12} * InfoS + \beta_{13} * InfoQ. + \beta_{14} * Coll. + \beta_{15} * Know.$$

Main Effect Variables

$$+ \beta_{16} * Pred._j * InfoA. + \beta_{17} * Pred._j * InfoQ \\ + \beta_{18} * Pred._j * Collab + \beta_{19} * Pred._j * Know$$

Interaction Effect Variables

The incremental approach facilitates the analysis of the interaction terms using the change in R-square, which is regarded the appropriate estimate of effect size (Carte and Russell, 2003). The variables were centered before the creation of the interaction terms to avoid problems with multicollinearity.

The results for the analysis can be seen in Table 4-10. The relationship between detail complexity and the disruption scale is moderated by information amount and knowledge. The interaction terms of detail complexity with these two dimensions are significant in the second model at the $p<0.01$ level. Knowledge has a negative interaction with detail complexity which complies with our hypothesized relationship. It indicates that more knowledge reduces the impact of detail complexity on disruptions.

Information amount has a positive interaction with detail complexity, which is opposite of our hypothesized relationship. It seems that information amount in large supply chains reaches an inclination point at which dealing with information becomes overwhelming (Huber, 1991). The overall interaction block has a significant change in R-square at the $p<0.01$ level.

The relationship between dynamic complexity and disruptions is moderated by the collaboration construct at the $p<0.10$ level. The interaction term is negative which confirms the hypothesized relationship. The overall R-square change for the interaction terms is significant at the $p<0.05$ level, indicating a relevant effect size for the interaction terms.

The relationship between interdependence and disruptions is moderated by knowledge at the $p<0.10$ level. The interaction term is negative, which we hypothesized,

Table 4- 10: Results regression analysis for interaction terms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	.175	.109	.190	.303	.162	.183	.220	.286
Dummy Country	-.225	-.124	-.244	-.345	-.208	-.212	-.283	-.337
Competitiveness	-.122	-.160	-.174†	-.246*	-.104	-.082	-.159	-.214
Regulation	.161†	.094	.151†	.150†	.148	.114	.136	.125
Volume	.025	.066	.051	.112	.028	.024	.035	.006
Product Configuration	.242*	.276*	.266*	.283*	.234†	.205†	.241†	.227†
Components	.182†	.176†	.210*	.186†	.207†	.223†	.221*	.234*
Revenue	.180	-.014	.211	.197	.197	.197	.294	.384
Employee	-.030	.207	-.061	-.039	-.035	-.053	-.140	-.189
Process	-.095	-.175	-.096	-.031	-.084	-.081	-.078	-.076
Detail Complexity	.075	.129†						
Dynamic Complexity			.152*	.160*				
Interdependence					.033	.019		
Coupling							.157*	.168*
IA	.137	.010	.118	.146	.124	.066	.088	.107
IQ	-.143	-.101	-.136	-.082	-.135	-.129	-.122	.-161
Collab	-.096	-.076	-.126	-.219*	-.103	-.107	.220	-.120
Know	.072	.254†	.060	.072	.056	.069	-.283	.072
DetC*IA		.240**						
DetC*IQ		-.062						
DetC*Collab		.134						
DetC*Know		-.192**						
DynC*IA				.044				
DynC*IQ				.063				
DynC*Collab				-.204†				
DynC*Coupling				.029				
Interdep*IA						.087		
Interdeo*IQ						-.020		
Interdep. *Collab						-.008		
Interdep *Know						-.144†		
Coupl*IA								-.017
Coupl*IQ								.081
Coupl*Collab								-.247**
Coupl*Know								-.153*
R-Square	.161	.237	.177	.242	.157	.193	.177	.242
R-Square change	.035	.076**	.028	.065*	.035	.037	.028	.065*

† p<.10; * p<.05; ** p<.01;

but the overall change in R-square is non-significant. The relationship between coupling and disruptions is being moderated by collaboration and knowledge. The interaction of coupling with collaboration is significant at the $p<0.01$ level and negative, while the interaction with knowledge is significant at the $p<0.05$ level and negative. The overall change in R-square is significant at the $p<0.05$ level.

