

## ABSTRACT

Title of Dissertation: SUPPLY CHAIN DISRUPTIONS: IMPACT  
ON COMPETITOR FIRMS AND THE  
INFLUENCE OF SUPPLY CHAIN  
COMPLEXITY ON DISRUPTION  
LIKELIHOOD AND RECOVERY TIME

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The two chapters of this dissertation focus on supply chain disruptions, with first chapter studying the impact of supply chain disruptions on the disrupted firm competitors and the second chapter, examining the impact of supply chain complexity on the manufacturing plant's frequency of disruptions and recovery time from disruption.

In chapter 1 of my dissertation, I investigate the horizontal spillover effects of supply chain disruptions to the disrupted firm's competitors, anecdotal evidence for the relationship between bystander competitor firms' financial performance and supply chain disruptions (SCDs) of a focal firm is equivocal. I consider two potential sources of this ambiguity by examining a multitude of SCDs over a 13-year period (2003–2015). I examine the vertical interdependence among competitor firms, along

with the visibilities of the disrupted firm, the undisrupted competitor firm, and the SCD event. I investigate the stock market reaction to bystander competitor firms after a focal firm SCD announcement. In addition, I measure operational performance of the bystander competitor firm measured through return on assets (ROA) in the period following a focal firm's SCD announcement.

The chapter 2 of my dissertation examines how supply chain complexity, an important structural characteristic of a supply chain structure, can impact a firm's supply chain resiliency to a disruption. The purpose of this study, is to first, examine the impact of the uncertain environment of the focal site on the likelihood of a site experiencing a disruption. Specifically, I study the peer-to-peer learning from the environment in which the focal site is located. Then, I explore how structural characteristics of the focal site can affect its proactive strategies to avoid disruption along with reactive strategies that aid the site in its recovery process after the disruption. Next, I theorize on how internal and external structural characteristics impact the likelihood of disruption along with the recovery time if the site goes down due to disruption. Finally, I closely look into the role of business continuity management (BCM) plans in the recovery process after disruption. In doing so, I examine the role of strategic, operational, and supplier orientation of BCM plans on the recovery time of the focal site.

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by

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# **Chapter 1: Impact of Supply Chain Disruptions on Competitors: Propagation of Disruption Impacts Through Supply Chain**

## **1. Introduction**

The relationship between bystander competitor firms' financial performance and supply chain disruptions (SCDs) is ambiguous. Take, for example, the case of Lululemon Athletica and its competitor, Nike. On March 20, 2013, when Lululemon Athletica announced that few of its shipments fell short of its high standards, Nike saw an increase in its shareholder value by 1.5%. At the end of the quarter in which the disruption occurred, Nike's revenue rose by 3.7%. However, not all disruptions have resulted in gains for the competitor. A case in point is the supply problems that Honeywell faced in October of 2013. When Honeywell announced supply problems in its defense unit, its competitor, Lockheed Martin's stock fell by 2.8% on the same day, and its revenue in the subsequent quarter fell by 2.5%. This ambiguity is also not settled in the academic literature, as mixed results are found in examining the relationship between disruptions and competitor firms' financial performance. For instance, while Hendricks, Jacobs, and Singhal (2019) found an increase in shareholder value of the competitors of the firms affected by the Great East Japan Earthquake, Filbeck, Kumar, Liu, and Zhao (2016) revealed a negative shareholder reaction from American automobile firms when Japanese automobile firms faced supply chain disruptions. This contradiction in the effects on competitor firms of SCDs implies a more nuanced effect than previously thought that is more significantly influenced by other factors. Here, I explore this ambiguity and help

explain the equivocal anecdotal evidence and academic findings by focusing on two of these contextual factors.

First, I examine the complexity of the relationships between the competing firms. Specifically, I consider any vertical relationship that may exist between the disrupted firm and the competitor. Given the costs of SCD on a disrupted firm (for e.g., Hendricks and Singhal, 2005, 2006), conventional wisdom would dictate a positive relationship between SCDs and the performance of unaffected bystander competitors. However, since suppliers' and/or customers' operational performance can be adversely impacted by disruptions to a chain member's operations as a result of the financial interdependence of integrated supply chains (Flynn, Huo, & Zhao, 2010; Yang, Birge, & Parker, 2015), I conjecture that the gains made by the bystander's competitor firm from an SCD are reduced, or even reversed, by vertical relationships that may exist between the two firms. I consider two forms of vertical connectivity between competing firms: direct connectivity, wherein the competitor is also a supplier/buyer or both to the disrupted firm; and indirect connectivity, which is defined by supplier commonality between the two firms. If the competitors' vertical connectivity effect is significant, the implications are important to both researchers and managers. The literature on coopetition, that is, the simultaneous pursuit of cooperation and competition between firms (Raza-Ullah et al., 2014), has looked mainly at the unifying and /or divergent forces between the competing/cooperating firms (for e.g., Raza-Ullah et al., 2014). However, I am looking at the complexities of competing while, at the same time, being interdependent on each other. I am also considering how a wrongdoing or unfortunate event at one firm affects performance

outcomes of the other. These insights, I believe, help firms better assess the complexities of their supply chains as well as the connectivity to their competitors as sources of disruption risks. This, I trust, will help firms mitigate the impact of the disruptions whose occurrences are beyond their own control.

Second, I contend that the competitor firm performance and SCD association are nuanced by the extent of visibility of 1) the disruption event, 2) the disrupted firm, and 3) the competitor firm. On the one hand, I argue that any or all these three forms of visibility are likely to escalate the nervousness emanating from the disruption to the entire industry. On the other hand, visibilities of the disruption event and the disrupted firm may amplify knowledge about the operational deficiencies of the disrupted firm. This may work in favor of the bystander competitor firm. Visibility, therefore, may bolster, reduce, or even reverse the positive association between SCDs and competitor performance. Paruchuri and Misangyi (2015) considered the effects of visibility in their study of financial misconduct contagion in an industry. However, I am the first to employ this factor in the context of spillover effects of SCDs to unaffected competitors. For managers planning to reduce the risks of, and soften the impacts of disruptions, it is crucial to understand the sources of the propagation of the impacts of SCDs. Specifically, as firms are always taking strategic actions aiming at brand awareness, it is important for managers to understand that the visibility of their firms, or competing with well-known firms, may be sources of supply chain risks or conduits for financial losses for failures that are unrelated to them or their own operations. This, I believe, helps firms to better prepare for the impacts of disruptions whose occurrences are beyond their own influence.

Our main interest is in manufacturing and other operational disruptions that are unique and limited to the disrupted firm. My focus is on spillover effects of disruption to undisrupted competitor firms. Any event whose direct impacts go beyond the focal firm to its competitors blurs the line between the event's effects on the competitors and the spillover effects from the announced affected firm. For example, events like natural disasters, government regulations, terrorist activities, and war can have a simultaneous impact on a firm and its competitors. Similarly, events such as the Rana Plaza collapse in Bangladesh can have a direct and concurrent impact on many manufacturers (Jacobs & Singhal, 2017). The effect of these disruptions on the competitors' performance may not be observed.

I use two proxies to measure the effects of SCDs on competitor firms. First, I use the stock market reaction (shareholder wealth) to SCD announcements. This is a common measure of the effects of events, and even major corporate decisions, in the literature (Hendricks & Singhal, 2003; Thirumalai & Sinha, 2011; Ba, Lisic, Liu, & Stallaert, 2013). Through the efficient market hypothesis, the stock market reaction comprehends the effects of any new information on both current and future firm performance (Ding, Lam, Cheng, & Zhou, 2018). In context, the stock market reaction will depend not only on the content, nature, and extent of the SCD announcement, but also on the complexities of the ties between the affected and unaffected competitor. Second, I measure operational performance through abnormal return on assets (ROA). Thus, I hope to capture any market inefficiencies by examining the operating metrics that demonstrate the actual impact of the event.

To test my hypotheses, I estimate two sets of econometric models to analyze SCDs over a 13-year period (2003–2015). My data set, used to estimate the effect on shareholder wealth and abnormal return on assets, consists of 1,060 disrupted firm-competitor firm dyads for 135 unique SCDs. This data set combines (a) SCD data extracted from the LexisNexis, (b) supply chain and competitor relationships from Factset Revere, (c) daily stock market prices extracted from Center for Research in Security Prices (CRSP), and (d) firm performance data extracted from the Compustat database. Estimation results support the hypothesized positive association between SCDs and competitor firm performance as well as the hypothesized dampening in this association due to vertical connectivity, direct and indirect, between the disrupted and the competitor firms, and competitor visibility. I find a surprising exacerbating effect of event visibility.

## **2. Literature and Hypotheses**

### **2.1. Literature Review**

Academic scholars have shown broad interest in the linkages among supply chain connectivity, supply network, supply chain disruptions, and supply chain performance. Various researchers have investigated aspects of supply chain configurations, their linkages to disruptions, and the overall impacts of the disruptions. For instance, Bode and Wagner (2015) examined the effects of supply chain complexity on frequency of disruptions. Craighead, Blackhurst, Rungtusanatham, and Handfield (2007) linked the density, complexity, and node criticality of supply chains to the severity of supply chain disruption. On the impacts

of disruptions, Hendricks and Singhal (2003, 2005, 2008, 2009, 2014) examined the effect of supply chain disruptions on various measures of firm performance, e.g., short- and long-term stock market reactions, equity risk and operating performance, operating income, return on sales, and return on assets. Many other studies have since corroborated the findings of Hendricks and Singhal, discovering a negative impact of supply chain disruptions on firm performance. For example, an operational disruption like a product recall can result in costs of the recall, costs to provide remedies well as legal liability costs. In addition, there is a loss in a firm's reputation (Hora, Bapuji, & Roth, 2011). Also, Ang, Iancu, and Swinney (2016) showed that disruptions can alter a firm's sourcing strategies.

Most relevant to my studies perhaps are the works of Filbeck et al. (2016) and Hendricks et al. (2019). Filbeck et al. (2016) studied the contagion effect of a supply chain disruption in the automobile industry in the context of economic market cycles. The authors revealed that market cycles and brand domicile have an impact on disruptions in the automobile industry and further identified a contagion effect only in bear markets. Hendricks et al. (2019) observed a contagion effect in the upstream and downstream partners of the firms affected by the Great East Japan Earthquake in the nuclear industry. Also, the authors found a competitive effect for the first one month after the event. While I build on the works of Filbeck et al. (2016) and Hendricks et al. (2019), I do not limit my studies to a single disruptive event, but rather I focus on a plethora of disruptions, each limited to only the disrupted firm. I also incorporate interfirm connectivity, direct or indirect through a third firm, which may exist between these otherwise horizontal competitors.

## **2.2. Competitive Effect of Supply Chain Disruptions**

Disruption at a firm can create new business opportunities for other unaffected firms in the industry (Lang & Stulz, 1992). First, disruptions at a firm can potentially increase the value of the unaffected firms in the industry by redistributing demand from the disrupted firms to their competitors (Lang & Stulz, 1992; Qi, Bard, & Yu, 2004). As disruptions can reduce the short- and long-term abilities of a company to meet its customer needs, competitors of the disrupted firm may respond to the demand shift and generate abnormal revenues by increasing their market share (Filbeck et al., 2016). Second, supply chain disruptions result in a decline in production efficiency for the disrupted firm (Chen, 2014). Decreased production efficiency could lead to higher marginal costs that can result in higher prices and lower output (Baumol & Bradford, 1970). As the products of competitors are substitutes for the products from the disrupted firm, now more expensive, competitor firms could increase their revenues by either increasing the prices or the quantity sold of their products. Third, supply chain disruptions weaken the firm, and the information on disruption reveals that the disrupted firm is negatively impacted (Wagner & Neshat, 2012). Competitors can take advantage of the firm's vulnerability to take predatory actions (Ferrier, Smith, & Grimm, 1999). A disrupted firm may find it difficult to respond to these actions, e.g., introduction of a new product and/or decreasing the price of a product to increase market share.

Based on the above discussion, I argue that supply chain disruptions will have a positive impact (competitive effect) on the disrupted firm's competitors in two

areas. First, given that equity prices reflect market information (Ding et al., 2018) and a measure of both short- and long-term performance prognosis (Jacobs & Singhal, 2014), I expect an increase in shareholder value of the competitors on the day of disruption announcement. Formally,

*H1a: Firm-specific supply chain disruptions will be associated with an increase in shareholder wealth of the disrupted firm's horizontal competitors.*

Second, I expect the competitors' profitability to increase owing to the vulnerable position of the disrupted firm caused by 1) the operational challenges created by the disruption and 2) the reduced credibility and damage to the reputation of the disrupted firm. Both vulnerabilities will result in higher operational performance for the bystander competitor firm.

*H1b: Firm-specific supply chain disruptions will be associated with an increase in operational performance of the disrupted firm's horizontal competitors.*

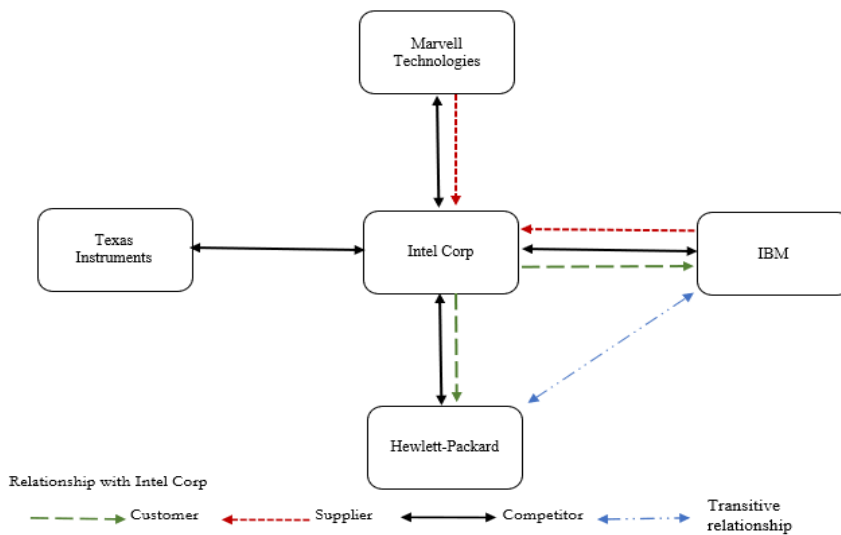
## **2.3. Propagation of the Impact of Supply Chain Disruptions**

### **2.3.1. Vertical connectivity of the competitor with the disrupted firm**

Some horizontal competitors have multifaceted relationships. Two competing firms can be connected to one another through different types of relationships, in some cases, with a clear and contractual links and, in other cases, less transparent and implicit links. Take, for instance, five competitors in the semiconductor industry: Intel Corp., Hewlett-Packard (HP), Marvell Technology Group, IBM, and Texas Instruments, as shown in Figure 1. Intel Corp. and Marvell Technology Group Ltd. are competitors in the industry, but Marvell Tech. is also a supplier to Intel Corp. In

fact, Hewlett-Packard (HP) and IBM are both not only competitors to, but also customers of, Intel Corp. While there is a direct vertical relationship between Intel and HP and between Intel and IBM, there is an indirect relationship between HP and IBM through their common supplier, Intel Corp. These intertwining relationships among competitors, I contend, influence the spillover effects of disruptions via bystander competitors.

**Figure 1. Intel Corp. and its supply chain partners**



#### 2.3.1.1. *Direct vertical and negative contagion effect*

I contend that a disruption at Intel Corp., as a supplier to HP, can have a negative effect on HP, thus reducing competitive positive gains in several ways. First, the disruption will increase Intel's manufacturing costs. This would result in higher prices for products sold to HP. Second, HP's costs will likely increase due to either stock-outs or delayed deliveries. HP will also incur switching costs if it decides to seek a new supplier. Finally, in some cases, HP may have to incur the costs of fixing the supply chain and increase supply chain governance to avoid further disruptions.

Therefore, on the one hand, HP experiences increased demand due to production losses at the disrupted competitor, but on a select range of products for which Intel is a supplier for HP, there will be a negative impact (Qi et al., 2004).

As a supplier to Intel Corp., Marvell Tech. will also be affected negatively from a disruption at Intel. Marvell Tech. depends, to different degrees, on customers like Intel to thrive in business, so it can buy more of its products. A disruption at Intel as a customer for Marvell's products will create an uncertain environment and, hence, uncertain demand for products from Marvell Tech. (Yu, Zheng, & Zhao, 2009). This may result in excess inventory at Marvell Tech., or it may have to look for alternative demand sources and offer discounted prices to generate sales. Hence, when a firm is sharing a dual relationship with a competitor and a supplier to a disrupted firm, the profits created by the production interruption at the disrupted firm, based on its role as a horizontal competitor, can be negatively moderated for the select range of products that it provides as a supplier to the disrupted firm.

In summary, I hypothesize that, when a disrupted firm's horizontal competitor, for a select range of products, is either its downstream customer or upstream supplier, or simultaneously both a customer and a supplier, the operational and financial performance of the disrupted firm's horizontal competitor will be less positive.

*H2a: The increase in shareholder wealth of the disrupted firm's horizontal competitors is negatively moderated if the disrupted firm and horizontal competitor are vertically connected.*

*H2b: The relationship between the supply chain disruption and the operational performance of the disrupted firm's horizontal competitor will be negatively moderated if the disrupted firm and horizontal competitor are vertically connected.*

#### **2.3.1.2. Indirect vertical connectivity and negative contagion effect**

Competitors can also be indirectly connected through their own vertical relationships. That is, the interdependency between two competitors not only comes from the presence of one firm in another firm's supply chain (vertical connectivity) but also stems from their common supplier base. This is based on the triadic relationship of customer (disrupted firm) – supplier – customer (competitor firm), wherein the two competitors on the horizontal level are connected vertically through a common supplier/s. Take, for instance, Mattel and Hasbro. These two manufacturers are not directly vertically connected, but they do share a majority of key suppliers. In fact, both list the exact same companies as their top suppliers, e.g., Air Products and Chemicals Inc, Ashland Global Holdings Inc, Avery Dennison Corporation, Corning Inc, Cummins Inc, Dow Inc, Dupont De Nemours Inc, Honeywell International Inc, Illinois Tool Works Inc, Johnson Controls International Plc (Source: Bloomberg SPLC).

Common key suppliers would reduce the positive impact a competitive firm may achieve because of a disruption at one of its horizontal competitors. Firms with common key suppliers share a transitive relationship, as illustrated in Figure 1, which shows that HP and IBM share a transitive relationship through Intel Corp. The failure

risk of one customer can traverse to the competitor through a common supplier for two reasons. First, disruptions at HP can create uncertainties in demand for Intel Corp's products. The uncertain demand at Intel Corp can affect all of Intel's supplier output through its capacity reallocation decisions. These uncertainties include excess capacities, inventories, and falling revenues. Therefore, a disruption at HP affects its supply base as a result of interrupted and diminished demand (Wang, Dou, Muddada, & Zhang, 2018). These factors can result in higher manufacturing costs and reduced overall supply capacity due to loss of scale economies at Intel and the rearrangement and reorganization of production. Higher costs could necessitate that Intel charges higher prices to its customers, such as IBM, which is unaffected by the disruption.

Second, many competitors belonging to the same industry that share common suppliers tend to make similar products and make use of similar processes (Barnett & King, 2008). In effect, the number of common suppliers is a measure of similarity of both the product and the process. A disruption at one firm to either the product or to the manufacturing process, therefore, will trigger, at the competitive similar firm, increased investigation, such as product or process testing or calibration, or increased supply chain monitoring and governance to preclude a similar fate, effectively resulting in reconfiguration costs (Tsai, 2000). For instance, Hasbro announced it drastically increased its testing and safety check investments on all toys for lead contamination and loose magnets after the Mattel toy recalls in 2007 (Grant, 2007) due to similarity in sourcing behavior. Such *ex-ante* preventive investment may not happen at firms with dissimilar products or processes with no common suppliers.

In conclusion, the negative impact of a disruption on a buying firm's suppliers through reduced and uncertain demand for the suppliers' products would result in higher costs for a competitor that shares the same key suppliers through the associated increases in the costs of production for the common suppliers. Further, disruptions at a firm would trigger pre-emptive expenditures at competitor firms with common suppliers and, therefore, common processes and substitutable products. I suggest, therefore, that the negative impact of a disruption on the disrupted firm would propagate to the disrupted firm's competitors to the extent that they share key suppliers. Such contagion effect would reduce any positive competitive effect the competitor may enjoy as a result of the disruption at the disrupted firm.

Consequently, I propose the following:

*H3a: The increase in shareholder wealth of the disrupted firm's horizontal competitors is negatively moderated by the number of common suppliers between the disrupted firm and the competitor.*

*H3b: The relationship between the supply chain disruption and the operational performance of the disrupted firm's horizontal competitor will be negatively moderated by the number of common suppliers between the disrupted firm and the competitor.*

**2.3.2. Visibility (of disruption event, of the disrupted firm and its competitors)  
and its impact on the association between SCD and competitor firm  
performance**

I argue that visibility of both the event and the firms, disrupted and competitor, will influence the association between SCDs and competitor firm performance. This is because the visibility influences 1) how firms in the industry are seen as vulnerable (perceived) to disruptions and to damages from disruptions and 2) how a disruptive event is perceived, or knowledge about the actual damage of the disruption is disseminated. A firm's visibility is a measure of how industry agents (customers and investors) are familiar with the firm. Information is the degree to which the data and knowledge about an event are available and accessible (Berkelaar & Harrison, 2017). Visibility will result in exposure of information that agents can compare with the information they are already familiar with (Azar, Khan, & Shavaid, 2015). Therefore, the higher the visibility of the firm or the event, or the higher the information that is available and accessible about the firm or the event, the more familiar are agents with the firm and/or event. Visibility, therefore, results in familiarity, and familiarity is a primary reason for the variation in this perceived vulnerability (Malt & Smith, 1982).

First, the disrupted firm's visibility, I argue, is associated with a negative contagion to the industry. Highly visible firms in the industry are tracked heavily by investors, customers, and analysts, thus facilitating higher information availability of a firm's activities. Further, highly visible firms are perceived as industry representatives (Paruchuri & Misangyi, 2015). Hence, when a highly visible firm suffers a supply chain disruption, the higher negative information available may be

attributed to firms with similar operational activity as defined by their industry classification (Barnett & King, 2008). The disrupted firm's extent of visibility, therefore, waters down any positive impacts of the disruption on the bystander competitor.

Similarly, the bystander competitor firm's visibility, I argue, is associated with a negative contagion to that competitor. The degree to which a firm is perceived as being as vulnerable as a misconducting firm depends on the firm's characteristics. More perceived vulnerability is assigned to the more familiar firms because they "are more readily categorized to the industry and thus perceived as instantiating the generalized culpability" (Paruchuri & Misangyi, 2015, p. 175). In other words, highly visible competitors are industry representatives. A disruption to a competing firm may be seen as potentially damaging the visible competitor. The competitor firm's extent of visibility, therefore, waters down any positive impacts of the disruption.

Last, I argue that the event visibility is associated with a negative contagion to the industry. As argued earlier, the degree to which a disruptive event is perceived as damaging depends on the characteristics of the event that makes it familiar to stakeholders. A supply chain disruption at a firm reveals negative information to outsiders about a firm's vulnerability (Zsidisin & Wagner, 2010). As firms are deemed to belong to the same industry when the outputs they produce tend to have similar characteristics, and make use of similar processes (Barnett & King, 2008), a highly visible disruption announcement, therefore, may convey bad news about the competitor firms, since the operational processes are correlated with those of a disrupted firm's operational processes (Porter, 1979). The higher the visibility of the

disruption event, therefore, the higher the exposure of negative information that can be common to firms with similar operations (Lang & Stulz, 1992) and, hence, the higher the negative impact of the disruption on disrupted firm's competitors. I conclude, therefore, that the disrupted firm, competitor firm, and disruption event visibilities increase the negative contagion and reduce positive gains the competitor may make from the disruption. Hence, I formally state:

*H4a: The increase in shareholder wealth of the disrupted firm's horizontal competitors is negatively moderated with the extent of visibility of the disrupted firm, competitor firm, and the disruption event itself.*

*H4b: The relationship between the supply chain disruption and the operational performance of the disrupted firm's horizontal competitor will be negatively moderated with the extent of visibility of the disrupted firm, competitor firm, and the disruption event itself.*

Although visibility results in identification of the firms by their industries and hence engenders negative contagion, visibility may also result in information abundance about a firm's unique vulnerabilities as well as capabilities. This may result in the ascription of the risks associated with the disruption as unique to the disrupted firm. That is, if stakeholders know enough about the two firms, they would be able to draw a line between the two firms. Similarly, a highly visible disruption may convey enough information about the disruption that aids stakeholders to limit blame or responsibility to the disrupted firm. Any or all of these scenarios will engender the bystander competitor firm to exploit the vulnerabilities created by the disruption

event, thereby exacerbating the positive association between SCDs and a competitor firm's operational performance.

Given this counterargument, I also propose a counterhypothesis to Hypotheses 4a and 4b.

*H4c: The increase in shareholder wealth of the disrupted firm's horizontal competitors is positively moderated with the extent of visibility of the disrupted firm, competitor firm, and the disruption event itself.*

*H4d: The relationship between the supply chain disruption and the operational performance of the disrupted firm's horizontal competitor will be positively moderated with the extent of visibility of the disrupted firm, competitor firm, and the disruption event itself.*

### **3. Data**

#### **3.1. Study Setting and Data Sources**

Our study is set in the manufacturing sector providing us with multiple advantages to study supply chain disruptions. First, the manufacturing sector affords the opportunity to assess the impact of unique disruptions as opposed to, for example, retail industry/distribution industries, in which one disruption to a single product may affect several retailers. Second, there is significant variation in the manufacturing industry with respect to their products, giving us an opportunity to study different types of disruptions (Gray & Massimino, 2014). Finally, supply chain disruptions in the manufacturing industry can have a long-term impact on a firm's performance, thus facilitating observations about the impact of disruptions on competitors' operating

performance in quarters after the disruption. The investigation is further limited to public firms, who are required to make public disclosures.

I collected data from four different sources to test my hypotheses. First, I gathered events data documented and tagged by LexisNexis. Second, I used the Factset Revere database to collect information on a firm's supply chain and its competitors. Third, daily stock market prices from Center for Research in Security Prices (CRSP). Finally, a firm's operational performance is derived from the Wharton Research Data Services (WRDS) Compustat records.

### **3.2. Events Collection**

To identify event announcements with the criteria discussed above, I utilized the information provided by LexisNexis. Researchers in operations management, strategy, and marketing use LexisNexis to collect news articles on different events, e.g., product design awards (Xia, Singhal, & Zhang, 2016), CEO departure announcements (Chang, Dasgupta, & Hilary, 2010), and new product preannouncements (Sorescu, Shankar, & Kushwaha, 2007). For every article that LexisNexis uploads to its database, it scans the document and tags it with one or more appropriate categories discussed in the document. Liu and Shankar (2015) used these tags to study product recalls.

I used publications from sources categorized as “Newspapers” and “Industry Trade Press” on LexisNexis. For the publications that are not daily, the news article consisted of the date on which it was documented. For example, an article that was extracted from the newspaper “The Salt Lake Tribune,” circulated weekly on every

Sunday. But the article consists the date it was documented (September 30, 2005, Friday) in this case. Hence, the event day was chosen as the day which the article was documented in the newspaper.

I followed a two-step approach to identify my sample of events (Hendricks & Singhal, 2003). First, I collected news articles tagged as *Supply Chain Disruption* and *Manufacturing Disruptions*. Second, I eliminated articles that fall into one of the following categories:

1. Articles reporting disruptions that have an industry-wide effect. I exclude these events because the event can have a simultaneous impact on a firm and its competitors. Thus, the effect of the disruption at a firm on the competitors' performance is not observed. These articles included disruption events such as natural disasters, government regulations, terrorist activities, and war.
2. Articles reporting a disruption with accompanying positive information. In this case, there can be a confounding effect of the positive information on the impact of a disruption event (Zhang, 2010).
3. Articles identifying potential disruptions and steps taken to either avoid/mitigate the disruption (Zhang, 2010).
4. If there are multiple articles on the same disruption event from a firm within a timeframe of 90 trading days from the day the disruption was disclosed for the first time (Jacobs, 2014), I just include the first announcement. In addition, to avoid confounding effects of multiple disruptions on operating performance, I do not include articles of a firm if it undergoes multiple disruptions in a quarter.

5. Articles that reported earnings or earnings preannouncements that also mentioned supply chain disruptions as a contributing factor. This is because these announcements may not be the first public disclosure of the disruption (Hendricks & Singhal, 2003).
6. Articles where the disrupted firm identified do not have sufficient financial data for analysis.

Our final sample contains 135 disruption events spanning 83 distinct firms over the years 2003–2015. A total of 53 firms have one disruption each in the sample, 17 firms appear twice, 13 firms appear three or more times in my sample.<sup>1</sup> Table 1 presents sample summary statistics of the disrupted firms based on the fiscal year preceding the date of disruption announcement. The sample means of total assets is \$110.59 billion, sales \$93.19 billion, and 108,690 employees.

**Table 1. Descriptive Statistics for the Disrupted Firms Identified in the News Articles<sup>2</sup>**

| <b>Measure</b> | <b>Total Assets (\$B)</b> | <b>Sales (\$B)</b> | <b>Employees<br/>(1000s)</b> |
|----------------|---------------------------|--------------------|------------------------------|
| <b>Mean</b>    | 110.59                    | 93.19              | 108.69                       |
| <b>Median</b>  | 68.94                     | 48.51              | 93.85                        |
| <b>SD</b>      | 113.85                    | 105.06             | 99.96                        |

### 3.3. Competitors' Data and Supply Chain Relationships

I utilize the Factset Revere database to identify firms mentioned in news articles, along with their horizontal competitors and upstream and downstream customers and

<sup>1</sup> See Appendix A for an example of announcements used in the study

<sup>2</sup> Financial data are based on the fiscal year completed before the date of disruption

suppliers, respectively.<sup>3</sup> I use this database to document both direct and indirect interfirm connectivity. This data set is also used to identify shared suppliers of a disrupted firm and its horizontal competitors. The shared competitors serve as the basis for investigating the impact of indirect interfirm connectivity on the direct competitors of the disrupted firms.

Identification of competitors is accomplished using a hybrid approach with data from Factset Revere and methodology from Lang and Stulz (1996) and Hendricks and Singhal (2006). I use stock tickers as the primary key to match the disrupted firm in the LexisNexis article to that in the Factset database.

1. First, I identify the competitor relationships involving the disrupted firm in the Factset database.
2. Second, I pick only the relationships where the event day falls between the relationship start date and relationship end date in the database.
3. Next, I retain the competitors where I am able to match the 4-digit SIC code of the disrupted firm with the 4-digit-SIC code of the competitor firm (Lang & Stulz, 1992). Using this method, I am able match competitors for disrupted firms for 103 disruptions (76.9%).
4. Further I use a 3-digit SIC code for the events where I am unable to match the competitors using a 4-digit SIC code (Hendricks & Singhal,

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<sup>3</sup> The Factset database tracks the relationship between two firms from their relationship start date to the date the relationship ended. Factset systematically compiles its database using public sources like SEC 10-K annual filings, investor presentations, and press releases. It updates its records by daily monitoring corporate actions and press releases. Factset data have been used in major streams of business literature, e.g., finance and business ethics (Almeida, Cunha, Ferreira, & Restrepo, 2017; Auer, 2016)

2006). This round of matching helped us match competitors for another 18 disruption events (13.4%).

5. Finally, I am able to match rest of the disruptions (13 disruption events) using a 2-digit SIC code.

The final number of event-disrupted firm-competitor dyads is 1,060.

Summary statistics for the competitor firms is given in Table 2.<sup>4</sup> I observe that the mean assets of competitors are \$30.53B, mean sales as \$23.59B, and the mean employees as 32,540.

**Table 2. Descriptive Statistics for the Competitors of the Disrupted Firms Identified in the News Articles<sup>5</sup>**

| <b>Measure</b> | <b>Total Assets (\$B)</b> | <b>Sales (\$B)</b> | <b>Employees (1000s)</b> |
|----------------|---------------------------|--------------------|--------------------------|
| <b>Mean</b>    | 30.53                     | 23.59              | 32.54                    |
| <b>Median</b>  | 14.69                     | 12.19              | 2.05                     |
| <b>SD</b>      | 72.23                     | 56.14              | 64.47                    |

#### 4. Methodology

I used event study, a well-established natural experiment methodology, to determine the impact of SCDs on competitors' performance (Jacobs & Singhal, 2014; Hendricks & Singhal, 2003) because SCD occurrences render themselves as natural experiments. I used different event windows starting two days prior to the disruption announcement until two days after the disruption announcement to test Hypothesis 1a. This is consistent with prior studies employing event studies generally, and specifically looking at SCDs. Similar to Xia et al., (2016) and Ba et al., (2013, ) I used event windows [-1, 0] and [-1, 1] to run regression models to test Hypotheses 2a,

<sup>4</sup> See Tables A1 and A2 of Appendix for distribution of competitor firms by disruption announcements and disrupted firms.

<sup>5</sup> Financial data are based on the fiscal year completed before the date of disruption.

3a, 4a, and 4c (). I assessed the operating performance of the competitors and estimated the abnormal operating performance impact by examining the effects on the competitors' returns on assets (Hypotheses 1b, 2b, 3b, 4b, and 4d) for four quarters (1 complete year) starting from the quarter of the disruption using the methodology described by Barber & Lyon (1996).

#### 4.1. Abnormal Stock Market Returns

The abnormal stock return associated with an event is quantified by calculating the difference between observed stock return of firm  $i$  and event day  $t$ ,  $R_{it}$ , and the expected return  $E(R_{it})$  on the event day, estimated using the four-factor model (Xia et al., 2016). Fama and French (1993) identified a model that is extensively used in calculating a firm's expected returns in event studies. In this method, the stock returns on day  $t$  are regressed on average market returns  $R_{mt}$ , risk-free returns  $R_{ft}$ , which is the rate of return on U.S. Treasury bonds, the difference between the rate of returns of small and large-firm stocks (small minus big)  $SMB_t$ , and the difference in returns between high and low book-to-market stocks (high minus low)  $HML_t$ . Note that all the factors are measured on day  $t$ . Carhart improved this model by considering the possibility of measured returns that accumulate due to a firm's prior performance (Carhart, 1997). This possibility is corrected by adding momentum factor  $UMD_t$ , which is defined as the difference in returns between firms with high and low past stock performance. Following prior work such as Robinson, Tuli, and Kohli (2015), the final model employed to calculate the expected returns is

$$E(R_{it}) = \alpha_i + R_{ft} + \beta_i[R_{ft} - R_{mt}] + \gamma_iSMB_t + \delta_iHML_t + \sigma_iUMD_t. \quad (1)$$

I estimate the expected returns for each event in the sample using the data of 200 trading days falling between day -11 and -210 with the event day defined as day 0. To ensure non stationarity in estimates, the event estimation period is ended 10 trading days prior to the event day. Events that do not have minimum 40 trading events that fall during these 200 trading days are eliminated from the sample.

Abnormal returns are calculated by subtracting expected returns from the observed returns:

$$\begin{aligned} AR_{it} &= R_{it} - E(R_{it}) \\ &= R_{it} - (\hat{\alpha}_i + R_{ft} + \hat{\beta}_i [R_{ft} - R_{mt}] + \hat{\gamma}_i SMB_t + \hat{\delta}_i HML_t + \hat{\sigma}_i UMD_t). \end{aligned} \quad (2)$$

Mean abnormal return on day  $t$  for a sample size of  $N$  is calculated as

$$\overline{AR}_t = \sum_{i=1}^N \frac{AR_{it}}{N}. \quad (3)$$

The cumulative abnormal returns across  $N$  events over the event window  $(t_1, t_2)$  is calculated as

$$CAR_{(t_1, t_2)} = \sum_{t=t_1}^{t_2} \overline{AR}_t. \quad (4)$$

As my data contains 135 events and 1,060 event-competitor dyads, cross-sectional dependence is expected. I address this issue in two ways. First, for each event, I take an average of abnormal returns of all the competitors. This gives us the overall performance of competitors on the event day which reduces the potential event day clustering impacts which might result in increased significance of the t-statistic. Second, I adjust the t-statistic for cross-sectional dependence using Brown and Warner (1985).

I then developed a cross-sectional OLS model to test the remaining hypotheses with  $\overline{AR}_0$  as the dependent variable. The functional form of the model is as follows:

$$\begin{aligned}\overline{AR}_0 = & \beta_0 + \beta_1 Supplier + \beta_2 Customer + \beta_3 Common\_Suppliers \\ & + \beta_4 Event\_Visibility + \beta_5 Competitor\_Firm\_Visibility \\ & + \beta_6 Disrupted\_Firm\_Visibility + Control\_Variables \\ & + Event\_Day\_Dummies + \varepsilon\end{aligned}\tag{5}$$

Variable definitions are discussed in Section 4.3.

#### 4.2. Operating Performance (Return on Assets)

I utilize the method proposed by Barber and Lyon (1996) and later used by many researchers in supply chain (Hendricks & Singhal, 2008) to study the effects of SCDs on the undisrupted competitor's performance. In this method, for each competitor in my sample, I identify a comparison group of firms using performance-industry matched, for ROA. The following steps are used in identifying the comparison group for each competitor.

- *Step 1:* I start by eliminating the set of disrupted and competitor firms from the comparison group.
- *Step 2:* For every firm in the sample, I identify the firms that match with the 2-digit SIC code and whose Return on Assets (ROA) lies between the 90% and 100% of the competitor firm. All the

comparisons are made using the performance in the year before disruption has taken place.

- *Step 3:* For the firms that are unmatched from Step 2, I use a 1-digit SIC code and ROA falling between the 90% and 100% of the competitor firm.
- *Step 4:* If there are firms, still unmatched, matching is done solely on ROA, ignoring the SIC code. I did not have to use this step for my analysis as I were able to identify comparison groups for all the competitors by Step 3.