4.6. Discussion and Contributions

The magnitude of the negative performance impact of supply chain disruptions has increased the criticality of effectively managing disruptions. Although there is much discussion in the literature on possible strategies to mitigate the impact of disruptions, it is lacking rigorous empirical evidence to support the effectiveness of the proposed strategies (Hendricks tet al., 2009). The focus on complexity as an antecedent of supply chain disruptions, and negative performance outcomes in supply chains in general (Bozarth et al., 2009), facilitates the better identification of effective mitigation techniques. In this paper, we have identified information processing capabilities as a potential mitigation technique for disruptions in complex supply chains. Information procession is a mitigation technique that does not change the structure of the supply chain as other previously proposed mitigation strategies like the usage of inventory, multiple suppliers, etc.

Our analysis shows that firms with high information processing capabilities seem to be able to mitigate the impact of complexity on the level of disruptions experienced in their supply chain. A sub-group analysis comparing firms with high and low information processing capabilities illustrates that all complexity dimensions are significant predictor variables for disruptions in the low information processing firm, while none of the complexity dimensions represent a significant predictor in the high information processing firms. This result shows the importance of high information processing capabilities in complex supply chains, as they mitigate the relationship between complexity and performance. The information processing in the sub-group analysis is developed as an aggregate measure for information processing capabilities based on the four dimensions used in this study: information amount, information quality, collaboration, and supply chain experience/knowledge. Therefore, the analysis illustrates the importance of an overarching approach toward information processing in the firm. It is critical for firms to improve on all four dimensions to mitigate the impact of complexity on disruptions, as we did not find strong results for the individual dimensions.

Furthermore, the subsequent moderation of form showed very mixed results. The overall information processing capabilities show no significant interactions with the complexity dimensions using the disruption scale as a dependent variable. The models with the individual disruption aspects as dependent variables showed small interactions with some of the complexity dimensions. The interaction effect of information processing and coupling is significant for frequency and impact as dependent variables, while the interaction effects with interdependence was significant with spread as the dependent variable, and the interaction effect with detail complexity was significant for spread 2 as the dependent variable. All the results are very small and exhibit insignificant R-square changes, indicative of their small contribution to the model. In conclusion, our data suggest little evidence for any form moderation for the overall information processing capabilities, but very strong support for moderation of strength.

However, we found that the individual information processing dimensions have significant moderating effects using the disruption scale as a dependent variable. The interaction effect for information amount was significant with detail complexity, collaboration showed significance with dynamic complexity and coupling, and knowledge was significant with all complexity dimensions except dynamic complexity. Hence, we might infer that the form moderation is more specific to the individual dimensions of information processing capabilities, and that its aggregate measure "clouds" these results.

The empirical analyses presented in this study are important for a number of reasons. First, there is only a small body of knowledge based on empirical evidence regarding the effectiveness of strategies aimed at mitigating supply chain disruptions. Much of the evidence is based on case studies and analytical models, with Hendricks and Singhal's (2009) large scale empirical study being the exception. Supplementing the findings from the conceptual pieces with a large scale empirical study provides a stronger foundation for judging the proposed strategies. Second, many strategies for dealing with disruptions are essentially demonizing previously heralded best practices as the inevitable causes for disruptions. Some examples of such best practices include outsourcing, lean supply chains, single sourcing, etc., which have been considered detrimental for the reliability of the supply chain. Furthermore, it has been asserted that the management of complex systems, and complex supply chains in particular, is an inherently impossible task deemed to experience significant disruptions. Our analysis shows that it is possible for firms to effectively manage complex supply chains and maintain good reliability records. Hence, it is not necessary to reverse the best practices, but rather improve the overall information processing capabilities as a new best practice necessary in supply chains. The focus hereby needs to be on the overall information processing capabilities and not, like often done, only on individual dimensions. Third, there are costs associated with the implementation of the mitigation techniques. We provide a theoretically grounded discussion about the inevitability of disruptions in complex supply chains. As such, it represents an empirical comparison of the main premises presented by Normal Accident Theory and High Reliability Theory. While Normal Accident Theory predicts that complex systems are inevitably doomed to fail, High Reliability Theory provides a more optimistic outlook and shows ways to mitigate the impact of complexity on system reliability. Our empirical findings support the premises posed by High Reliability Theory, as information processing capabilities are able to overcome the impact of complexity on disruptions.