I use the following equation to measure the abnormal operating performance (Return on Assets) for my sample firms

$$\begin{aligned} \text{Abnormal Return on Assets} & \\ &= \text{Return on Assets of the Competitor} \\ &- \text{Expected Return on Assets} \end{aligned} \tag{6}$$

where *Expected Return on Assets* is measured as the average of *ROA* of the control group. After I calculate the *Abnormal Return on Assets* for each competitor in the sample, I aggregate them at the event level to identify the overall competitor's reaction to the disruption, thus testing Hypothesis 1. Hypothesis 2-4 are tested using a cross-sectional regression similar to equation (5) with abnormal return on assets as the dependent variable.

### 4.3.Explanatory Variables

I used Factiva, Compustat, and LexisNexis to calculate various independent variables to test my hypotheses as follows:

- *Supplier* =  
$$\begin{cases} 1, & \text{if the competitor is also a part of disrupted firm's supplier group} \\ 0, & \text{else} \end{cases}$$
- *Customer* =  
$$\begin{cases} 1, & \text{if the competitor is also a part of disrupted firm's customer group} \\ 0, & \text{else} \end{cases}$$
- *Common Suppliers* is the total number of suppliers that the disrupted firm and its competitor have in common on the event day.
- *Event Visibility* is a latent variable used to identify the visibility of a disruption event. I quantify this variable in terms of media coverage of the disruption event. First, I used LexisNexis to identify all the news outlets that published articles about the disrupted firm on the event day. Then, I read through each article to count the number of news outlets that discussed the disruption event. Thus, *Visibility* is the total number of news outlets that has coverage of disruption on the event day.
- *Disrupted Firm Visibility* is identified similar to the *Event Visibility*. It is calculated as the total number of news articles that are published in the news media outlet (aggregated by LexisNexis) in the year of disruption (Eftekhari, Li, Wassenhove, & Webster 2017) mentioning the firm. The total number of articles in a year is then divided by 365 to get the average number of articles per day to keep it consistent with the *Event Visibility* variable which is measured on a single day.

- *Competitor Firm Visibility* is calculated in a similar way as *Disrupted Firm Visibility* is calculated.

Summary statistics of the variables are provided in Table 3. As shown in the table, on average, a disrupted firm and its competitor have 6.65 common suppliers; further, 10% of the competitors are also suppliers for the disrupted firm, while 5% of the competitors also act as customers. The average event visibility is 8.76, i.e., 8.76 articles per disruption event are aggregated by LexisNexis. I also summarize the disrupted firm and competitor visibilities.

**Table 3. Descriptive Statistics of the Hypothesized Variables**

| Variable                   | Mean  | Std. Dev |
|----------------------------|-------|----------|
| Supplier                   | 0.10  | 0.31     |
| Customer                   | 0.05  | 0.22     |
| Common Suppliers           | 6.65  | 13.79    |
| Event Visibility           | 8.76  | 14.70    |
| Competitor Firm Visibility | 10.16 | 69.53    |
| Disrupted Firm Visibility  | 25.04 | 32.62    |

## 5. Results

### 5.1. Abnormal Returns

First, though not hypothesized, I examine the abnormal stock performance of the disrupted firms around the event day. Abnormal stock returns for the disrupted firm are documented in Table 4. I observe that the mean abnormal stock returns for the disrupted firms are negative around the event day with  $CAR_{(-1,0)}$  significant at 5% and  $CAR_{(-2,2)}$  significant at 1% level which verifies that the disruption events are indeed negative in accordance with Hendricks and Singhal (2003).

**Table 4. Abnormal Stock Returns for the Disrupted firm Around Announcement Date**

| Events | Mean Abnormal Return |                     |                     |
|--------|----------------------|---------------------|---------------------|
|        | (%)                  | <i>t</i> -Statistic | Confidence Interval |

|                       |     |          |       |                |
|-----------------------|-----|----------|-------|----------------|
| Day 0                 | 135 | -0.55    | -1.21 | [-1.45, 0.36]  |
| CAR <sub>(-1,0)</sub> | 135 | -1.01**  | -2.02 | [-1.99, -0.02] |
| CAR <sub>(0,1)</sub>  | 135 | -0.53    | -1.54 | [-1.22, 0.16]  |
| CAR <sub>(-2,2)</sub> | 135 | -1.36*** | -2.93 | [-2.28, -0.44] |

\*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$

### 5.1.1. Event study results: Effects of SCDs on Undisrupted Competitor Firms

Table 5 presents the abnormal returns for 132 disruptions (1% outliers trimmed) with different event windows. I observe that event windows -2, -1, [-1, 0], [-2, 0], and [-1, 1] are positive and highly significant while event windows 0, 1, [0, 1], [0, 2], [-2, 2] are marginally significant, which provides strong support for Hypothesis 1a. That is, supply chain disruptions are positively associated with the undisrupted competitors' performance. My results suggest that information leakage effects prevail until 2 days prior to the disruption while the effect of disruption on competitors dampen up rapidly to day +2. I also observe that medians are positive for the event windows -2, -1, 2, [-1, 0], and [-2, 0].

**Table 5. Abnormal Stock Returns Around Announcement Date (n = 132 disruptions)**

| Event window | Mean Abnormal Return (%) | t-Statistic | Median Abnormal Return (%) | % positive |
|--------------|--------------------------|-------------|----------------------------|------------|
| -2           | 0.62                     | 2.10**      | 0.02                       | 50         |
| -1           | 0.65                     | 2.17**      | 0.08                       | 55.37      |
| 0            | 0.38                     | 1.71*       | -0.01                      | 49.19      |
| 1            | 0.51                     | 1.75*       | -0.12                      | 45.45      |
| 2            | 0.41                     | 1.48        | 0.02                       | 50         |
| -1, 0        | 0.97                     | 2.02**      | 0.03                       | 50.82      |
| -2, 0        | 1.56                     | 2.07**      | 0.11                       | 51.24      |
| 0, 1         | 0.85                     | 1.78*       | -0.10                      | 45.46      |
| 0, 2         | 1.26                     | 1.73*       | -0.03                      | 48.77      |
| -1, 1        | 1.53                     | 2.06**      | -0.04                      | 47.94      |
| -2, 2        | 2.42                     | 1.90*       | -0.34                      | 44.63      |

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$ ;  $p < 0.1$

### 5.1.2. Event study results: Effects of Supply Chain Connectivity, Event, and Firm Visibility

Multicollinearity is a potential econometric concern for all empirical model specifications. I check for potential multicollinearity in the model by examining the correlations between independent variables. Table 6 shows the correlations among all the hypothesized variables. Based on O'brien (2007), correlations greater than 0.4 can cause significant multicollinearity issues. I observe that all the correlations are well below the proposed threshold. Also, the highest variance inflation factor (VIF) for the independent variables is 1.03, indicating that multicollinearity is not an issue. Hence, I proceed to the regression analysis.

**Table 6. Correlations among Hypothesized Variables**

|                            | Supplier | Customer | Common Suppliers | Event Visibility | Competitor Firm Visibility | Disrupted Firm Visibility |
|----------------------------|----------|----------|------------------|------------------|----------------------------|---------------------------|
| Supplier                   | 1        |          |                  |                  |                            |                           |
| Customer                   | -0.01    | 1        |                  |                  |                            |                           |
| Common Suppliers           | -0.06**  | -0.05*   | 1                |                  |                            |                           |
| Event Visibility           | 0.07**   | -0.01    | 0.06**           | 1                |                            |                           |
| Competitor Firm Visibility | -0.02    | 0.07**   | 0.07**           | -0.03            | 1                          |                           |
| Disrupted Firm Visibility  | 0.06**   | 0.10***  | 0.17***          | -0.11***         | 0.06**                     | 1                         |

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

Table 7 presents the estimation results of Equation (5). As I observe from Table 5 that investor reaction is concentrated in the  $[-1, 0]$  and  $[-1, 1]$  period, I use CAR for these two event windows as my primary event period of interest for cross-

sectional regression analysis (Modi, Wiles, & Mishra, 2014). Assets of disrupted firm and the competitor firm in the dyad are added as controls along with market-to-book ratio of the competitor (Hendricks & Singhal, 2003). Since a larger relationship between a disrupted firm and its competitor are more prone to propagation than minor relationships, and thus potentially might affect my results. Hence, I control for this phenomenon by adding the number of business segments overlapped (*Segments Overlap*) between the disrupted firm and the competitor as a control variable<sup>6</sup>. As my data follows a nested structure (1,060 firms and 135 dates), residuals may be non-independent. Hence, I cluster my robust standard errors on the event day.

The coefficients of *Supplier* are negative (Model 1: -1.74; Model 2: -2.44) and highly significant ( $p < 0.01$ ), thus indicating that the abnormal returns created by the disruption are brought down when the competitor is simultaneously acting as a supplier to the disrupted firm. The coefficients on the variable *Customer* are insignificant, suggesting that the competitors' abnormal returns are not affected if the competitor is a part of the downstream supply chain of the disrupted firm. Thus, Hypothesis 2a is partially supported. As hypothesized in Hypothesis 3a, I observe a negative sign (Model 1: -0.03; Model 2: -0.05) on *Common Suppliers* with a high statistical significance ( $p < 0.05$ ). This result supports Hypothesis 3a, i.e., that an increase in common suppliers of the competitor with the disrupted firm can result in a decrease in abnormal returns of the competitor created by the disruption. The coefficients on the *Competitor Firm Visibility* (Model 1: -0.003; Model 2: -0.005) are highly significant ( $p < 0.01$ ) while the coefficients on the *Disrupted Firm Visibility* are

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<sup>6</sup> An example of business segment is as follows. Amazon: Online stores, Physical stores, Third-party seller services, Subscription services etc.

insignificant. Interestingly, the coefficients on the *Event Visibility* (Model 1: 0.07; Model 2: 0.12) variable are positive and highly significant ( $p < 0.001$ ), indicating that I find partial support for both Hypothesis 4a and alternate Hypothesis 4c.

**Table 7. Cross-Sectional Regression Results (Clustered Robust Standard Errors in Parenthesis)**

| Variables                     | Model 1:<br>D.V.: Cumulative<br>Abnormal Stock Returns<br>[-1, 0] | Model 2:<br>D.V.: Cumulative<br>Abnormal Stock<br>Returns [-1, 1] |             |
|-------------------------------|-------------------------------------------------------------------|-------------------------------------------------------------------|-------------|
| Supplier                      | -1.74***<br>(0.579)                                               | -2.44***<br>(0.862)                                               | H2a         |
| Customer                      | -0.735<br>(0.630)                                                 | -1.23<br>(1.035)                                                  | H2a         |
| Common Suppliers              | -0.04**<br>(0.014)                                                | -0.05**<br>(0.021)                                                | H3a         |
| Event Visibility              | 0.07***<br>(0.007)                                                | 0.12***<br>(0.010)                                                | H4a,<br>H4c |
| Competitor Firm<br>Visibility | -0.003**<br>(0.001)                                               | -0.005***<br>(0.001)                                              | H4a,<br>H4c |
| Disrupted Firm<br>Visibility  | 0.0006<br>(0.0013)                                                | 0.0003<br>(0.002)                                                 | H4a,<br>H4c |
| Segments Overlap              | 0.0002<br>(0.002)                                                 | 0.0001<br>(0.002)                                                 |             |
| Market-to-Book Ratio          | -0.005<br>(0.004)                                                 | -0.006<br>(0.006)                                                 |             |
| Disrupted firm assets         | 0.004**<br>(0.001)                                                | 0.005***<br>(0.001)                                               |             |
| Competitor firm assets        | 0.002<br>(0.0011)                                                 | 0.003*<br>(0.001)                                                 |             |
| Event Day Dummies             | Included                                                          | Included                                                          |             |
| R-Squared                     | 0.11                                                              | 0.10                                                              |             |
| Observations                  | 1,060                                                             | 1,060                                                             |             |

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

## 5.2. Return on Assets

I provide first, the abnormal operating performance of the disrupted firms in the quarter the disruption took place and the quarter after the disruption event. Results are documented in Table 8. I observe that the mean abnormal return on assets is negative with the abnormal ROA in the quarter after disruption significant at 5% level. This is in line with expectation (e.g., Hendricks & Singhal, 2008).

**Table 8. Abnormal Operating Performance of the Disrupted Firm**

|           | Mean Abnormal ROA (%) | t-Statistic | Confidence Interval |
|-----------|-----------------------|-------------|---------------------|
| Quarter 0 | -0.21                 | -0.73       | [-0.75, 0.35]       |
| Quarter 1 | -0.37**               | -2.15       | [-0.71, -0.29]      |

\*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$

I next present the results of my main hypothesis of competitive effect. Results for Event quarter 0 (the quarter in which disruption has taken place), Event quarter +1, Event quarter +2 and Event Quarter +3 are documented in Table 9. I calculate the abnormal operating performance for 4 quarters starting from the disrupted quarter. I observe that the abnormal operating performance is positive and significant for all the quarters, indicating a strong support for my Hypothesis 1b. Further, I observe that as time passes after disruption, abnormal performance of competitors decreases, indicating a recovery by the disrupted firm. My results further echoes with the existing literature (Hendricks & Singhal, 2005) which identified a negative impact on the disrupted firm until 8 quarters after disruption.

**Table 9. Abnormal Return on Assets Starting from Disruption Quarter (n=132 disruption events)**

|             | Event<br>quarter 0 | Event quarter<br>+1 | Event quarter<br>+2 | Event Quarter<br>+3 |
|-------------|--------------------|---------------------|---------------------|---------------------|
| Mean        | 1.34               | 1.16                | 0.93                | 0.70                |
| t-statistic | 4.59***            | 3.74***             | 2.64***             | 2.33**              |
| Median      | 0.54               | 0.51                | 0.54                | 0.56                |
| % positive  | 65.52              | 66.96               | 67.28               | 66.36               |

Table 10 presents the cross-sectional regression analysis with different quarter windows of Abnormal Return on Assets and Cumulative of Abnormal Return on Assets. Similar to the analysis with stock market performance, my hypothesized variables include *Supplier*, *Customer*, *Common Suppliers*, *Event Visibility*, *Competitor Firm Visibility*, & *Disrupted Firm Visibility*. In addition, I added *Segments Overlap* & *Market-to-Book Ratio*. Also, I control for size of the competitor and disrupted firms. Finally, I added the ROA of the quarter before disruption to reduce plausible inferences endogenous to the study (Bellemare, Masaki, & Pepinsky, 2017).

The coefficients of *Supplier* are negative (Model 1: -3.18; Model 2: -7.19; Model 3: -8.09; Model 4: -2.85) in all the models and highly significant in the first three Models ( $p < 0.01$ ), indicating that when the competitor is connected to the disrupted firm in the upstream supply chain, the negative propagation of the disruption impacts take place, thus providing strong support to my Hypothesis 2b. Similar to my abnormal stock returns model, *Customer* variable is insignificant indicating no downstream propagation. I also find that *Common Suppliers* (Model 1: -0.05; Model 2: -0.21; Model 3: -0.21; Model 4: -0.01) is negative and significant at least  $p < 0.05$  in all models. This finding provides a strong support for my Hypothesis 3b indicating that common suppliers are a strong source of negative contagion. Also, the sign on coefficient of *Competitor Firm Visibility* is negative (Model 1: -0.004; Model 2: -0.009; Model 3: -0.14) and marginally significant providing some support to my Hypothesis 4b. Also, a positive and significant sign (Model 1: 0.01;  $p < 0.05$ ) on *Disrupted Firm Visibility* indicates some support to my alternate Hypothesis 4d. This

finding along with insignificant *Event Visibility* provides motivation for future research on the information visibility during disruption.

**Table 10. Cross-Sectional Regression Results for Abnormal ROA (Clustered Robust Standard Errors in Parenthesis)**

| Variables                     | Model 1:<br>D.V.:<br>Abnormal<br>ROA in Q0 | Model 2:<br>D.V.:<br>Cumulative<br>Abnormal<br>ROAs for<br>Q0-Q1 | Model 2:<br>D.V.:<br>Cumulative<br>Abnormal<br>ROAs for<br>Q0-Q2 | Model 2:<br>D.V.:<br>Cumulative<br>Abnormal<br>ROAs for<br>Q0-Q3 |             |
|-------------------------------|--------------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------|-------------|
| Supplier                      | -3.18***<br>(0.807)                        | -7.19***<br>(2.208)                                              | -8.09***<br>(2.281)                                              | -2.85<br>(8.918)                                                 | H2b         |
| Customer                      | 1.54<br>(3.447)                            | -1.62<br>(3.409)                                                 | -7.12<br>(5.991)                                                 | -11.58<br>(8.083)                                                | H2b         |
| Common<br>Suppliers           | -0.05**<br>(0.022)                         | -0.21***<br>(0.079)                                              | -0.21**<br>(0.084)                                               | -0.01<br>(0.218)                                                 | H3b         |
| Event<br>Visibility           | 0.03<br>(0.045)                            | 0.02<br>(0.030)                                                  | 0.06<br>(0.172)                                                  | 0.08<br>(0.221)                                                  | H4b,<br>H4d |
| Competitor<br>Firm Visibility | -0.004*<br>(0.002)                         | -0.009*<br>(0.005)                                               | -0.14*<br>(0.008)                                                | -0.02<br>(0.014)                                                 | H4b,<br>H4d |
| Disrupted<br>Firm Visibility  | 0.01**<br>(0.005)                          | 0.05<br>(0.041)                                                  | 0.05<br>(0.039)                                                  | 0.04<br>(0.047)                                                  | H4b,<br>H4d |
| Segments                      | -0.03***<br>(0.007)                        | -0.07***<br>(0.016)                                              | -0.11**<br>(0.026)                                               | -0.13***<br>(0.048)                                              |             |
| Overlap                       | 0.078<br>(0.060)                           | -0.09<br>(0.094)                                                 | -0.04<br>(0.116)                                                 | -0.15<br>(0.183)                                                 |             |
| Market-to-<br>Book Ratio      | -0.002<br>(0.004)                          | -0.04<br>(0.048)                                                 | -0.04<br>(0.059)                                                 | -0.06<br>(0.078)                                                 |             |
| Disrupted firm<br>assets      | -0.001<br>(0.003)                          | 0.05*<br>(0.030)                                                 | 0.04<br>(0.029)                                                  | -0.02<br>(0.059)                                                 |             |
| Competitor<br>firm assets     | 0.16*<br>(0.003)                           | 0.46**<br>(0.189)                                                | 0.95**<br>(0.435)                                                | 0.88<br>(0.801)                                                  |             |
| Competitor<br>firm ROA Q-1    | Included                                   | Included                                                         | Included                                                         | Included                                                         |             |
| Event Day<br>Dummies          |                                            |                                                                  |                                                                  |                                                                  |             |
| R-Squared                     | 0.05                                       | 0.12                                                             | 0.10                                                             | 0.07                                                             |             |
| Observations                  | 958                                        | 958                                                              | 958                                                              | 958                                                              |             |

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

### 5.3. Endogeneity

Endogeneity refers to a situation where the independent variables are correlated with the error term, resulting in biased estimates, and can occur in three ways

(Wooldridge, 2009): First, when there is an omitted variable that is correlated with both the dependent variable and the independent variable. In my study, I add event day dummies to control for unobserved time-varying factors that can result in omitted variable bias (Greene, 2008). In estimating the operational performance (ROA), in addition to the event day dummies, I also added the ROA during Q-1 to reduce plausible inferences that are endogenous to the study (Bellemare, Masaki, & Pepinsky, 2017).

The second source of endogeneity is the measurement error. My regression analysis has six independent variables. The direct vertical connectivity of upstream or downstream is a dummy variable, which is not a concern for endogeneity. I used comprehensive data provided by LexisNexis and Factset to measure common suppliers and visibility elements. LexisNexis is one of the largest electronic databases for information related to public records. The chances of having missed news sources to calculate event visibility are therefore limited. Also, the use of Factset is increasing in the supply chain field, thus providing comfortable ground for measures calculated from the data (Chae, Yan, & Yang, 2019). I also compared Factset with the Bloomberg SPLC data, thus making measurement error less of a concern in my study.

The last source of endogeneity is the issue of reverse causality. My unique data and robust research design largely eliminate the concerns of simultaneity. In my first study, reverse causality is not an issue, as my independent variables are “fixed” on the event day, thus ruling out any causality from the opposite direction. In Study 2, as the supply chain variables are tracked by Factset even before the disruption and

updated regularly, it is reasonable to conclude that the reverse causality is not a concern.

#### 5.4. Robustness Analyses

I checked the robustness of my findings with two additional analyses. One analysis determines how sensitive my results are to alternative dependent/performance variables. Specifically, I test if my results hold if the abnormal returns on event windows [-2, 0] and [-2, 2] are used instead.

##### 5.4.1. Alternate abnormal stock returns measure as dependent variables

To test the robustness of the regression results of the stock market reaction, I use two alternate dependent variables. The alternate dependent variables used are the cumulative abnormal stock returns on event windows [-2, 0] and [-2, 2] (Ba et al., 2013; Lo, Tang, Zhou, Yeung, & Fan, 2018; Robinson et al., 2015). Results are presented in Table 11. I observe that the signs of coefficients are consistent with the main results in Table 6. My findings are therefore robust to these alternative measures of abnormal stock returns.

**Table 11. Cross-Sectional Regression Results with Alternate Dependent Variables (Clustered Robust Standard Errors in Parenthesis)**

| Variables        | Model 1:<br>D.V.: Cumulative<br>Abnormal Stock Returns<br>[-2, 0] | Model 2:<br>D.V.: Cumulative<br>Abnormal Stock<br>Returns [-2, 2] |     |
|------------------|-------------------------------------------------------------------|-------------------------------------------------------------------|-----|
| Supplier         | -2.64***<br>(0.871)                                               | -4.08***<br>(1.476)                                               | H2a |
| Customer         | -1.21<br>(1.027)                                                  | -2.51<br>(1.702)                                                  | H2a |
| Common Suppliers | -0.05**<br>(0.020)                                                | -0.08**<br>(0.034)                                                | H3a |

|                               |                      |                      |             |
|-------------------------------|----------------------|----------------------|-------------|
| Event Visibility              | 0.13***<br>(0.010)   | 0.19***<br>(0.015)   | H4a,<br>H4c |
| Competitor Firm<br>Visibility | -0.004***<br>(0.001) | -0.008***<br>(0.002) | H4a,<br>H4c |
| Disrupted Firm<br>Visibility  | 0.001<br>(0.001)     | 0.001<br>(0.002)     | H4a,<br>H4c |
| Segments Overlap              | 0.0004<br>(0.002)    | -0.001<br>(0.003)    |             |
| Market-to-Book Ratio          | -0.003<br>(0.006)    | -0.006<br>(0.009)    |             |
| Disrupted firm assets         | 0.005***<br>(0.001)  | 0.007***<br>(0.001)  |             |
| Competitor firm assets        | 0.003**<br>(0.002)   | 0.00*<br>(0.002)     |             |
| Event Day Dummies             | Included             | Included             |             |
| R-Squared                     | 0.10                 | 0.09                 |             |
| Observations                  | 1,060                | 1,060                |             |

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

## 6. Discussions and Implications

Our research objective is to explore the underlying reasons that help explain the conflicting findings regarding the relationship between SCDs and competitor firms' operational performance. As expected, I find support for a positive effect on competitors of disrupted firms both in terms of stock market reactions to the disruption announcements and actual operational performance measured through abnormal *ROA*. I further find that both the stock market reaction and operational performance are less positive when the competitor firm is a supplier to the disrupted firm and when they share common key suppliers. I also find that the stock market and operational performance does not appear to change any differently when the competitor is also a customer of the disrupted firm. Finally, I find that the stock market reacts in a significantly more positive direction when the disruption event is visible, in a significantly less positive direction with higher competitor visibility and

does not react any differently to the disrupted firm's visibility. The competitor's operational performance, however, is less positive with the competitor's visibility; further, both the event or the disrupted firm's visibility appear to have no impact. The significance that I find for vertical connectivity, event visibility, and competitor firm visibility factors help to explain the mixed results of existing studies. Next, I discuss the research and managerial implications of my findings.

Our first finding is on the impact of a supply chain disruption on the disrupted firm's competitors. This confirms the findings of Hendricks et al. (2019) and conforms with expectations that investors will turn their attention toward a firm's competitors when it suffers a supply chain disruption, with concerns on the disrupted firm's vulnerable situation to act competitively in the market. This finding also confirms studies in other disciplines, suggesting that innocent competitors gain from industry wrongdoing (e.g., Paruchuri & Misangyi, 2015). The shareholders' enthusiasm for the competitor firms during an SCD is also validated through the fact that I find an increase in competitors' operational performance (*ROA*) in the quarter of the disruption and in subsequent quarters. This finding also fulfils the call for research into the impacts of disruptions beyond the disrupted firm (Hendricks & Singhal, 2005; Tomlin, 2006). Managerially, this finding implies that, beyond the negative consequences on the disrupted firm's financial and operational performance (e.g., Hendricks & Singhal, 2003; 2005; 2008; 2009; 2014), supply chain disruptions result in eroding the competitive position of the disrupted firm by redirecting the market and other stakeholders toward the undisrupted competitor.

I next consider the empirical evidence that supply chain interdependency between the disrupted firm and its competitors can have a negative moderating effect on the undisrupted competitor's performance during a disruption event. The stock market, I observed, reacts differently when the competitor firm is also a supplier to the disrupted firm from when no known vertical relationship exists between the two firms. The average abnormal return (event window [-1, 1]) is 1.54<sup>7</sup>, and the coefficient on the *Supplier* variable is -1.74. Therefore, when the competitor is also a supplier to the disrupted firm, the net market reaction is negative (-0.20). My operational performance of the bystander competitor study corroborates this finding. That is, in situations when a vertical relationship between the competitor and the disrupted firm is evident, I find ROA during the disruption to be lower. Indeed, when the competitor is both a supplier and a customer to the disrupted firm, the effect of the disruption on operational performance becomes negative.

I next examine the negative moderating effect of common suppliers between the disrupted firm and its competitors on the competitors' operational performance. Both the stock market and the operational performance of the undisrupted competitor are negatively associated with supply chain disruptions of the focal firm when they share suppliers. My findings suggest that it takes about 25-35 common key suppliers to reverse the positive association between SCDs and competitor firms' stock market and operational performance. This finding contributes to, and reconciles the findings of Filbeck et al. (2016), with my base hypothesis as well as the findings of Hendricks

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<sup>7</sup> This abnormal return is similar to studies that have examined stock market reactions to major events and announcements. The average abnormal returns found by Hendricks and Singhal (2003, 2005) and Jacobs (2013) on Day 0 is about 1%.

et al. (2019). There is tremendous interdependency between Japanese auto manufacturers and their US counterparts. All Japanese auto manufacturers have a transitive relationship with the US “Big Three” through their common supply base. Both the American and Japanese automakers also have the same supply base (Wang et al., 2018). In fact, Toyota and General Motors (GM) have at least 102 (as calculated from Factset) common first-tier suppliers in North America, Japan, and China. If a disruption at these Japanese automakers affects these supply bases, their finances or operations or both, the suppliers may not be able to supply the US manufacturers, thus resulting in operational and financial problems for the US manufacturers even though they (the US manufacturers) are not directly involved in the disruption. To put this into perspective, with a modest 50 common suppliers between GM and Toyota, for example, a disruption at Toyota would reduce GM’s *ROA* by -1.16 ( $1.34 - 0.5 \times 50$ ) and result in an abnormal stock return of -0.47% ( $1.53 - 0.04 \times 50$ ).

Our findings on the negative impact of vertical connectivity between a focal firm on a bystander competitor’s performance during an SCD have significant managerial implications. My research directs managers to the complexities of their supply chains as well as the connectivity to their competitors as sources of disruption risks. My study establishes that firms will still suffer consequences of disruption events even if their own processes are immune to disruptions when interconnectivity exists between them and their competitors. While I am not advocating that competitors should not share suppliers, or should not collaborate, I am suggesting that

managers consider that these relationships might be a source of great loss and hence put measures into place to mitigate these losses if and when they occur.

Next, I discuss the effects of visibility on the undisrupted competitor's performance during an SCD. I observe that the competitors' operating performance is decreased in the post-disruption period with an increase in its visibility. Interestingly, investors do not seem to be sensitive to the differential impacts of disruption with respect to the competitor's visibility. However, I find, as suggested by alternate Hypothesis 4c, that the stock market reaction due to a competing firm's SCD is positively associated with the event visibility. That is, investors believe that a highly visible disruption can in fact strengthen the competitor's position in the industry. This puts the findings of Hendricks et al. (2019) into context and reconciles it with the opposing findings. The earthquake in Japan that Hendricks et al. (2019) investigated, was a visible event dominating print, television, and Internet media. In fact, the East Japan earthquake had about 4,451 mentions in LexisNexis within two days of the event.

This finding is also of interest to managers. To both the disrupted firm and the undisrupted competitor, high coverage of a disruptive event by the popular media should be a signal of shifting momentum toward the undisrupted competitors. This finding lends credence to the fact that Hasbro specifically named Mattel and its toy woes of 2006 and 2007 during press briefings of its own actions to avoid the same fate (Grant, 2007). A second example is that Sanitarium specifically stated that unlike its biggest competitor Kraft, its peanut butter was not contaminated with salmonella

in their commercials in newspapers and on radio during Kraft's peanut butter-salmonella problems (Van Heerde, Helse, & Dekimpe, 2007).

Next, I examine the anecdotal evidence from Lululemon Athletica and Nike, on the one hand, and Honeywell and Lockheed Martin on the other. Lululemon and Nike are not part of each other's supply chains, have one common supplier, and the event was not that visible. The disruption event had only one announcement. With this information, Nike's fitted abnormal returns is 1.46% compared with an actual return of 1.5%. On event announcement day, Honeywell and Lockheed Martin had 10 common suppliers, and Lockheed Martin is a supplier to Honeywell. The fitted abnormal return is -0.68%, matching the negative stock market performance of Lockheed Martin on the event day, though at a much higher magnitude. My study in totality, therefore, helps to explain the divergence in findings on competitor performance during an SCD.

## **7. Limitations and Future Research**

As is the case with every research study, my research has limitations. First, to facilitate the study of operating performance using difference-in-difference methodology, I eliminated the events of firms with more than one disruption in a period of five consecutive quarters to reduce the confounding effects of multiple disruptions in the treatment and control periods. Techniques that can synthetically control for these effects while looking into all disruptions can be a significant contribution to my study. Second, I do not categorize the type of disruption and treat all disruptions as having similar impacts. There is anecdotal evidence suggesting that

type of disruption can have a differential impact on supply chain performance (Wagner & Bode, 2008). Therefore, it will be interesting to examine if the type of disruption can have varying effects on the horizontal propagation of disruption. Finally, surprising results of Hypotheses 4a and 4c suggest an in-depth exploration of the mechanism behind information dissemination in disruption context is study-worthy.

## **8. Conclusions**

In this paper, I examined the prevalence of competitive and contagion effects in the context of supply chain disruptions. I observe that, when a firm suffers from a supply chain disruption, the operational performance of the disrupted firm's competitors increases in the form of abnormal stock returns and return on assets. However, when the competitor is vertically connected directly as an upstream supplier or downstream customer, I observe a contagion effect, i.e., negative spillover effects. This phenomenon is also extended to indirect connectivity in the form of common suppliers. I further find that visibility of the disruption event exacerbates the positive impact of SCDs on a bystander firm's stock market performance, and that the visibility of the bystander competitor firm reduces the positive gains from the focal firm's disruption woes. Put together, my study in totality, therefore, helps to explain the divergence in findings on bystander competitor performance during a focal firm SCD. These findings, I believe, contribute significantly to research in supply chain disruptions in particular and industry wrong-doing in general. I also trust that my study will be of importance to practitioners, as it points to potential sources of loss that are generally beyond their individual control.

## **Chapter 2: Impact of Supply Chain Complexity on the Likelihood of Plant's Man-made Disruptions and Recovery Time From a Supply Chain Disruption**

### **1. Introduction**

The occurrence of supply chain disruptions represents a major problem to many firms in today's global economy. Indeed, the Covid-19 Pandemic, a natural supply chain disruption, has created a significant exogenous shock to every supply chain (Choi, Rogers, and Vakil, 2020). Prior to the Covid-19 Pandemic, a study by Resilinc Corporation identified that over 1,000 supply chain disruptions occurred in the first half of 2018. At that time, this number represented the highest number of disruptions in a six-month time period since Resilinc's monitoring service began in the Year 2010 (Resilinc, 2018). Despite the potential negative affect that disruptions can have on the firm, many supply chain managers have not proactively implemented strategies to mitigate the impact these unexpected events can have on the flow of goods, information, and financial transactions (Narasimhan and Talluri, 2009; Wuttke, Blome and Henke, 2013). In this study, I define a supply chain disruption as any "event that adversely affects a manufacturing plant's normal operations" (Schmidt and Raman, 2012). Specifically, I focus on man-made supply chain disruptions that have occurred at a manufacturing plant including but not limited to factory fires, power outages, supply shortages and recalls. Several empirical studies have documented that supply chain disruptions can present operational challenges to a firm, curtail a firm's growth plans, and reduce profit margins (Hendricks and Singhal, 2003, 2005; Craighead, Blackhurst, Rungtusanatham and Handfield, 2007).

Many firms find it difficult to manage the complexity that exists in their supply chains, especially during the occurrence of a supply chain disruption. Choi, Rogers, and Vakil (2020) and Lambert (2005) point out that many firms have not sufficiently mapped their supply chains and, thus, do not have a complete understanding of potential locations of risk and vulnerability. However, some firms have embraced the need to develop superior supply chain capabilities to reduce their vulnerability to supply chain risk (Ellinger et al., 2011). Indeed, Unilever's supply chain consistently receives a premier ranking because it operates a fully integrated supply chain with over 66,000 suppliers located in more than 90 countries. Employing a risk-based mitigation approach, Unilever regularly audits and classifies its suppliers on the potential supply risk to the firm. Indeed, Unilever identified that 19,000 suppliers present risk to the firm. Unfortunately, especially in times of supply chain disruptions, many other firms continue to struggle to proactively manage the complexity associated with the sourcing, manufacturing, and logistics activities needed to meet customer demand.

Prior research in the supply chain disruptions literature has mostly focused on the impact of supply chain complexity on the occurrence of supply chain disruptions at the firm-level (Craighead et al., 2007; Zhao et al., 2019) and scholars have found a negative relationships (Bode and Wagner, 2015; Wiedmer et al., 2021). This stream of research has taken an aggregate view of all sites and considering them as one firm with a focus on the headquarters of the firm regardless of the actual geographical location of the disruption. While this aggregate firm level view helps in understanding the complex supply chain structure of the firm, it does not provide

sufficient insight necessary to isolate the impact of disruptions on individual sites. As most disruptions take place at individual sites, and sites are distributed across multiple geographic locations, it is important to understand the complexities at the site level for a better insight into firm's response to disruption. In addition, previous research has not attempted to distinguish between man-made and natural disasters which can significant implications regarding a manufacturing site's capability to proactively plan and respond to these unfortunate events.

The purpose of this study, then, is to first, examine the impact of the uncertain environment of the focal site on the likelihood of a site experiencing a disruption. Specifically, I study the peer-to-peer learning from the environment in which the focal site is located. Then, I explore how structural characteristics of the focal site can affect its proactive strategies to avoid disruption along with reactive strategies that aid the site in its recovery process after the disruption. Because firms are increasingly exposed to multiple dimensions of complexity in their supply chain, I theorize on how internal and external structural characteristics impact the likelihood of disruption along with the recovery time if the site goes down due to disruption. Indeed, some firms may have a stronger ability to manage the complexity and risk present at their plant locations compared to the abilities of other firms to manage their complexity. Likewise, I closely look into the role of business continuity management (BCM) plans in the recovery process after disruption. In doing so, I examine the role of strategic, operational, and supplier orientation of BCM plans on the recovery time of the focal site.

Our study builds-upon and extends prior supply chain complexity and disruption research in multiple ways. First, I contribute to this nascent literature stream by developing a theoretical model and empirically testing the interface of supply chain complexity on focal site's likelihood to experience man-made disruptions and also the recovery from a disruption (Bode and Wagner, 2015; Zsidisin, Melnyk, and Ragatz, 2005; Vachon and Klassen, 2002). Capitalizing on the supply chain complexity theoretical literature (Bozarth et al., 2019; Bode and Wagner, 2015; Lu and Shang, 2017), I theorize on how information, internal, and external dimensions of supply chain complexity impact a site's vulnerability to disruptions along with recovery time from a disruption.

Second, although prior research has examined the important role of organizational learning within the firm (Ambulkar et al., 2015; Azadegan et al., 2020), to the best of my knowledge, prior research has not studies why and how peer-to-peer learning among firms can mitigate the negative impact of disruption on the manufacturing site, leaving a major gap in what I know about vicarious organizational learning. I try to address this gap by empirically examining the impact of prior disruptions at peer sites on the subsequent frequency of disruptions at the focal site.

Third, I also add to this research stream by theorizing and empirically examining the impact of business continuity management (BCM) plans on the recovery process from a disruption. Although BCM plans are gaining strong support in corporate boardrooms, there is limited evidence in the supply chain literature on the efficacy of these efforts (e.g., Zsidisin, Melnyk, and Ragatz, 2005; Azadegan et

al., 2020). In this study, I examine how comprehensive BCM plans that have a strategic, operational, and supplier orientation can support the focal site's recovery process.