In this study we focus on information processing as a mitigation technique for the link between complexity and disruptions. There are a number of directions for future research to expand our analyses toward other constructs related to information processing. First, a differentiation between information amount and information richness promises to provide further insights based on previous findings in inter-organizational studies (Daft and Lengel, 1984). Daft and Lengel (1984) found that information richness was specifically suited to overcome dynamic complexity caused by differences between organizational departments, while the information amount was better suited to address the problems for the other complexity dimensions. Second, while we predominantly focus on the mitigation of the link between complexity and disruptions, future research should also address the link between disruptions and specific performance dimensions. Hendricks and Singhal (2009) were pioneers in this research area and examined the effect of organizational slack, business diversification, geographical diversification, and vertical relatedness as mitigation techniques on the impact of disruptions on a firm's stock market performance. However, as previously stated, these techniques implicitly alter the design of the supply chain. Future research should examine the effectiveness of information processing capabilities and related concepts regarding their ability to mitigate the impact of disruption on the firm's financial performance.

Appendix 4- 1: Diagnostics for Sub-Group Analysis

Furthermore, we evaluated the compliance of our regression model with the assumptions of regression models (Kutner et al., 2004; Hair et al., 1998). The variables showed no indication of high correlation and the variance inflation factors (VIF) are far below their suggested cut-off points in the literature (Kutner et al.2004 and Hair et al., 1998 suggest 10 as a cut-off, while other suggest more conservative cut-off of 4 or 5).

A chart plots the predicted Y values against the standardized residuals, which show a random scattered pattern, supporting the assumption of linearity and homoscedaticity. In addition, normal probability plots showed only moderate deviation for normality, which does not create any problems, as regression is very robust against moderate deviations from normality. The tests indicate no violations of the underlying regression assumptions.

Figure 4- 8: PP-Normality plot and scatterplot for high information group

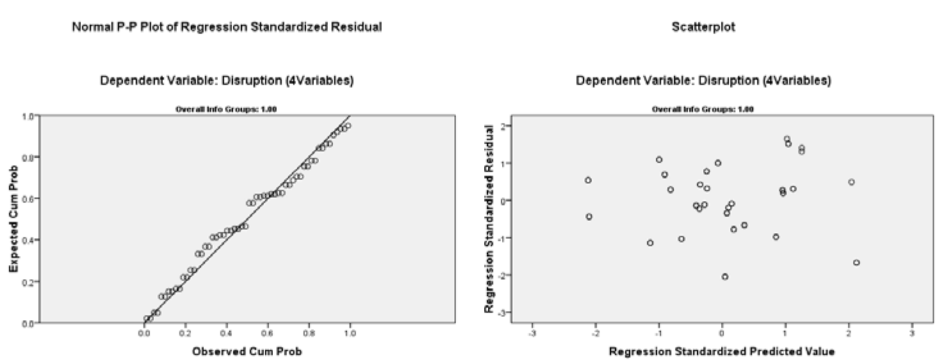
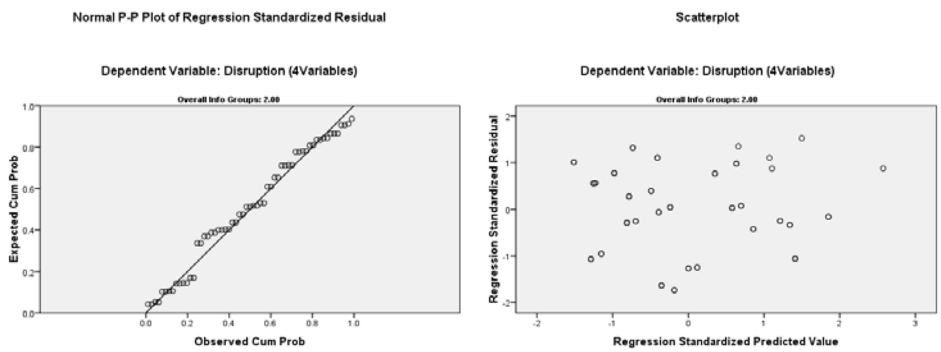


Figure 4- 9: PP-Normality plot and scatterplot for low information group



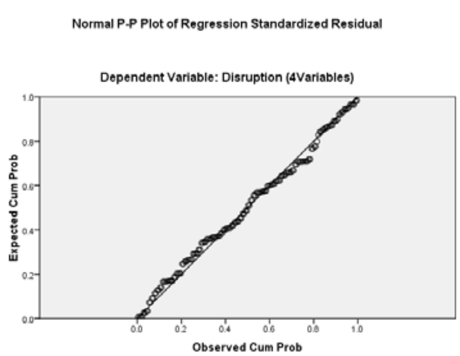
We used several statistics to check for outliers in the model, i.e., leverage statistic, Cook's distance, Mahalabobis distance, dfFit, and DfBeta (see section 3.5.1. for more detail on the various outlier statistics). The model was run with and without the identified outliers, but no significant difference between the two models could be detected. As a consequence, we retained the outliers in the analysis.