Next, using my comprehensive database, I add to my theoretical and empirical understanding about the antecedent factors that influence the occurrence of supply chain disruption by formulating unique constructs such as like proportion of business processes with alternative sites, and proportion of parts with multi-sourcing. Sheffi and Rice (2005) indicate that it is important to examine the role of alternate manufacturing resources in managing supply chain disruptions. Although, the concept of alternate manufacturing resources play a very important role in supply chain resilience, the literature has mostly studied this concept in mathematical modelling (Zhang et al., 2010; Zheng, Feng, and Tan, 2017) due to unavailability of archival data. I am able to overcome this difficulty by measuring this variable through access to the Resilinc database. In addition, I am able to drill down the supplier base to as deep as 4 echelons, further providing a comprehensive assessment of supply chain complexity of a focal site including direct and indirect connectivity between the focal sites and OEMs.

Finally, my research represents an important empirical contribution to the literature because I test my theoretical model using a secondary database of site level disruption data derived from global supply chains. Specifically, I created a unique data set representing over 4 years of repeated observations at the site level representing 70 countries. Indeed, a limitation of previous supply chain research is the reliance upon perceptual survey data of supply chain complexity and firm

performance which is confined to a single country or a region and static in nature (Bozarth et al., 2009; Bode and Wagner, 2015). My confidential secondary dataset provided by Resilinc Corporation contains actual supply chain complexity, supply chain disruption, and plant recovery data across global supply chains, thus enabling us to overcome the limitations of previous survey-based research (Choi, Rogers, and Vakil, 2020). Indeed, my dataset affords us with the opportunity to develop granular insight into the role of external and internal elements of supply chain complexity that was not possible in previous research. In addition, I am able to take a dynamic view as I have data across multiple time periods at each site in the network. In so doing, my research directly builds-upon previous supply chain complexity and disruption research such as Bozarth et al. (2009), Zsidisin et al. (2005), Vachon and Klassen (2002), among several others.

Through my careful review of supply chain complexity and disruptions literature, I contend that previous research has not examined the impact of supply chain complexity on a site's likelihood of having a disruption and recovery from a disruption. Beyond Bode and Wagner (2015), I did not identify any other study that theorizes and empirically examines the relationship between supply chain complexity and disruptions where they study the impact of different supply side complexity dimensions on the frequency of disruptions. The disruption recovery literature review by Ivanov et al. (2017) emphasizes this fact and calls for studies that incorporate the supply chain structure's impact on the firm's recovery performance. Thus, my study seeks to fill this void in the literature by theorizing and empirically analyzing the

impact of supply chain complexity on the likelihood of disruption and a focal site's recovery time.

I organized rest of the paper as follows. In section 2, I present supply chain complexity as the overarching theory to this study. Section 3 I develop different direct and moderating hypotheses on the impact of supply chain complexity on the plant's recovery time. Section 4 describes the methodology, databases, and results. Section 5 presents the discussion and section 7 concludes.

## **2. Supply Chain Complexity Theoretical Foundation**

Supply chain complexity is the theoretical foundation for this study. As presented earlier, supply chain complexity is defined as the number and interactions among the structural linkages between the firm and its upstream partners (Bozarth et al., 2009; Vachon and Klassen, 2002), along with the number and pattern of internal activities of the firm. These structural linkages and internal activities provide the paths through which physical parts, information, and financial transactions are exchanged. In the short term these linkages and activities are fixed and static in nature. However, with a longer-term perspective, these linkages and activities are subject to change and are, as a result, dynamic with frequent changes occurring. In this research, I leverage the supply chain complexity framework developed by Bozarth et al. (2009) to examine the static and dynamic elements that characterize supply chain complexity that is present in both the upstream and internal supply chain operations of manufacturing plants. In so doing, I theorize on how supply chain complexity affects plant level performance. Given the potential negative effects, it is a critical for a firm to

proactively manage its supply chain disruption activities (Macdonald and Corsi, 2013). Thus, an important element of my theoretical model is on how firms can mitigate disruption risk through the use of business continuity plans (Blackhurst, Craighead, Elkins, and Handfield, 2005).

Supply chains are complex adaptive systems which are interconnected with multiple entities and exhibit adaptive action as a response to factors present in the environment and the entities in the systems (Choi et al., 2001). Zhao, Zuo, and Blackhurst (2019) showed that this adaptive behaviors from firms can reduce the impact of supply chain disruptions in a network. In this study, I theorize about how peer sites are able to from each other over time in order to adapt to complex supply chains and to act more proactively in preparing for any potential disruptions.

As noted, supply chain complexity theory purports that elements in supply chains that, in the short term, are static (Duncan, 1972). The static element refers to the structure and connectivity of different subsystems such as suppliers, customers, internal manufacturing processes, and business functions that do not frequently undergo significant change in the short term (Senge, 1990; Serdarasan, 2013). Because static elements persist in modern supply chains, I develop theory on how these factors impact a plant's proactive strategies to reduce their likelihood of disruptions and reactive strategies that aids them in recovery time performance.

Supply chain complexity theory also suggests supply chains are dynamics in nature. Indeed, Vachon and Klassen (2002) contend that supply chains are unpredictable in nature because the linkages connecting a firm and its upstream suppliers can change. Firms switch their suppliers due to a range of factors, including

quality issues, lead time variability, and price increases (Bozarth et al., 2009). Furthermore, the information flowing across the linkages is dynamic as firms either increase or decrease the amount and type of information they exchange with their supplier partners. Changing partnerships and fluctuations in information exchanges also lead to fluctuations in the financial exchanges across the linkages in the supply chain. In general, the extent of these types of dynamic factors are precipitated, in many cases, by supplier unreliability. In addition, the dynamic relationship between the firm and its partners leads to changes in the number and pattern of internal activities. Indeed, shifts in a firm's linkages to its supplier base may require additional activities be processed internally as opposed to being outsourced. Dynamic supply chain complexity exists because of the unpredictability of information flows that propagate across complex supply chains (Serdarasan, 2013). Since this is an important element in the supply chain complexity literature, my theoretical model focuses on the dynamics of supply chain complexity.

Supply chain complexity theory suggests that internal complexity impacts a firm's performance. Indeed, complexity arises at manufacturing facilities because plants are responsible for managing thousands of parts, multiple manufacturing steps, and numerous supply chain activities such as fabrication, testing, and assembly (ElMaraghy, ElMaraghy, Tomiyama and Monostori, 2012). The static dimension of internal complexity consists of structure related elements like number of products, parts, and processes. The dynamic dimension represents uncertainties related to processes, employees, and forecasting plans. The vulnerability of a supply chain to disruption increases due to centralization resulting from an increase in the number of

activities at the plant (Haywood and Peck, 2003). Pettit (2008) suggested that firms must conduct analysis between benefits from centralization strategies and costs of potential disruptions due to centralization.

**Figure 1. Theoretical Model of the Factors That Affect Focal Site's Frequency of Disruptions**

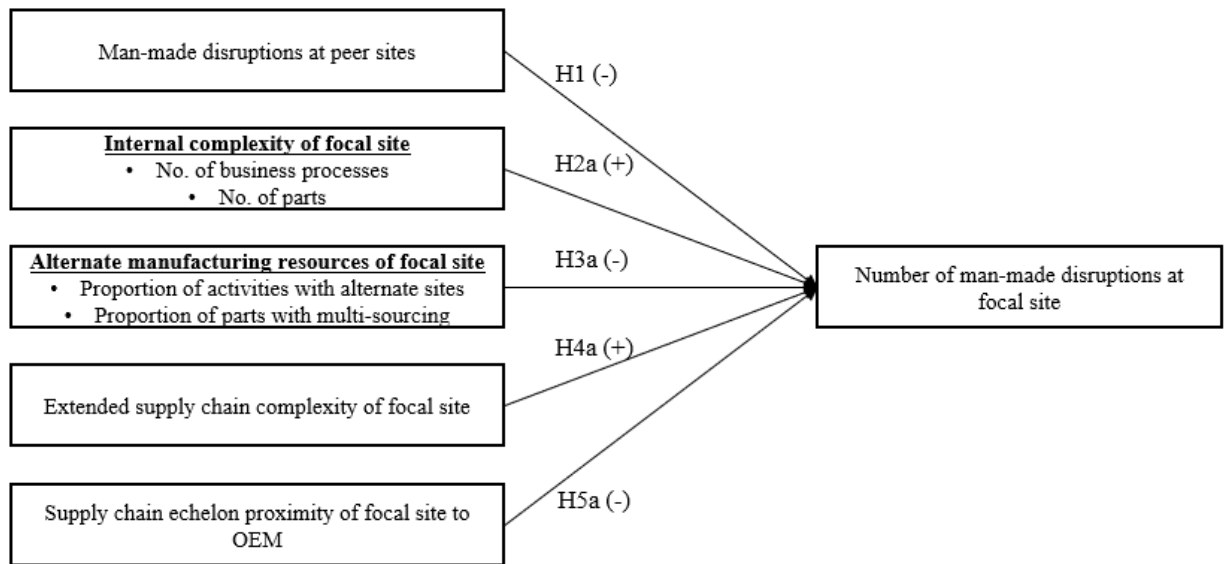
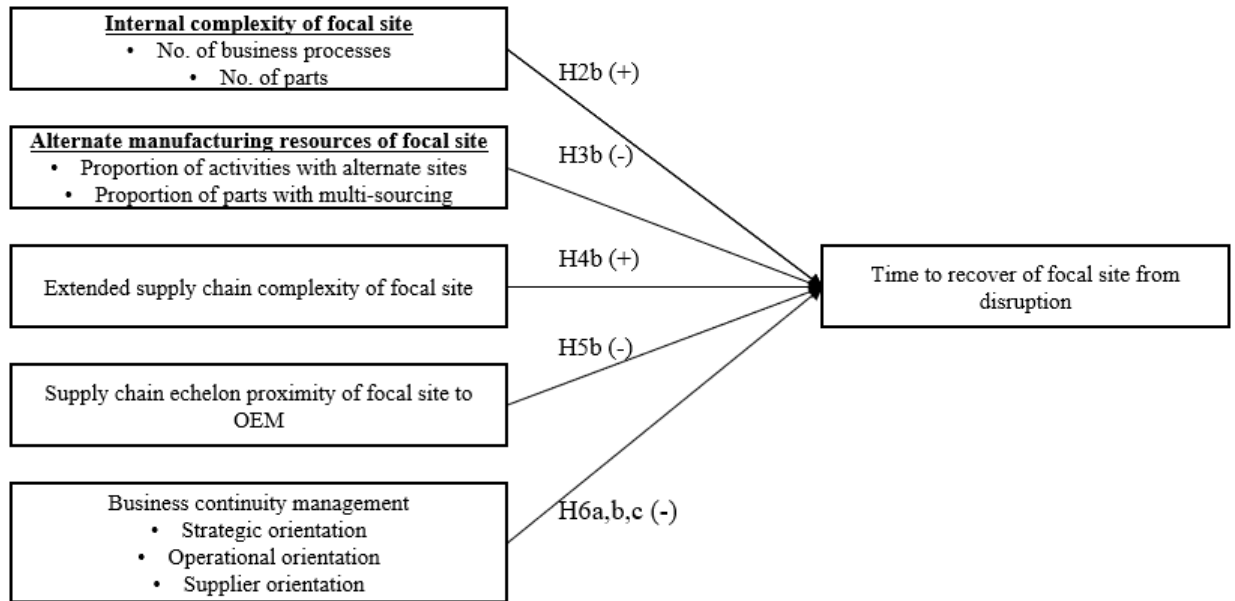


**Figure 2. Theoretical Model of the Factors That Affect Focal Site's Time to Recover After Disruption**



### 3. Hypotheses Development

Our theoretical models are presented in Figure 1 and Figure 2. Figure 1 presents the factors that impacts the number of man-made disruptions at focal site. Figure 2 presents the factors that affect the time to recover of the focal site from disruption

#### 3.1. Peer-to-Peer Interfirm Learning

The ability to learn how to respond to supply chain disruptions from peer sites is the first factor in my supply chain complexity and disruption model. In this study, I define peer-sites as the sites that are in the same zip code as the focal site and are not owned by the firm that operates the focal site. Poor information sharing and information complexity is a serious contributor to a firm's involvement in supply

chain disruptions (Chopra & Sodhi, 2004; Narasimhan & Talluri, 2009). For example, the lack of prior experience in dealing with severe winter storms resulted in the failure of utilities, thus disrupting several manufacturing facilities in Texas during the winter storms of February 2021 (King & Bloomberg, 2021). Peer-to-peer interfirm learning can potentially lessen the occurrence of these and related disruptions. I define peer-to-peer interfirm learning as those organizations that can learn from each other because they are co-located within a close geographic proximity. Traditionally, close proximity makes it more likely that the firm's employees will frequently interact via in-person meetings that fosters the development of trust and collaboration. The in-person meetings and interactions can occur through social networks such as industry groups, trade associations, or casual gathering places (Saxenian, 1994). Firms that are in a close geographical area can also engage in interorganizational learning through Industry Peer Networks (IPNs) (Leung, Xu, Wu, & Luthans, 2019). In IPNs, small groups of peer firms gather and participate in a series of formal and informal discussions which facilitates each firm sharing their knowledge and experience with others. This facilitates the development of interorganizational learning which helps focal site managers to make decisions that are pragmatic and avoid any events or situations that could lead them to a disruption in their operations. For example, Haunschild and Sullivan (2002) showed that accident rates at U.S. airlines decline with the increase in number of accidents experienced by their peer firms. Undoubtedly, these examples illustrate how inter-organizational learning can reduce uncertainty at the focal site that experience unexpected events (Gupta & Misangyi, 2008).

Notwithstanding the positive aspects of inter-firm collaboration, learning from peer firms is very complex for several reasons. First, employees at the focal firm's plant are typically *external* observers of the peer's behaviors. As such, the employees and their colleagues employed by other firms need to have established high level of inter-organizational trust in support of inter-firm learning. Trust is critical or otherwise managers at the focal site will not be allowed to observe their peers day-to-day tasks, policies, operations mechanisms that could have led to their disruptions (Ching, 2010). In addition, peer-to-peer inter-firm learning is unlikely to result in the development of the *internal* "know-how" on how to implement practices to reduce the occurrence of future disruptions because these firms could be potential competitors to one another. In many industries, firms often perceive competition as a zero-sum game; thus, peer firms may create barriers that limit access to resources thereby restricting the focal plant's ability to learn from them (Lado et al., 1997). In addition, many firms have limited internal resources that can be mobilized to leverage external knowledge resources including in the supply chain domain. Indeed, organizational support structures need to be in place to leverage such resources (Cantor, Morrow, & Montabon, 2012) to address the lack sufficient information that could increase the plant's exposure to disruptions (Unhelkar & Gonsalves, 2020). Hence, I hypothesize the following.

*H1. Prior man-made disruptions experienced by peer sites will reduce the likelihood that the focal site will experience man-made disruptions.*

### **3.2.Internal Complexity**

I now turn to describing the internal sources of supply chain complexity grounded in my theoretical model. Internal sources of supply chain complexity within the plant make it more difficult for an organization to effectively coordinate and manage tasks that are vital to identify any events that have the potential to cause disruptions at the site (Christopher & Helen, 2004; Bode & Wagner, 2015). In this study, I focus on attributes related to parts and manufacturing processes as prominent internal sources of complexity. In so doing, I theorize about how the number of parts associated with the manufacturing site increases its complexity (Bozarth et al., 2009). Likewise, as the uncertainty about the manufacturing process increases, supply chain complexity increases (Blecker, Kersten, & Meyer, 2005).

The first internal complexity factor that I explore is the number of parts associated with the manufacturing plant. I view this factor as a source of complexity to a site because greater part varieties requires a complex set of operations needed to manage the design, manufacturing, and distribution process. For a plant to manage a large volume and variety of parts creates stress on purchasers and schedulers to execute manufacturing operations in a systematic manner. In so doing, high quantities of parts require a plant to have increased variety of production machines, greater variety of raw materials, work-in-process, and finished goods inventory. Because of this complexity, uncertainties at a plant will increase with increased part numbers, thus creating an increased risk for disruptions (Thonemann & Bradley, 2002).

The next source of internal complexity that I examine is the number of internal manufacturing processes at a manufacturing plant (Thun & Hoenig, 2011).

The manufacturing processes at a manufacturing plant comprise the tasks and sets of conditions that can determine the order and direction of these processes (Du, Lai, Cheung, & Cui, 2012). Some examples of these processes include assembling, fabrication, and molding. An increase in manufacturing tasks will result in a higher complex interaction between different functional areas of the plant and a higher level of decentralized decision-making, thus increasing the uncertainties in the operational process at the manufacturing plant (Bozarth et al., 2009). I view these changes as dynamic because they are fluid in response to changes in the linkages among a firm's upstream suppliers as well as changes in response to fluctuations in customer preferences and buying patterns.

The complexity of processes in a supply chain represents the degree of variability and the interdependency of tasks. As the degree of variability and interdependency increase, the work performed at the manufacturing plant tends to be unstructured (Du et al., 2012). The unstructured nature of production work makes the assessment of events that lead to disruptions difficult and creates hardships in formulating appropriate rules and procedures to avoid disruptions, thus creating an uncertainty in the operations of the plant. Hence, I hypothesize the following.

*H2a. The greater the internal complexity of the focal site, the higher the likelihood that the focal site will experience man-made disruptions.*

Increased uncertainties in the internal business operations (higher parts and processes) can have an impact on the recovery time for multiple reasons. First, mechanization is the required technical skill and know-how to perform operational tasks in a manufacturing process (Frohlich & Dixon, 1999). As manufacturing

procedures become more complicated, more advanced know-how and skill are required to operate them (Quinn, Anderson, & Finkelstein, 1998). As personnel with advanced skill set are not always readily available, it hampers the ability of the focal site to recover from the disruption. Second, greater internal complexity can also increase the manufacturing and order cycle times, thus increasing the recovery time from a disruption (Rao & Young, 1994). Higher order cycle times can be a source of higher variance in demand forecasts and price fluctuations, which further complicating the recovery process. Third, increased complexity makes the parts and process mapping difficult (Soliman, 1998). This difficulty in mapping undermines the manufacturing plant's efforts in eliminating nonvalue-adding activities that may not be required during the recovery process. Finally, a complex internal business environment can reduce the transparency of material flows, making it difficult to control the recovery process.

However, it is important to note that some firms will prioritize the allocation of resources to ensure plants that manage parts in greater demand recover faster than their other locations. Likewise, several firms have proactively streamlined their internal business process through Kaizen events; for example, Handfield and McCormack (2007), in their interviews with practitioners, identified that firms that put more resources into reducing process complexity are able to speed up the recovery time after a disruption. While there are certainly industry exemplars on how some firms can manage their internal complexity effectively, based on my overall arguments, I present the following hypothesis:

*H2b. The greater the internal complexity of the focal site, the longer the recovery time of the focal site from a man-made disruption.*

### **3.3.Alternative Manufacturing Resources**

Now, I discuss how alternative manufacturing resources can reduce the likelihood that a plant experiences a disruption and enable for faster recovery after the focal site suffers a disruption. Specifically, I examine how business processes with alternate sites and multi-sourced parts provides resilience to the focal site against events that can cause disruptions in its operations (Sheffi & Rice, 2005).

Many firms differ in the risk management strategies that they employ. Some organizations follow proactive strategies and are more planning oriented while other focus on reactive strategies (Angkiriwang et al., 2014). The firms which follow proactive risk mitigation strategies invest in slack resources to build redundancy in their organizations. They do so because of the belief that they cannot afford to experience failure in their systems for fear of lost customers and/or bankruptcy (Elluru, Gupta, Kaur, & Singh, 2019). Other firms are risk-neutral and/or are constrained by financial and human resources, thus preventing them from making investment into slack resources for redundancy purposes (Hendricks, Singhal, & Zhang, 2009). Here, I discuss how slack resources and redundancies enable firms to mitigate the risk that the complexity presents, by examining the role of alternate sites and multi-sourcing.

Alternate sites are used in when the primary site experience a disruption or it is difficult for suppliers to access them. A firm having an alternate site indicates its

proactive posture towards investment into supply chain risk management (Saenz & Revilla, 2014). Proactive firms aim to reduce the likelihood of being harmed by disruptions as they routinize the identification and analysis of business situations that could become threats to their business operations (Norrman & Jansson, 2004). A firm implements a contingency plan such as enabling an alternate site when it correctly identifies the drivers of risks, assessing and prioritizing these risks. Thus, a firm that has proactively assessed potential sources of risk is better prepared to face potential threats and neutralize them before they disrupt the facility.

Similar to alternate manufacturing sites, multi-sourcing can help reduce the risk of supply chain disruptions in many ways. First, multiple suppliers for a single part can reduce the probability of bottlenecks in production due to insufficient capacity to meet peak demand (Kraljic, 1983). Second, it reduces the risk of opportunistic behavior from suppliers. Next, alternate sources for supply are critical when there is a delivery stoppage by the primary supplier (Knemeyer, Zinn, & Eroglu, 2009). Finally, increased competition among suppliers can lead to a better quality of product, better prices and delivery, along with product innovation from suppliers, thus further reducing the likelihood of disruption (Shin, Collier, & Wilson, 2000). Hence, I hypothesize the following.

*H3a: The greater the alternative manufacturing resources at the focal site, the lower the likelihood that the focal site will experience man-made disruptions.*

Alternate sites provide higher flexibility for an organization to react to unexpected events that could halt the operations of the focal site. These alternate sites

reduce the dependency of the firm on a single facility by implementing its contingency plan to shift business processes and manufacturing operations from the primary site in case of an emergency (Lumley & Misra, 1994). They act as substitutes to primary sites when the primary site faces an unexpected event that could disrupt the business processes, thus ensuring business continuity and speeding up the recovery process (Knemeyer et al., 2009).

In addition to reducing the risk of a disruption, multi-sourcing also impacts the speed by which the focal site can recovery from a disruption. First, a more diverse supply base means less dependence on any individual supplier which helps in parallel sourcing from multiple suppliers to speed up the recovery process (Kohiluoto, Makinen, & Kaseva, 2020). As opposed to “lock-in” due to specific dependencies on single supplier, multi-sourcing enables the focal site to better negotiate the price and terms that can enhance the recovery process (Sheu, 2016). Also, a shortage of parts from a single-sourced supplier can hamper the progress of recovery after disruption. Finally, multi-sourcing enables the focal site to monitor supplier’s performance and choose the best among the lot that can help focal site speed up the recovery process (Goren, 2018).

*H3b: The greater the alternate manufacturing resources at the focal site, the shorter the recovery time of the focal site from a man-made disruption.*

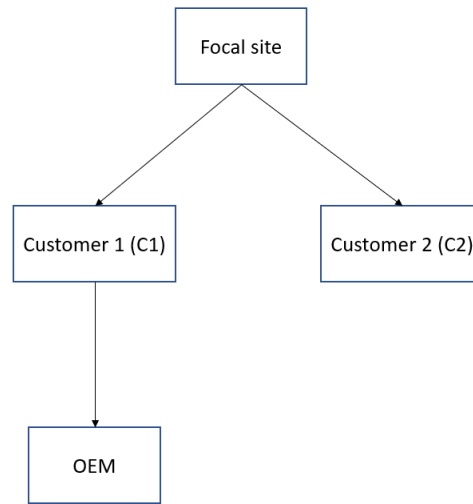
### **3.4.Extended Supply Chain Complexity**

Our theoretical model considers how extended supply chain complexity of the manufacturing plant can result in increased probability of disruptions and also

likewise, dampen the recovery process after a disruption. I define extended supply chain complexity as reflected in the management of multiple supply chains and correspondingly, multiple relationships. Indeed, many firms can become vulnerable to opportunistic behavior as the number of supply chains that requires oversight increases. In this section, I look beyond the traditional way of measuring extended supply chain using suppliers and customers (Vachon & Klassen, 2002; Lu & Shang, 2017; Wiedmer et al., 2021). I characterize extended supply chain complexity as the number of supply chains a focal site is involved in. This is illustrated in Figure 3.

To illustrate the multiple supply chain concept in my study, I turn my attention to Figure 3, that depicts how the focal site is involved in multiple relationships. The focal site is directly connected to its downstream partners C1 and C2, but also indirectly connected to the OEM through C1 creating an indirect relationship i.e., Focal site-C1-OEM. Traditionally, the supply chain complexity literature has referred to the external complexity of a site or a firm as the relationship between the focal site and its upstream and downstream partners (Isik, 2011; Serdarasan, 2013; Bode & Wagner, 2015). In this study, I extend this notion to incorporate multiple direct and indirect relationships into the supply chain complexity and refer to it as extended supply chain complexity.

**Figure 3. Extended Supply Chain Complexity of the Focal Site**



A focal site gains access to valuable resources through its participation in extended supply chains. Scholarly evidence suggests that firms form collaborative relationships with external upstream and downstream partners to address deficiencies in the availability of internal resources (Bode et al., 2011). Resource dependence scholars suggest that a focal firm should not rely too much upon resources from external partners because of supply chain uncertainties and potential opportunism issues (Bode et al., 2011). In an extended supply chain, these uncertainties are further exacerbated (Choi & Krause, 2006). Hence, in complex supply chains, a firm needs to consider the optimal level of external partner engagement in order to reduce any transaction costs from occurring.

A significant amount of coordination, communication, and oversight is needed to manage a firm's extended partner base (Bozarth et al., 2009; Boyson, Corsi, Dresner, & Rabinovich, 1999). Because of cognitive limitations, plant managers typically do not have sufficient capacity to monitor and respond to changes in supply and demand conditions, as there is a greater amount of communication needed

between the plant and a larger and deeper partner base, as reflected in the multiple relationships that it needs to manage. This situation becomes further exacerbated in times of a supply and demand uncertainties, as the quality and volume of information transmission between the plant and the external partner base is further reduced, modified, or blocked (Brandon-Jones, Squire, & Rossenberg, 2015). Likewise, a larger and deeper partner base requires a higher intensity of administrative management that can reduce a firm's ability to proactively identify and mitigate events that lead to disruptions (Boulding, 1953). The high task complexity can reduce the quality of decision-making, thus affecting the timeliness of the response to avoid potential disruptions (Wally & Baum, 1994). Further, although advantages are associated with increasing a firm's partner base, previous research has identified an increased risk and a negative impact on a firm's performance (Choi & Krause, 2006). The E. coli bacteria outbreak at Chipotle provides an example of difficulties in managing a large supplier base (Perkins, 2016).

*H4a: The greater the extended supply chain complexity of the focal site, the higher the likelihood that the focal site will experience man-made disruptions.*

The manufacturing plant's ability to recover quickly from a supply chain disruption is dependent on the reliable delivery of shipments from a firm's suppliers and certainty of demand coming from customers (Zsidisin et al., 2004). This becomes increasingly difficult as the complexity of the extended supply chain increases. Unreliable lead times and uncertain demands will increase the planning horizon of the manufacturing process and, hence, increase the time needed by the manufacturing plant to restore to normal operations (Vollmann, Berry, Whybark, & Jacobs, 2005). In

addition, these uncertainties arise as the plant has to coordinate with multiple supply chain partners thus increasing the level of contingency planning needed and the increase in the cost of planning activities. A poor production planning process will affect production schedules negatively and, thus, hamper the recovery process (Kallrath, 2002). Also, the focal site will find it more complex to navigate a disruptive event when their large external partner base also experiences disruptions such as a production problem, transportation accident or crash, data breach, or contaminated product.

In summary, while there are reasons to believe that the greater the extended supply chain complexity provides a firm with redundancy in sources of supply and demand, I believe that a great deal of monitoring, management, and control is required for sufficient oversight over a large partner base, including in situations of a supply chain disruption. Hence, I present the following hypothesis.

*H4b: The greater the extended supply chain complexity of the focal site, the longer the recovery time of the focal site from a man-made disruption.*

### **3.5. Supply Chain Echelon Proximity**

Next, I turn to discussing the echelon location of the focal site and how the echelon distance from the OEM to focal site can influence the likelihood of disruption and affect the recovery process. The supply chain echelon proximity is a network component of a focal site and represents how close and accessible the focal site is to the OEM.

The lower the echelon proximity, the higher the tier of the focal site (ex. 1<sup>st</sup> tier suppliers are considered higher tier than 2<sup>nd</sup> tier suppliers). An increase in the supply chain echelon proximity, i.e., the lower the tier of focal site in the OEM's supply chain, the more likely it can face a supply chain disruption (Bode & Wagner, 2015). First, the lower the tier of the site, the higher the uncertainty in demand (Metters, 1997). As the focal site moves farther from the OEM, demand variability increases resulting in an uncertain environment vulnerable to disruptions (Lee, Padmanabhan, & Whang, 1997). Generally, firms in the second, third, and fourth tier supply chains are small and are not in a position to handle any higher variance of orders, which can have serious consequences to the firm and make it vulnerable to running over capacity or under capacity, which can prove dangerous to such small manufacturers.

Second, as the proximity of the focal site to the OEM decreases, the OEM's site's visibility into focal site decreases (Van Donk, van der Vaart, & Awaysheh, 2010). The poor level of monitoring hinders accountability and transparency which places the focal site at higher levels of disruption risk. These are the sites which are least monitored, least regulated, and least equipped to deal with unexpected events. In fact, Villena and Gioia (2018) found that lower tier sites are prone to significant environmental and social risks.

Finally, lower supply chain echelon proximity can lead to a complex information exchange process between OEM and the focal site further increasing the complexity and uncertainty of the operating environment (Melville and Ramirez, 2008). Kembro, Naslund, and Olhager (2017) found that it is difficult to implement

information sharing beyond dyadic relationships into lower-tiers due to several factors like power structures, legal issues, cultural differences, and technology utilizations. This lack of information exposure makes it difficult to lower tier firms in forecasting demands and lead times making its site vulnerable to disruption. This leads to my next hypothesis

*H5a: Higher the supply chain echelon proximity of the focal site to the OEM, the lower the likelihood that the focal site will experience man-made disruptions.*

The lower the supply chain echelon proximity of the focal site to the OEM leads to demand variability, also known as the bullwhip effect. To say this differently, the bullwhip effect can have detrimental effects on a focal site's recovery process. Uncertain demand can lead to poor product forecasts, product back logs, inefficient production scheduling, and high correction costs such as expedited shipping (Lee et al., 1997). Also, the higher levels of demand variability will increase the size and scope of the demand management system, thus complicating the recovery process (Bozarth et al., 2009).

*H5b: Higher the supply chain echelon proximity of the focal site to the OEM, the shorter the recovery time of the focal site from a man-made disruption.*

### **3.6. Business Continuity Management (BCM)**

In this section, I theorize on the impact of the comprehensiveness of different business continuity management plans in reducing a plant's recovery time from a disruption. Specifically, I examine three different types of plans: (i) Strategic

orientation BCM, (ii) Operational orientation BCM, and (iii) Supplier orientation BCM. Firms need to consider both long-term and short-term strategies when responding to disruptions. A long term perspective is much more comprehensive and strategic in the development of responses to disruptions (Pujawan & Geraldin, 2009). A short-term perspective is more focused on reacting towards a disruption because it is hard to predict when a disruption is going to occur and I need a short term reaction plans (Saenz & Revilla, 2014).

Business continuity management is a critical element for any type of business to recover from business interruptions caused by the multitude of internal and external sources such as natural disasters, power outages, labor strikes, and bankruptcies (Cerullo & Cerullo, 2004). While firms have business continuity management plans on file, it is important to have comprehensive management procedures documented. While I acknowledge the importance of business continuity management plans in improving performance of the organization, I emphasize the importance of a comprehensive plan. Comprehensive business continuity management plans enable the manufacturing plant to recover quickly from a disruption by strengthening its objectives in three areas as follows.

First, the initial objective of business continuity management is to perform a business risk assessment and impact analysis (Gibb & Buchanan, 2006). The identification of a firm's critical business resources, processes, and potential single points of failure will enable a firm to identify the hotspots of disruption in its business (Elkins, Handfield, Blackhurst, & Craighead, 2005). Once the critical hotspots are identified, the impact of these hotspot failures and a business's maximum tolerance

period of the disruptions can be assessed theoretically, thus facilitating a process to prioritize the most vulnerable points in the business (Tenggren et al., 2020).

Narrowing down the vulnerable points will allow a firm to draft a focused and effective mitigation plan, thus facilitating the recovery process.

The next objective of BCM is to develop a mitigation plan to the above-identified supply chain risks. These mitigation plans contain different strategies and techniques that can minimize the impact of a disruption occurring at a manufacturing plant. These plans accelerate the recovery process by developing contingency measures and proposing recommendations for implementation of process improvements and buffer strategies, e.g., transferring the production capacity to a backup manufacturing plant, switching to an alternate supplier, and/or choosing a different transportation route (Zsidisin, Panelli, & Upton, 2000; Kırılmaz & Erol, 2017).

Finally, the last objective of a BCM is to train, test, and update the processes suggested in the plan (Botha & VonSolms, 2004). The disruption recovery team is trained with the protocols enlisted in the continuity plan to ensure the team has sufficient knowledge when the plan is invoked. Once the team undergoes training, it is tested to verify if all the contingency plans are appropriately written and can be implemented in a timely fashion. The process of BCM not only has a focus on the development of contingencies but is also required to be reviewed regularly and updated, if required (Hiles, 2010).

### **3.6.1. Strategic Orientation BCM**

The strategic orientation of BCM provides the focal site with the ability to understand and learn about the environment they operate which helps them to recognize associated patterns and trends in events that take place around them (Herbane, Elliott, & Swartz, 2004). In addition, it provides the focal site the capability to anticipate issues that arise within their operating environment and helps them to form contingency plans to act swiftly and reduce the impact of the event (Manuj & Mentzer, 2008).

One way firms achieve strategic orientation is by detailing a comprehensive business continuity plan (BCP) (Herbane et al., 2004). A BCP is a more strategic and long-term focussed plan that takes a holistic approach towards a disruption (Yoon, Talluri, & Yildiz, 2018). It layouts how business operations will continue during an unplanned supply chain disruption. It is a more comprehensive plan than other operational plans like crisis management or emergency response plans because it includes key elements such as risk mitigation plans, tasks required to keep operations going, information backups, and plant maintenance protocols that enables the focal site to continue providing acceptable service after the disruption and hence speed up the recovery process (Cerullo & Cerullo, 2004).

*H6a: The greater the comprehensiveness of the strategic orientation BCM such as the business continuity plan at the focal site, the shorter the recovery time of the focal site from a man-made disruption.*

### **3.6.2. Operational orientation BCM**

The operational orientation of BCM provides short-range planning and emphasizes current operations of different parts at the focal site. Managers at the focal site can use plans drafted for operational orientation to quickly respond to the disruption event. These operational plans include emergency response plan (ERP) and crisis management plan (CMP). An ERP outlines the steps that are required to follow in the initial moments of the disruption so as to reduce the event's impact while a CMP describes how a site will react to a disruption and who will be involved along with the job assignments of the response team.

A comprehensive emergency response plan is key to minimizing the disruption of a focal site's services during an event of man-made disruption (Ross & Bing, 2007). The protocols laid out in the ERP are vital in the first minutes of disruption and help the response team at the focal site to quickly respond and minimize the impact of disruption event. The two stages of the ERP, "sustaining response" and "self-sufficiency response" focus on necessary steps required to bring the site back to initial operations after disruption (Thevenaz & Resodihardjo, 2010). The first stage, sustaining response, includes rescue operations, for instance, rescuing personnel trapped inside the building, clearing debris that cover machinery, and providing temporary shelter and medical care to any victims. The second stage, self-sufficiency response consists of reducing the focal site's dependence on outside resources to continue basic operations. A few examples include repairing the water supply structures, restoring the internet connectivity, and restoring transportation connectivity to the focal site.

On the other hand, a crisis management plan includes crisis management team members, list of main emergency contacts, steps to processing and assessing the incident, and identification of the procedures to respond when the disruption takes place. These steps will help the focal site to quickly identify the disruption and bring in contingencies that can speed up the recovery process. Hence, I hypothesize

*H6a: The greater the comprehensiveness of the operational orientation BCM such as a emergency response plan and crisis management plan at the focal site, the shorter the recovery time of the focal site from a man-made disruption.*

### **3.6.3. Supplier Orientation BCM**

In addition to hypothesizing how business continuity management helps the focal site in recovering from disruptions, I also theorize how monitoring suppliers' business continuity management plans can aid the focal site in its recovery process. When a focal site emphasizes the importance of a supplier's business continuity plan, suppliers are motivated to plan for an alternate approaches when their services or facilities are down, identifying key vendors, and communicating with public entities and emergency services. Having a sight of these important issues can increase the recovery performance of the focal site.

First, the manufacturing plant's ability to recover quickly from a supply chain disruption is dependent on the reliable delivery of shipments from a firm's suppliers (Zsidisin et al., 2004). When the suppliers are disrupted along with the focal site, unreliable or long supply lead times will increase the planning horizon of the manufacturing process and, hence, increase the time needed by the manufacturing

plant to restore to normal operations (Vollmann, Berry, Whybark, & Jacobs, 2005). Unreliable lead times will increase the level of contingency planning needed and thus contribute to an increase in the cost of planning activities. Hence, monitoring supplier's business continuity will enable the focal site to respond to the disruption event and form contingency plans quickly and effectively according to its own continuity plans.

Second, when suppliers are disrupted, they are bombarded with questions from other customers inquiring their status of recovery (Sawik, 2019). This will result in critical supplier resources diverting from important recovery tasks such as damage assessment, repair coordination, supply resumption to answering inquiries from customers which can further compound delays. Monitoring supplier's business continuity can reduce this issue and speed up their recovery and consequently, the focal site's recovery. Hence, I hypothesize

*H6C: The greater the comprehensiveness of the supplier orientation BCM at the focal site, the shorter the recovery time of the focal site from a man-made disruption.*

## **4. Methodology**

### **4.1. Sample and Data**

To test my hypotheses, I partnered with Resilinc. Corp., a Silicon Valley based provider of an end-to-end supply chain risk management solutions, founded in 2010 by former Cisco supply chain practitioners and technology experts. Resilinc. Corp. maps the entire supply chain of its customers drilling down to supplier, site,

product and part level data in one centralized system and actively monitors 24x7, any man-made or natural disaster events that take place at their customer's and the customer's supplier sites that have a potential to disrupt the firm's operations. This unique dataset enables us to quantify the supply chain complexity of multiple firms down to the part level which, to the extent of my knowledge has not been previously done in the supply chain/operations literature.