Appendix 4- 2 : Diagnostics for Interaction Analysis

The underlying assumptions of regression analysis (Kutner et al., 2004; Hair et al., 1998) were evaluated through several test statistics. None of the variables showed any indication of high correlation. All variance inflation factors (VIF) are far below their conservative cut-off points in the literature (Kutner et al.2004 and Hair et al., 1998 suggest 10 as a cut-off, while other suggest more conservative cut-off of 4 or 5), suggesting that multicollinearity is not a problem in our models.

The predicted Y values were plotted against the standardized residuals, which show a random scattered pattern, supporting the assumption of linearity and homoscedaticity. Furthermore, normal probability plots showed no major deviation for normality. Regression analysis is very robust against moderate deviations from normality. The tests indicate no violations of the underlying regression assumptions.

Figure 4- 10: PP-Normality plot and scatterplot for detail complexity



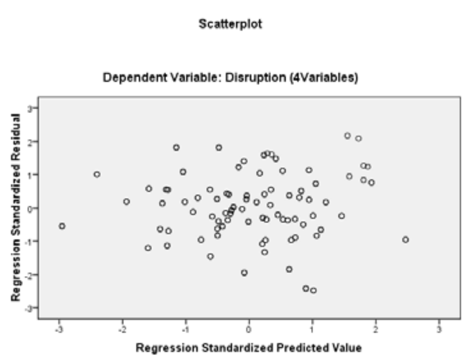


Figure 4- 11: PP-Normality plot and scatterplot for dynamic complexity

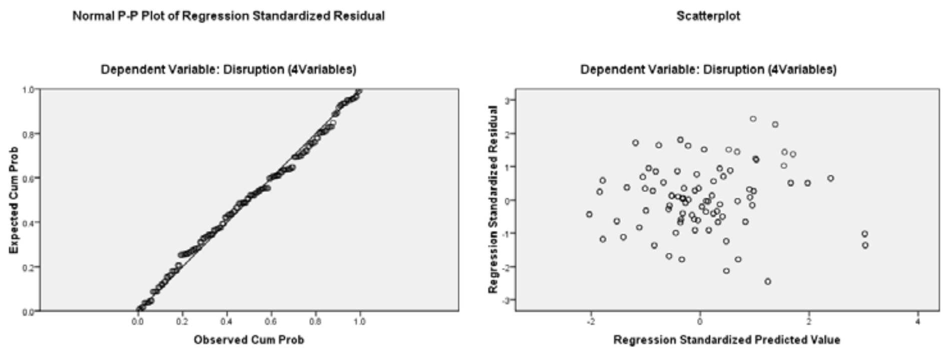


Figure 4- 12: PP-Normality plot and scatterplot for interdependence

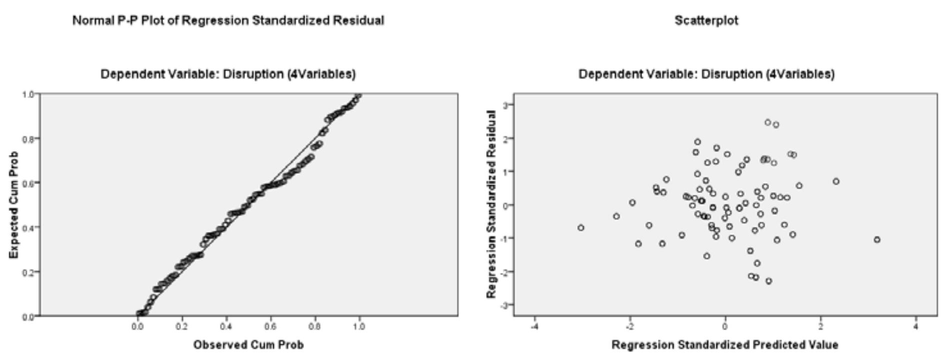
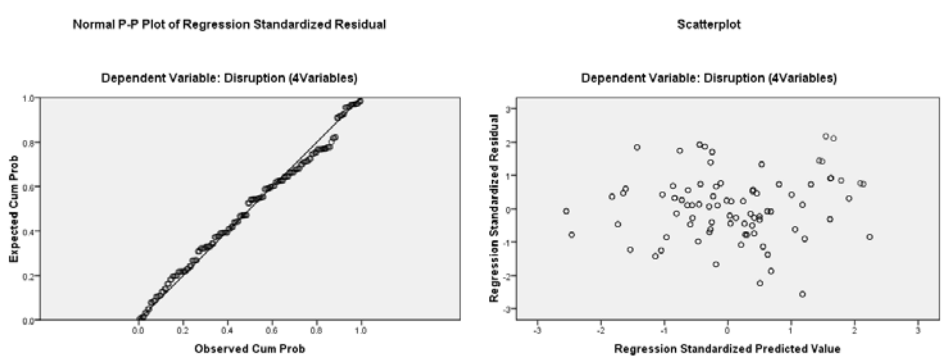


Figure 4- 13: PP-Normality plot and Scatterplot for Coupling



We used several statistics to check for outliers in the model, i.e., leverage statistic, Cook's distance, Mahalabobis distance, dfFit, and DfBeta. We used several statistics to check for outliers in the model, i.e., leverage statistic, Cook's distance, Mahalabobis distance, dfFit, and DfBeta (see section 3.5.1. for more detail on the various outlier statistics). The model was run with and without the identified outliers, but no significant difference between the two models could be detected. As a consequence, we retained the outliers in the analysis.

Appendix 4- 3: Measurement Items

Please indicate **whether you agree or disagree with the following statements** about your supply base.

Detail Complexity Supply Base
(5=Strongly Agree; 1=Strongly Disagree)

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
(5=Strongly Agree; 1=Strongly Disagree)

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
(5=Strongly Agree; 1=Strongly Disagree)

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
DynC4: Our suppliers are co-located within close proximity of our production facilities
DynC5: Our suppliers are globally dispersed

Coupling
(5=Strongly Agree; 1=Strongly Disagree)