Here, I briefly describe the structure of the data as tailored towards my research questions. Figure 3, Figure 4, and Figure 5. illustrate the structure of my database. First, Resilinc maintains a database of OEMs (Original Equipment Manufacturers). Second, they map out the supply chain of the OEM by collecting information on their suppliers. In most cases they are able to identify until Tier-3 suppliers and in few cases, it is as deep as Tier 5. This is illustrated in Figure 3. Next, partnering with the OEM, they collect data at the focal site level of these suppliers along with the sites of OEMs. At each site, they collect information such as parts, manufacturing activities, BOMs, alternate sites, and a formal BCP (Business Continuity Plan) availability as illustrated in Figure 4 (Choi et al., 2020). In addition, they document different risk scores such as sourcing risk, resiliency risk, macro economic risk, financial risks etc. Finally, once the mapping is completed, they start monitoring these sites 24x7 for events that can cause potential disruption to operations at the site (Figure 5).

**Figure 3. Supply Chain Mapping of OEM**

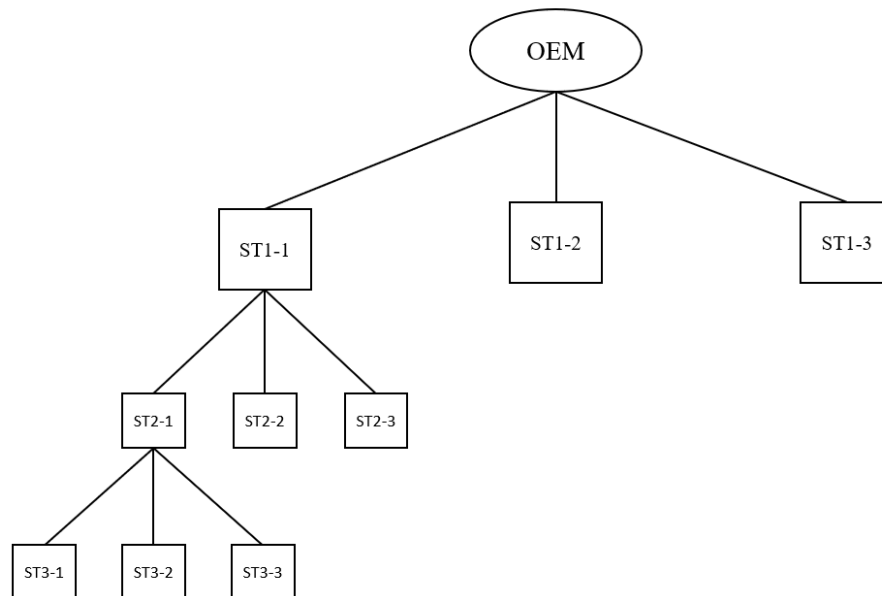


**Figure 2. Information of Sites Documented for Each Firm**

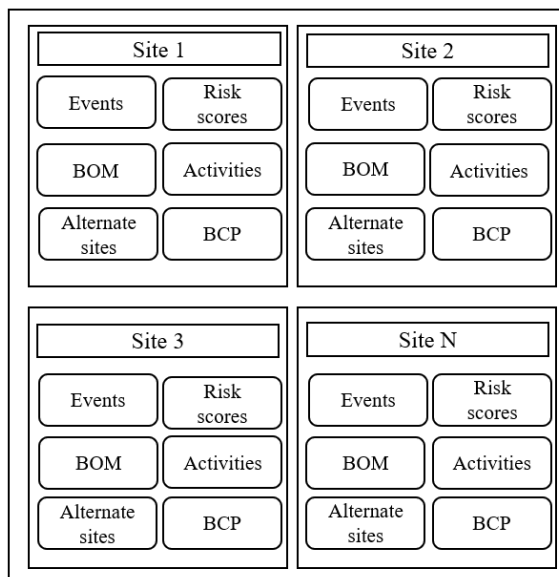
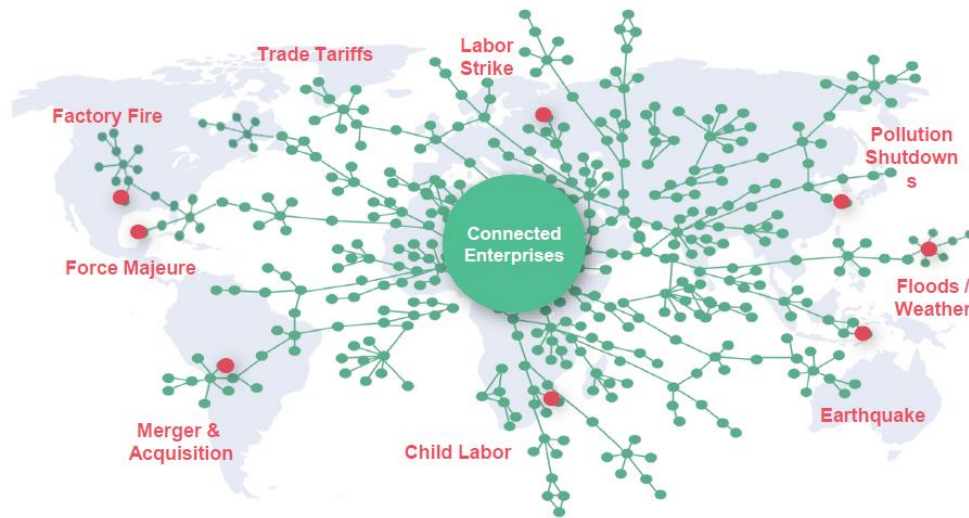


**Figure 3. Example Events Documented by Resilinc. Corp. That Can Cause Disruptions at Sites**



The resulting data set includes 12,487 sites across 5,462 firms from five industries (automotive, biotechnology, high-tech, life sciences, and pharmaceuticals) in 69 countries. The data contains both public and privately held firms. Data were collected from the 2015 to 2019 time period. This represents the most recent time period of data provided by Resilinc. The unit of analysis for my Study 1 is site and Study 2 is supply chain disruption event-site dyads. An advantage of my secondary data set is that it reduces concerns such as key informant bias and common methods bias that are often associated with survey research (Roth, 2007; Gattiker & Parente, 2007).

## 4.2. Study 1: Likelihood of Disruptions

### 4.2.1. Dependent Variable

Our dependent variable in Study 1 is *Frequency of Man-Made Supply Chain Disruptions*. Bode and Wagner (2015) measured frequency of supply chain disruptions to study supply base complexity as drivers of disruptions. To demonstrate that I have a dataset that is comparable in regards to frequency of disruptions, I

compared the summary statistics of the number of disruption events in my database (Mean: 1.71; S.D.: 1.98) with the average number of disruptions Bode and Wagner (2015) (Mean: 1.49; S.D.: 1.30) identified in their sample. I observe that the summary statistics from the sample they collected from 2005 are similar to my sample. Resilinc documents events faced by a focal site and assign them into one of 45 different categories. As my study is based on the frequency of man-made disruptions, I use the categories listed in Table A3 of appendix to identify the number of man-made disruptions.

#### **4.2.2. Independent Variables**

To test my first hypothesis regarding how the focal site is able to learn from peer sites, my first independent variable is the number of man-made disruptions experienced by peer sites. This variable is operationalized as the number of man-made disruptions experienced by the focal firm's peer sites within the same zip code as the focal site. This count variable is included in the analysis using four separate time lags because learning occurs over long time horizons. Four-year lags are selected as the maximum length due to data availability from 2015-2019. Madsen (2009) used a similar lag structure to investigate organizational learning in the mining industry.

Our second set of independent variables describe internal complexity and their respective alternate manufacturing resources of the focal site. I use two variables to measure internal complexity, *number of internal business processes* and *total number of parts* associated with the site (Bozarth et al., 2009). Examples of internal processes include but are not limited to fabrication, assembly, and molding. Because of

skewness and kurtosis (skewness: 29.45; kurtosis: 1143.81) of the *number of parts* variable, I perform a log transformation.

Next, I use two measures to identify the availability of alternate manufacturing resources (Sheffi & Rice, 2005) that correspond to activities and parts that are originally performed at the focal site. My first variable measures the availability of alternate production sites as a back-up to the focal site. The granularity of my database allowed us to calculate the activities that can be shifted to an alternate production site when the business process gets disrupted at the focal site. I use the formula in (1) to calculate the redundancy in focal sites. Next, I calculated the proportion of alternate resources for the parts associated with the focal site as depicted in the formula in (2).

$$\text{Proportion of activities with alternate site} \quad (1)$$

$$= \frac{\text{Activities with alternate site}}{\text{Total number of activities}}$$

$$\text{Proportion of parts multi – sourced} \quad (2)$$

$$= 1 - \frac{\text{Number of parts single sourced}}{\text{Total number of parts}}$$

Our next two hypotheses examine extended supply chain complexity and supply chain echelon proximity of the focal site. Extended supply chain complexity is defined as the *number of supply chains* associated with the focal site. As discussed in Figure 3, I include all the direct and indirect partnerships that the focal site is involved with. For the *supply chain echelon proximity* variable, I reverse code the echelons. As the number of echelons in my dataset is 3, if the site is located in the same echelon as the OEM, I code it as 3, if the site is in the first tier of the OEM's

supply chain, I code it as 2, if it is associated with the second-tier of the OEM's supply chain, I code it as 1, and if the focal site is in the third-tier of OEM's supply chain, it is coded as 0.

#### **4.2.3. Control Variables**

To control for omitted variable bias, I include several control variables. First, I control for the downstream complexity using the *number of customers* that are served by the plant (Bozarth et al., 2019). I also control for the focal site's location's *natural disaster risk* score using a 10-point score available in the database that measures a geographic location's threat from natural disasters. For example, Houston, Texas which is rated as one of the 10 risky cities for natural disasters in U.S.A. is given a score of 8, and a city like Portland, Oregon which features among 10 safest cities is given a score of 3, indicating its low risk to natural disasters. Lastly, I add year dummies to control for year fixed effects.

The unit of observation in this study is a site. The dataset is an unbalanced panel with a total of 12,487 sites between 2016-2019. The total number of site-year observations is 21,583. Descriptive statistics for the independent and control variables are provided in Table 1. The average number of disruptions at peer sites to the focal site in year T-1 is 7.1, year T-2 is 2.71, year T-3 is 0.18 and year T-4 is 0.08. The average number of parts managed is 9.42. On average, a manufacturing plant has 1.27 internal business processes. 16% of the activities at the focal sites have alternate sites and 83% of the parts are multi-sourced. On average, each focal site is part of 8.09 supply chains and lies at a proximity of 1.58 (between 1<sup>st</sup> and 2<sup>nd</sup> tier echelons) from

the OEM. Each focal site serves on an average 2.67 customers and the natural disaster risk mean is 5.96, which falls in the moderate risk category.

**Table 1: Descriptive Statistics (N = 21,583)**

| <b>Variable</b>                              | <b>Mean</b> | <b>Std. deviation</b> |
|----------------------------------------------|-------------|-----------------------|
| Man-made disruptions at peer sites. Yr. T-1  | 7.10        | 24.54                 |
| Man-made disruptions at peer sites. Yr. T-2  | 2.71        | 12.08                 |
| Man-made disruptions at peer sites. Yr. T-3  | 0.18        | 1.04                  |
| Man-made disruptions at peer sites. Yr. T-4  | 0.08        | 0.84                  |
| Number of internal business processes        | 1.27        | 0.68                  |
| Number of parts                              | 9.42        | 90.12                 |
| Proportion of activities with alternate site | 0.16        | 0.36                  |
| Proportion of parts multi-sourced            | 0.83        | 0.35                  |
| Number of supply chains                      | 8.09        | 13.01                 |
| Supply chain echelon proximity               | 1.58        | 0.49                  |
| Number of customers                          | 2.67        | 1.66                  |
| Natural disaster risk                        | 5.96        | 2.00                  |

#### **4.2.4. Model Specification**

As disruptions in one year may depend on disruptions in the following year at a focal site, in my study 1, I used a panel data poisson generalized estimating equations (GEE) model that accounts for this potential dependence (Agrawal, Mukherjee, & Muthulingam, 2019). I use exchangeable covariance structure for the estimation which considers all data points with a focal site correlated to each other. Poisson regression models are generally used for modelling when the dependent variable is a non-negative count variable (Cameron and Trivedi, 1998; Bode and Wagner, 2015). Another estimating strategy that is used to model count dependent variable is negative binomial. But, it is often used in over-dispersed count data (Hofer, Cantor, and Dai, 2012). I find that the over-dispersion statistics (alpha) is 1.01 which is close to the acceptable threshold of 1.0. Hence, I use a poisson regression model. In addition, to

address potential autocorrelation and unobserved cross-sectional heterogeneity in my panel data, I used a GEE regression.

Before proceeding to the regression analysis, I first check the pairwise correlations for potential collinearity. I do not find any significant bivariate correlations between my independent variables. All the bivariate correlations are less than accepted threshold of 0.7 (Dormann, Elith, and Bacher, 2013). I also calculate variance inflation factor which is 1.69 indicating that multicollinearity is not an issue in my study.

**TABLE 2. Pairwise Correlation Matrix**

|           | 1                                                | 2        | 3        | 4        | 5        | 6        | 7        | 8        | 9        | 10       | 11      | 12 |
|-----------|--------------------------------------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|---------|----|
| <b>1</b>  | Man-made disruptions at peer facilities. Yr. T-1 | 1        |          |          |          |          |          |          |          |          |         |    |
| <b>2</b>  | Man-made disruptions at peer facilities. Yr. T-2 | 0.46***  | 1        |          |          |          |          |          |          |          |         |    |
| <b>3</b>  | Man-made disruptions at peer facilities. Yr. T-3 | 0.33***  | 0.14***  | 1        |          |          |          |          |          |          |         |    |
| <b>4</b>  | Man-made disruptions at peer facilities. Yr. T-4 | 0.16***  | 0.63***  | 0.13***  | 1        |          |          |          |          |          |         |    |
| <b>5</b>  | Number of internal business processes            | 0.03***  | 0.03***  | 0.04***  | 0.02***  | 1        |          |          |          |          |         |    |
| <b>6</b>  | Log of number of parts                           | -0.01*   | -0.01    | -0.01    | 0.11***  | 1        |          |          |          |          |         |    |
| <b>7</b>  | Proportion of activities with alternate site     | -0.02*** | 0.003    | 0.03***  | 0.15***  | 0.10***  | 1        |          |          |          |         |    |
| <b>8</b>  | Proportion of parts multi-sourced                | 0.004    | -0.02*** | -0.05*** | -0.24*** | -0.13*** | -0.31*** | 1        |          |          |         |    |
| <b>9</b>  | Number of supply chains                          | 0.02***  | 0.03***  | 0.06***  | 0.19***  | 0.06***  | 0.08***  | -0.16*** | 1        |          |         |    |
| <b>10</b> | Supply chain echelon proximity                   | -0.02*** | 0.004    | 0.02**   | -0.12*** | -0.04*** | -0.03*** | 0.06***  | -0.42*** | 1        |         |    |
| <b>11</b> | Number of customers                              | 0.01*    | 0.04***  | 0.09***  | 0.33***  | 0.11***  | 0.24***  | -0.28*** | 0.55***  | -0.24*** | 1       |    |
| <b>12</b> | Natural disaster risk                            | 0.18***  | 0.19***  | 0.11***  | 0.10***  | 0.01*    | 0.05***  | -0.06*** | 0.03***  | -0.03*** | 0.04*** | 1  |

•  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

#### 4.2.4. Results

**Table 3: Poisson GEE Regression Results (N = 21,583)**

| <b>D.V.: Number of man-made disruptions at the focal site</b> | <b>Model Coef.</b>  |
|---------------------------------------------------------------|---------------------|
| Man-made disruptions at peer sites. Yr. T-1                   | 0.003***<br>(0.001) |
| Man-made disruptions at peer sites. Yr. T-2                   | 0.003***<br>(0.001) |
| Man-made disruptions at peer sites. Yr. T-3                   | -0.08***<br>(0.011) |
| Man-made disruptions at peer sites. Yr. T-4                   | -0.08***<br>(0.016) |
| Number of internal business processes                         | 0.07***<br>(0.016)  |
| Log of number of parts                                        | 0.07***<br>(0.013)  |
| Proportion of activities with alternate site                  | -0.45***<br>(0.041) |
| Proportion of parts multi-sourced                             | -0.32***<br>(0.045) |
| Number of supply chains                                       | 0.01***<br>(0.001)  |
| Supply chain echelon proximity                                | -0.21***<br>(0.024) |
| Number of customers                                           | -0.05***<br>(0.008) |
| Natural disaster risk                                         | 0.14***<br>(0.006)  |
| Year dummies                                                  | included            |
| Constant                                                      | -3.26***<br>(0.234) |
| Wald $\chi^2$                                                 | 2642.71             |

\*\*\*  $p < 0.01$

I now describe my GEE estimation results as presented in Table 3. I find that the disruptions at peer facilities in years T-3 and T-4 (T-1: 0.003,  $p < 0.01$ ; T-2: 0.003,  $p < 0.001$ ) are negative and highly significant, but the coefficients on years T-1 and T-2 (T-3: -0.08,  $p < 0.01$ ; T-4: -0.08,  $p < 0.001$ ) are positive and highly significant. This finding indicates that firms take time to learn from their peer sites about disruptions

and implement strategies to avoid any events causing disruption in their operations. This finding provides support to my hypothesis 1.

Our next set of variables *number of internal business processes* (0.07,  $p < 0.001$ ) and *number of parts* (0.07,  $p < 0.01$ ) which indicate the internal complexity of a focal site are positive and highly significant, providing a strong support to my hypothesis H2a indicating that a focal site's internal complexity will lead to higher man-made disruptions at the site.

Next, I find that my alternate manufacturing resource variables, *proportion of activities with alternate site* (-0.45,  $p < 0.01$ ) and *proportion of parts multi-sourced* (-0.32,  $p < 0.01$ ) are negative and highly significant indicating a strong support to hypothesis H3a. These results show that having alternate manufacturing resource will in fact reduce the probability of a site undergoing disruption.

The coefficient on *number of supply chains* (0.01,  $p < 0.01$ ) is positive and highly significant indicating that the extended supply chain complexity will increase the probability of disruptions at the focal site while the *supply chain echelon proximity* (-0.21,  $P < 0.01$ ) which is negative and highly significant decreases the probability of disruptions at the focal site thus conforming hypotheses H4 and H5.

### **4.3. Study 2: Recovery Time**

#### **4.3.1. Dependent Variable**

The dependent variable for study 2 is the time to recover from a supply chain disruption (TTR). This variable measures the time taken by the focal site to resume its plant-level operations from a man-made supply chain disruptive event. The TTR in

the Resilinc database is based on the actual experience of the production site's recovery from a disruption. TTR is a widely used construct in the supply chain disruption literature (Hopp, Iravani, & Liu, 2012; Simchi-Levi, Wang, & Wei, 2018). My construct represents the capability of a plant to respond and recover from a disruptive event (Falasca, Zobel, & Cook, 2008). Hence, the lower the TTR, the higher the resiliency of a plant to recover from the disruption.