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
Coupl4:Multi-sourcing

Disruption
Origin of disruption

Refers to the initial location of the disruption in the supply chain. Disruptions in the supply base negatively affect your firm's ability to procure the required quantity of inputs. This section contains questions related to **disruptions originating in the supply base.**

Frequency

How frequently have **disruptions (for any reason) originated** in your **supply base** during the last three months? (7-Continously; 1=Never)

How quickly were the **supply base disruptions usually resolved** during the last three months? (7=Very Slow; 1=Very fast)

How much did these disruptions **affect your competitiveness** during the last three months? (5=Very significantly; 1=Not at all)

Spread of disruption

Refers to the extent to which disruptions affect other parts of the supply chain. For example, an input material shortage from the supply base may reduce your production output.

How often did disruptions originating in the supply base **spread** to your **production base** during the last three months? (7=Always; 1=Not Once)

How often did disruptions originating in the supply base **spread** to your **customer base** during the last three months? (7=Always; 1=Not Once)

Information Exchange

Please indicate to what **extent the following information are being shared** in the supply chain.(5=Great Extent; 1=Not at all)

InfoS1: Sales forecast
InfoS2: Master production schedule
InfoS3: Inventory status
InfoS4: We jointly develop net requirements of components with our suppliers
InfoS5: The suppliers are authorized to automatically replenish the component inventory

Please indicate whether you agree or disagree with the following statements about **the information that is being exchanged between the focal firm and its suppliers.**
(5=Strongly Agree; 1= Strongly Disagree)
The information exchanged is…
InfoQ1: Accurate
InfoQ2: Timely
InfoQ3: Reliable

Collaboration

Please indicate whether you agree or disagree with the following statements about **supply chain collaboration** (5=Strongly Agree; 1=Strongly Disagree)
Collab1: We consider our suppliers as partners
Collab2: We work closely with our suppliers in many areas
Collab3: We involve our suppliers early on in new product development
Collab4: Our relationship with the suppliers is characterized by a high degree of mutual understanding
Collab5: We collaborate closely with our suppliers

Control Variables

(5=Strongly Agree; 1=Strongly Disagree)
We are in a highly competitive industry.
Our industry is highly regulated.

Approximate volume (in ‘000s) produced during the last 12 months?
(7=>5,000; 1= <500)
Approximate number of final product configurations offered to customers during last 12 months? (7=>1,000; 1=<10)
Approximate number of components/parts for most common product configuration?
(7= >1000; 1=<5)
Product line accounted for what % of total business unit’s revenue last year? (5=100%; 1=<25%)

Appendix 4- 4: Correlation table

	Info Amount	Info Quality	Collaboration	Knowledge	Detail Complexity	Interdependence	Coupling	Dynamic Complexity
Info Amount	***1.00***	0.29**	0.33**	0.26**	-0.15*	0.03	0.20**	0.13†
Info Quality	0.29**	***1.00***	0.45**	0.33**	-0.08	0.16*	-0.03	0.10
Collaboration	0.33**	0.45**	***1.00***	0.40**	-0.19**	0.16*	0.15*	0.22**
Knowledge	0.26**	0.33**	0.40**	***1.00***	-0.24**	0.10	0.14*	0.13†
Detail Complexity	-0.15*	-0.08	-0.19**	-0.24**	***1.00***	0.18**	-0.22**	0.14*
Interdependence	0.03	0.16*	0.16*	0.10	0.18**	***1.00***	-0.05	-0.02
Coupling Factor	0.20**	-0.03	0.15*	0.14*	-0.22**	-0.05	***1.00***	0.33**
Dynamic	0.13†	0.10	0.22**	0.13†	0.14*	-0.02	0.33**	***1.00***

† p<.10; * p<.05; ** p<.01;

Chapter 5
Contributions, Limitations and Future Research

In this dissertation we set out to analyze the disruption phenomenon in supply chains. We are motivated by the increasing interest of practitioners and academics in the topics of supply chain disruptions. While there is significant evidence of the negative effects of supply chain disruptions on firm performance (Enslow, 2004; Latour, 2001; Hendricks and Singhal, 2005) the understanding of disruption antecedents and mitigation techniques remains limited in the literature. Even as an increasing number of practitioner and academic studies have devoted their attention to addressing the challenges posed by supply chain disruptions, much of what continues to be studied is based predominantly on anecdotal evidence, analytical models, or case studies.

A primary obstacle to the lack of theoretically grounded, empirically-based studies regarding supply chain disruption research is the divergent usage of terminology in this emerging area of research. This dissertation makes an effort to address some of the gaps in theory and practice by proposing a concise definition and related measurement items for disruptions. Furthermore, we strive to identify theory based antecedents and mitigation techniques of supply chain disruptions and to test these empirically using a large scale survey instrument.

This chapter briefly summarizes the contributions made to theory and practice by this dissertation. We highlight the limitations of our work and identify future areas of research to expand on the presented work.

5.1 Contributions to Theory

This dissertation contributes to the literature base on supply chain disruptions and supply chain complexities in multiple ways. First, in chapter two we develop a concise and narrow definition of supply chain disruptions. It is intended to differentiate disruptions from other terms used in the literature, like accidents, uncertainty, risk, etc. We define a disruption as *"an unplanned stoppage of the material, information, or monetary flow within the supply chain."* Furthermore, we identify frequency, duration, impact and spread as relevant aspects to capture supply chain disruptions. The definition provides the basis for the subsequent development of empirical measurement of disruptions for survey instruments. To the best of our knowledge, the development and use of disruption measures represents the first such endeavor in a supply chain context. Future research should use the developed measures and characterization of disruptions as a starting point for a more differentiated discussion of the disruption phenomenon.

Secondly, we use a strong theoretical foundation for the argument linking supply chain complexity with disruptions. We conducted an extensive literature review and apply organizational theory to identify complexity as a key driver of supply chain disruptions. We draw on Normal Accident Theory (NAT) a relatively unknown theory in the area of operations management to link complexity and disruptions. Hence, the use of NAT in this dissertation hopefully increases the awareness about the theory in the area of operations management. Our research complements the stream of literature linking supply chain complexity to declining performance (Bozarth et al., 2009). We utilized previous research on complex systems to identify four dimension of complexity that are relevant in supply chains. The four dimensions are: 1) detail complexity, 2) dynamic complexity, 3) interdependence, and 4) coupling. We propose four research hypotheses linking each of the four complexity dimensions with supply chain disruptions and develop operational measures for each dimension in supply chains. Our data analysis shows a positive relationship between supply chain complexity and disruptions. However, the strength of the relationship between the constructs depends strongly on the dimensions of complexity and the measurement of disruptions. The empirical findings from this study are important because there is little empirical research identifying the antecedents of supply chain disruptions. The presented study supplements findings from case studies and empirically validates ideas from conceptual pieces on links between complexity and disruptions. Additionally, our study allows for a differentiated analysis of the relationships between individual complexity dimensions and specific aspects of disruptions.

Third, in chapter four we examine the impact of information processing capabilities as a mitigation tool on the relationship between complexity and disruptions. The negative performance impact of supply chain disruptions has increased the criticality of effectively managing disruptions. Although there is much discussion in the literature on possible strategies to mitigate the impact of disruptions, the literature is lacking rigorous empirical evidence to support the effectiveness of the proposed strategies (Hendricks et al., 2009). Our study aims to provide the literature with empirical evidence regarding the effectiveness of mitigation techniques, specifically information processing. Information processing is an interesting mitigation technique as it does not change the structure of the supply chain compared to other previously proposed mitigation strategies like the usage of inventory, multiple suppliers etc

The use of information processing is based on strong theoretical support from information processing theory, high reliability theory, and complex systems theory. Our analysis shows that firms with high information processing capabilities seem to be able to mitigate the impact of complexity on the level of disruptions experienced in their supply chain. A sub-group analysis comparing firms with high and low information processing capabilities illustrates that all complexity dimensions are significant predictor variables for disruptions in the low information processing firm, while none of the dimensions represented a significant predictor in the high information processing firms. This result shows the importance of high information processing capabilities in complex supply chains, as they mitigate the relationship between complexity and performance. This analysis also represents a comparison between NAT and HRT in the supply chain context. There have been long standing arguments between the proponents of the two theories about their applicability. At least for the supply chain context HRT seems to be more appropriate theoretical lens. We have seen that complexity is a statistically significant driver of supply chain disruptions, however, the impact of complexity is not inevitable as stated by NAT, but rather conditional on the information processing environment as postulated in HRT.

Overall, the major contribution of our study is the empirical validation of theoretical based propositions in the area of supply chain disruptions. We create measures for supply chain disruptions and validate the importance of complexity in explaining the occurrence of supply chain disruptions. Furthermore, our results show the importance of specific complexity dimensions in relation to different disruption characteristics. Finally, we show that the relationship between complexity and disruptions can be effectively managed using information processing.

5.2. Contributions to Practice

Practitioners have been increasingly sensitized toward the importance of supply chain disruptions due to the overwhelming evidence regarding their negative performance impact. Hence, practitioners urgently require empirical research to provide insights regarding the drivers of supply chain disruptions and their mitigation strategies. Our effort in this study is to present practitioners with empirical evidence regarding the criticality of supply chain complexity as a driver of disruptions and information processing as a mitigation strategy.

The presented disruption framework provides practicing supply chain managers with several important insights. First, the four tested hypotheses offer guidance for managers to systematically evaluate their supply chain for potential disruption problems. The insights regarding the complexity-disruption link should sensitize managers toward the potential impact on supply chain reliability of certain management practices, i.e., the implementation of JIT delivery by suppliers leads to a tighter coupled supply base, which is more prone to disruptions. Hence, management needs to consider the hidden costs of such practices, or counter their impact through the usage of adequate mitigation techniques. However, our research shows that it is not necessary to demonize previously heralded best practices as the inevitable causes for disruptions. Some examples of such best practices include outsourcing, lean supply chains, single sourcing etc., which have been considered detrimental for the reliability of the supply chain. Our analysis suggests that it is possible for firms to effectively manage complex supply chains and maintain good reliability records. Hence, it is not necessary to reverse the best practices, but rather improve the overall information processing capabilities as a new best practice necessary in supply chains. The focus hereby needs to be on the overall information processing capabilities and not like often done, only on individual dimensions.

5.3. Limitations

Any empirical study has inherent limitation based on its research design. This study is no exception and the reader needs to be aware of the following limitation due to the chosen research design for this study.

The use of a single informant for collecting information about a firm's supply chain limits this study. Multiple informants provide the possibility for increased reliability to the study's findings, through inter-rater reliability assessments. However, multiple respondents are often only a possibility 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 of a large of firms to provide a heterogeneous sample for the assessments of different complexity and disruption levels. Therefore, we approach 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 the study is the use of the focal firm's perspective. Researchers favor the use of supplier-buyer dyads for their research designs. The focal firm perspective omits any analysis from the supplier's perspective of the reported disruption levels from 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 the priority over a dyadic approach. Future research should examine the tested relationships from this study in more detail using dyadic approaches. Such research is promises to reveal deeper insights for specific supply chain contexts.

Another limitation of the study is the absence of explicit performance measures. The focus of this study is on the identification of disruption antecedents, and therefore, the disruption-performance link is omitted from the tested framework. While the disruption-performance link is well established in the literature (e.g., Hendricks and Singhal, 2005), future research should examine a two-stage model testing antecedents, disruptions, and performance into a single, uniting framework. Furthermore, the use of regression analysis for the hypothesis testing permits only the separate testing of dependent variables. Future research could unite the antecedents, several disruption and performance measures in a path model, or structural equation model. This analysis technique would permit the researcher to simultaneously evaluate the relationships in the model, in contrast to the separate approach chosen for this initial study.

5.4. Future Research

This research can serve as a stepping stone for future research aimed at better understanding supply chain disruptions and the reliable management of complex supply chains. Future research needs to focus on further enhancing our knowledge regarding the three main constructs in this study: disruptions, complexity, and mitigation techniques.

The characteristics of supply chain disruptions presented in Chapters 2 and 3 provide ample research opportunities. Within this study we chose not to distinguish between different causes of disruptions and focused solely on supply chain complexity. Future research needs to further differentiate between the individual aspects of disruptions to advance our understanding of the phenomenon. Human errors and the general environment are factors that contribute to disruptions that are beyond the scope of this study. However, a comprehensive supply chain disruption approach will be required to integrate all potential causes for supply chain disruptions in an overarching model.

To further the understanding research needs to examine the interactions of the system levels in the supply chain. Complexity theory is hierarchical and a full analysis needs to examine the interaction of different levels of analysis. In this study we controlled for lower and higher system levels, but the results showed that further examination of system level interaction is warranted.

A critical extension is the examination of complexities in other parts of the supply chain and its impact in disruptions. The present dissertation was limited to complexities in the supply base; future research should further analyze the complexities in the production and customer base. The integration of all complexity sources would generate a more complete and holistic view of supply chain complexities. The aim of the research should be to enhance the understanding of the complexity location on the location of the disruptions in relation to the focal firm. It is possible that delay effects of complexity are present in supply chains, i.e., supply base complexity drives production based disruptions more than supply base disruptions. A clear mapping between the locations of antecedent and disruption would greatly aid the application of necessary mitigation techniques.

Furthermore, future research needs to integrate the complexity-disruption relationship with its impact on performance metrics. So far, we present an examination of the relationship between complexity and disruptions, while previous research tested the relationship between disruptions and performance (Hendricks and Singhal, 2005). An integrated model is needed to examine the two relationships simultaneously in one model.

Complexity theory is an inherently dynamic theory that captures the behavior of organizations in an evolving landscape. Hence, a longitudinal approach promises insights that are not accessible with a cross-sectional design. A longitudinal approach could examine the evolutionary process of the organization as a consequence of changes in its complexity landscape. The aim of such research is to go beyond simple main effects to determine if, and to what extent, the four complexity dimensions might compensate for one another with respect to individual disruption dimensions. Such trade-offs can only be assessed by studying changes in the complexity dimensions over time, but promises to provide insights into the changing complexity landscape of supply chains and ways to effectively manage these transitions in the complexity structure. A longitudinal study can be a difficult and time-consuming endeavor, but it would allow for the generation of prescriptive recommendations regarding the management of complexity in supply chains.

There are a number of directions for future research to expand our analyses of mitigation techniques. First, a differentiation between information amount and information richness promises to provide further insights based on previous findings in inter-organizational studies (Daft and Lengel, 1984). Second, while we predominantly focus on the mitigation of the link between complexity and disruptions, future research should also address the link between disruptions and specific performance dimensions. Third, it is ultimately necessary to contrast the effectiveness of different mitigation techniques. Research needs to compare the effectiveness of complexity reducing and mitigating techniques in one study, preferably a longitudinal study.

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