#### **4.3.2. Independent Variables**

Our independent variables representing the supply chain complexity and alternate manufacturing resources of a focal site: *Number of internal business processes, number of parts, proportion of activities with alternate site, proportion of parts multi-sourced, number of supply chains, and supply chain echelon proximity* are all calculated similar to section 4.2.2.

In this study, in addition to the above-mentioned variables, I measure the strategic orientation, operational orientation and supplier orientation of business continuity management using three different business continuity plans. As discussed in hypotheses 6a-6c, strategic orientation is measured using the comprehensiveness of business continuity plan, operational orientation is measured using the comprehensiveness of crisis management plan and emergency response plan. The questionnaire for the comprehensiveness of these plans is documented in Table A4 of appendix. Finally, supplier orientation is measured using the questionnaire in Table A5. This questionnaire is administered by Resilinc to the managers who handle the business recovery at the focal site. Each question in the table is coded as 1 if the

response is “Yes” and 0 if the response is “No”. For each BCP plan, I operationalize the variables by the summing all responses.

Similar to analysis 1, I control for *customers* and *natural disaster risk*. In addition, I add year dummies. The unit of observation is a focal site-event pair. Descriptive statistics for the independent and control variables are provided in Table 4. The average number of parts managed is 12.99. On average, a manufacturing plant has 1.39 internal business processes. 24% of the activities at the focal sites have alternate sites and 63% of the parts are multi-sourced. On average, each focal site is part of 11.65 supply chains and lies at a proximity of 1.67 (between 1<sup>st</sup> and 2<sup>nd</sup> tier echelons) from the OEM. Each focal site serves on an average 2.64 customers and the natural disaster risk mean is 6.19, which falls in the moderate risk category. The average comprehensive ratings for Business continuity plan, Emergency response plan, Crisis management plan, and Supplier orientation are 2.77, 2.95, 2.89, and 2.83 respectively.

**Table 4: Descriptive Statistics (N = 57,805)**

| <b>Variable</b>                              | <b>Mean</b> | <b>Std. deviation</b> |
|----------------------------------------------|-------------|-----------------------|
| Number of internal business processes        | 1.39        | 0.91                  |
| Number of parts                              | 12.99       | 81.33                 |
| Proportion of activities with alternate site | 0.24        | 0.40                  |
| Proportion of parts multi-sourced            | 0.63        | 0.44                  |
| Number of supply chains                      | 11.65       | 17.99                 |
| Supply chain echelon proximity               | 1.67        | 0.47                  |
| Business continuity plan                     | 2.77        | 0.54                  |
| Emergency response plan                      | 2.95        | 0.31                  |
| Crisis management plan                       | 2.89        | 0.47                  |
| Supplier orientation                         | 2.83        | 0.39                  |
| Number of customers                          | 2.64        | 2.98                  |
| Natural disaster risk                        | 6.19        | 2.03                  |

### **4.3.3. Model Specification**

I conduct the empirical analyses using panel data methods, as several characteristics of my data suggest that ordinary-least-squares (OLS) regression may be an inappropriate estimation method. Because I have multiple observations for each manufacturing plant (e.g., each observation represents a site-event pair), a potential concern with my dyadic model is that observations within each cross section may be interdependent, thus creating a common-actor effect (Lincoln, 1984). Furthermore, the cross-sectional nature of my data raises potential heteroscedasticity concerns, the presence of which I verified using a Breusch-Pagan/Cook-Weisberg test (I reject null hypothesis of equal error variances with  $p < 0.001$ ). One strategy for addressing the nonindependence and heteroscedasticity issues that I employ is to use either a fixed or random effects regression model and use robust standard errors. As my business continuity management variables are invariant over time, I use a random effects model (Abdulsalam et al., 2018). In addition, because my data are censored to the left of 0, as a robustness check, I estimated a random effects Tobit model (Merkert & Hensher, 2011). Before proceeding to the regression results, I first check the pairwise correlations for potential collinearity. Similar to study 1, I all my bivariate correlations are less than acceptable value of 0.7 (Dormann et al., 2013). In addition, the variance inflation factor in 1.56 indicating that multi collinearity is not an issue in study 2.

**TABLE 5. Pairwise Correlation Matrix**

|    | 1                                            | 2        | 3        | 4        | 5        | 6        | 7        | 8        | 9        | 10      | 11      | 12 |
|----|----------------------------------------------|----------|----------|----------|----------|----------|----------|----------|----------|---------|---------|----|
| 1  | Number of internal business processes        | 1        |          |          |          |          |          |          |          |         |         |    |
| 2  | Log of number of parts                       | 0.08***  | 1        |          |          |          |          |          |          |         |         |    |
| 3  | Proportion of activities with alternate site | 0.23***  | 0.12***  | 1        |          |          |          |          |          |         |         |    |
| 4  | Proportion of parts multi-sourced            | -0.20*** | -0.09*** | -0.23*** | 1        |          |          |          |          |         |         |    |
| 5  | Number of supply chains                      | 0.22***  | 0.04***  | 0.003    | -0.09*** | 1        |          |          |          |         |         |    |
| 6  | Supply chain echelon proximity               | -0.23*** | -0.09*** | -0.05*** | 0.04***  | -0.65*** | 1        |          |          |         |         |    |
| 7  | Business continuity plan                     | -0.05*** | 0.01     | -0.08*** | 0.04***  | -0.02*** | 0.06***  | 1        |          |         |         |    |
| 8  | Emergency response plan                      | -0.02*** | -0.06*** | -0.06*** | 0.03***  | -0.05*** | 0.46***  | 1        |          |         |         |    |
| 9  | Crisis management plan                       | -0.05*** | -0.11*** | -0.10*** | -0.003   | -0.03*** | 0.48***  | 0.53***  | 1        |         |         |    |
| 10 | Supplier orientation                         | -0.13*** | -0.05*** | -0.18*** | 0.08***  | 0.10***  | 0.39***  | 0.28***  | 0.43***  | 1       |         |    |
| 11 | Number of customers                          | 0.40***  | 0.08***  | 0.27***  | -0.10*** | -0.37*** | 0.07***  | 0.01***  | 0.03***  | 0.0001  | 1       |    |
| 12 | Natural disaster risk                        | 0.06***  | -0.01**  | 0.09***  | -0.04*** | -0.01**  | -0.04*** | -0.02*** | -0.04*** | -0.06** | 0.10*** | 1  |

•  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

#### 4.3.4. Results

**Table 6: Random Effects Tobit Regression Results (N = 57,805)**

| <b>D.V.: Time to recover of the focal site</b> | <b>Model Coef.</b>  |
|------------------------------------------------|---------------------|
| Number of internal business processes          | 2.79***<br>(0.039)  |
| Log of number of parts                         | 1.22***<br>(0.104)  |
| Proportion of activities with alternate site   | 4.62***<br>(0.313)  |
| Proportion of parts multi-sourced              | 2.58***<br>(0.314)  |
| Number of supply chains                        | -0.09***<br>(0.010) |
| Supply chain echelon proximity                 | -0.76**<br>(0.297)  |
| Business continuity plan                       | -0.65**<br>(0.265)  |
| Emergency response plan                        | -1.24***<br>(0.475) |
| Crisis management plan                         | 0.28<br>(0.289)     |
| Supplier orientation                           | -1.09***<br>(0.206) |
| Number of customers                            | 0.43***<br>(0.072)  |
| Natural disaster risk                          | -0.23***<br>(0.066) |
| Year dummies                                   | included            |
| Constant                                       | 6.20**<br>(2.63)    |
| Log-likelihood                                 | -179965.97          |

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

The Random effects Tobit regression results are presented in Table 6. I observe a positive and highly significant sign on the internal complexity variables (Number of internal business processes: 2.79,  $p < 0.01$ ; Log of number of parts: 1.22,  $p < 0.01$ ) indicating that an increase in internal complexity at a plant will result in an

increase in time to recover from a disruption, thus providing strong support to Hypothesis 2b. The coefficient on *Supply chain echelon proximity* is negative and significant ( $-0.76; p < 0.05$ ), indicating that the closer the focal site is to the OEM, the faster it can recover from the disruption, thus providing support to Hypothesis 5b.

Finally, I discuss my last set of variables that indicate the comprehensiveness of business continuity management. First, I observe that the coefficient on *Business continuity plan* ( $-0.65, p < 0.05$ ) is negative and significant indicating that the comprehensiveness of a business continuity plan- a long term strategic orientation of business continuity management will decrease the time to recover, thus providing support to my Hypothesis 6a. Next, I find that among the operational orientation variables, *Emergency response plan* ( $-1.24; p < 0.01$ ) is negative and highly significant but *Crisis management plan* is insignificant, thus providing some support for my Hypothesis 6b on operational orientation plan's impact on recovery process. Finally, I find a strong support for my last Hypothesis 6c which states that a supplier orientation of business continuity management will enhance the recovery process through a negative and significant coefficient on the variable *Supplier orientation* ( $-1.09; p < 0.01$ ).

Interestingly, I find that the coefficients on alternate resource variables (Proportion of activities with alternate site:  $4.62, p < 0.01$ ; Proportion of parts multi-sourced:  $2.58, p < 0.01$ ) are positive and highly significant which is alternate to my proposed hypothesis 3b indicating that alternate manufacturing resources will in fact increase the recovery time as the firm has a lesser urgency to bring back the primary site back to operational activity owing to it's capability to use its alternate resources

to continue its regular operations. Also, I find that the coefficient on *Number of supply chains* ( $-0.09, p < 0.01$ ) is negative and significant, indicating that extended supply chain complexity of the focal site will aid its recovery.

## 5. Discussion

The occurrence of supply chain disruptions represents a major problem to many firms in today's global economy. Because many firms continue to find it difficult to manage the complexity that exist in their supply chains, especially during the occurrence of a supply chain disruption, my study seeks to develop further theoretical and empirical insight into how supply chain complexity have an impact on the frequency of disruptions and manufacturing plant's recovery time. In doing so, the basis of my theoretical model is the supply chain complexity and disruptions literature. Specifically, I examine the environmental and structural components of a focal site in the form of peer site disruptions, business processes, number of parts, alternate sites, multi-sourcing, extended supply chain, and supply chain echelon proximity. Collectively, my research directly adds to previous supply chain complexity and disruptions research by developing a theory and empirically testing my model using a confidential secondary data set provided by the Resilinc Corporation. This data set contains actual supply chain complexity, supply chain disruptions, and plant recovery data, thus enabling us to overcome the limitations of previous survey-based research. My study extends prior research including but not limited to Bode and Wagner (2015), Bozarth et al. (2009), Zsidisin et al. (2005),

Vachon and Klassen (2002), among others. In addition, I contend that my study has important managerial implications.

Our first hypothesis examines how sites respond to supply chain disruptions by learning from the disruptions their peer sites encounter. I used 4 time period lags of peer site disruptions to test the extent of temporal support for the hypothesis. As hypothesized, I find that learning occurs with a two-year lag, i.e., focal sites take 2 years to learn from their peer sites and implement proactive strategies to reduce their vulnerability to undergo disruption. This support to my hypothesis conforms that in a close geographical area, there is interorganizational learning through observation and in-person interactions. Future research should investigate how the learning phases out and if this learning has diminishing returns.

Our second hypothesis states that, as the number of processes and products managed at a manufacturing location increases, the likelihood of focal site experiencing a man-made disruption increases. I find strong support for this hypothesis, suggesting that internal complexity makes a site vulnerable to disruptions. A large volume of parts and processes creates stress on purchasers and schedulers to execute manufacturing operations in a timely manner. The plant needs to have increased variety of production machines, greater variety of raw materials, work-in-process, and finished goods inventory. In addition, greater number of processes and parts creates a degree of variability and interdependency of tasks resulting in increase in uncertainty of events at the focal site. Because of this complexity, a plant will experience a higher probability of supply chain disruption (Thonemann & Bradley, 2002). Future research should explore how prioritization of resources dedicated to a

plant's parts and processes can facilitate recovery time during a supply chain disruption.

I found strong support for my next hypothesis, i.e., that the greater the number of internal business processes and parts, the longer the time to recover from a supply chain disruption at a firm's manufacturing plant. My logic is that an increase in the number of processes and parts can result in increased mechanization, increased order cycle times, and decreased visibility, thus resulting in an increase in recovery time. My results suggest and highlight the importance of creating more structure and standardization of processes and parts; otherwise, a plant is at risk of incurring longer recovery times from a supply chain disruption. Given that there are firms that employ strategies such as Kaizen and related process-improvement practices, future research should investigate how these efforts can mitigate the risks present in plants that have an extensive array of business processes in place on a plant's ability to recover from disruptions.

Our third hypothesis theorizes how alternate manufacturing resources reduce the focal site's vulnerability to disruption. Specifically, I explored how the presence of alternate sites for business processes and multi-sourcing are effective in curbing down the risk of disruption. I find strong support to this hypothesis indicating that such proactive strategies employed by focal sites mitigates the risks presented by complexity elements like higher business processes and large number of parts. This finding further demonstrates the importance of proactive planning for supply chain disruptions (Knemeyer et al., 2009).

Interestingly, I do not find support for my next hypothesis which hypothesize the role of alternate manufacturing resources in the recovery process after disruption at the focal site. Instead, I find that the coefficients are significant in the opposite direction indicating that alternate manufacturing resources diminish the reactive strategies of recovery process. This surprising finding indicates that alternate sites and multi sourcing further adds to the complexity of existing supply chain elements and reduces the firm's ability to coordinate sourcing and production. The complexity rises because a large number of sites and supply base can be a significant source of supply chain risk due to complex management systems required to monitor and hence hampers the recovery process. Future research should further explore this tension in supply chain complexity literature as to which conditions complexity favors flexibility as opposed to the conditions which it is detrimental to the focal site (Wiedmer et al., 2021).

Our next hypothesis examines the role of extended external supply chain complexity of the focal site. I measure this variable by including all the direct and indirect supply chain relationships. I find a strong support to this hypothesis indicating that the complexity generated through involvement in multiple supply chains make the focal site vulnerable to disruption. The larger and deeper the partner base expands, higher the administrative management and coordination required to maintain the quality of decision making to avoid disruptions. Further, future research can explore the graph theoretical perspective of external complexity and include elements like length and breadth of the partner base.

Our hypothesis 4b theorizes the dampening impact on recovery efforts of the focal site after disruption. Surprisingly, I do not find this effect, but the coefficient is negative and significant, indicating that extended complexity will in fact speed up the recovery process. This alternate effect could be due to two reasons. First, when the focal site is heavily connected, it has an abundance in resources from its supply chain partners which helps the site to speed up the recovery. Second, as the focal site is highly connected, the longer it is down, the larger the losses are. Hence, the firm might put in extra resources and efforts to bring the site back online as quickly as possible. Either way, this reinforces the importance to further study the tension of complexity vs flexibility in supply chain networks.

Our final supply chain structural element is the supply chain echelon proximity of the focal site to the OEM. I hypothesize that the closer (higher tier) the focal site is to the OEM, less likely it will be disrupted due to less demand variations, higher visibility, and less complex information exchanges between OEM and the focal site. I find a strong support to this hypothesis confirming my logic. Also, I find that higher proximity reduces the bullwhip effect and reduce its detrimental effects on focal site, thus enhancing the recovery process, supporting my hypothesis 5b.

Finally, I also found strong empirical evidence on the impact of a BCM plans on a plant's recovery time. BCM can facilitate a plant's recovery from supply chain interruptions caused by events such as natural disasters, power outages, labor strikes, and bankruptcies (Cerullo & Cerullo, 2004). Business continuity management also serve several functions, including identifying locations of potential risk and impact, providing a mitigation plan in situations when a potential or current disruption exists,

and providing documentation and training where deemed appropriate. I contribute to the supply chain literature by providing empirical evidence on the impact of the strategic, operational, and supplier orientations of the business continuity management. This is an important contribution to the literature because most of the previous BCM research is conceptual and descriptive in nature (Azadegan et al., 2020; Cerullo & Cerullo, 2004). In addition, my study is responsive to Azadegan et al. (2020) who call for more empirical evidence on the impact of BCMs.

As noted earlier, prior research has been predominantly surveyed based or qualitative in nature regarding the study of supply chain structure and complexity in a supply chain risk and disruption context. My unique data set afforded us with the opportunity to study how supply chain structure and complexity has an impact on likelihood of disruption and recovery time by employing secondary data that empirically documents the individual plant-level details regarding the supply chain structure as well as documenting actual recovery time from past disruptions.

## **6. Managerial Implications**

In today's complex supply chains, I am observing a plethora of supply chain disruptions. It is important for firms to understand how the structure of their supply chains can enable them to respond to supply chain disruptions to become resilient in order to gain a competitive advantage in their industry. Hence, it is crucial for a firm to identify the factors that can reduce their likelihood to suffer disruption and shorten the recovery time from a supply chain disruption. My research provides important suggestions for how a firm might achieve this goal. As such, my study offers several

critical implications for supply chain managers. My findings suggest firms can learn from their peer sites who suffer disruptions. This finding provides an interesting implication to the strategies that firms can consider when opening a new site or considering a site for relocation.

From an internal perspective, my results have important implications as well. My results point to both parts and process complexity as contributors to increased disruption frequency and recovery time. A takeaway is to eliminate specific process activities that do not contribute to productivity. Furthermore, at the parts level, there may be opportunities to standardize parts or re-engineer designs in a way that will simplify bills of material and provide greater standardization of operations. Also, alternate manufacturing resources like alternate sites and multi-sourcing efforts should be carefully evaluated because my results demonstrate that increases in alternate resources although decreased the frequency of disruptions but resulted in increased recovery time from disruptions.

I also suggest that plant-level managers need to carefully maintain the balance of being involved in multiple supply chains. Although involving in multiple supply chains can help in increasing revenues, it might also lead to increased likelihood of disruptions. Although the number of supply chains decreased the recovery time, managers have to cautiously balance the flexibility it offers with complexity generated by multiple connecting points. In addition, trying to stay closer to OEM can reduce the likelihood of disruptions and increase the recovery speed.

Finally, the results stress the need for the initiation of BCM efforts. Indeed, the above considerations could be incorporated into the planning process, as they

represent ways to streamline upstream and internal operations. The empirical results demonstrate that the existence of BCM plans at the plant level lead to significant reductions in the disruption recover time.

## Appendices

### Appendix A. Examples of Disruption Articles

1. “Parts stalemate means no work for Ford workers,” April 20, 2007. This article reported a production disruption at one of the Ford’s manufacturing plants due to a delay in parts supplies because of an industrial dispute.
2. “Refinery problems spark shortages at Shell stations,” February 13, 2008. This article included the details of a supply shortage at Shell’s retail stores due to a problem at one of its oil refineries.
3. “GlaxoSmithKline faces shortages of three drugs,” January 13, 2006. This article stated that the Food and Drug Administration blocked the shipments of three GSK drugs due to manufacturing problems.

**Table A1. Distribution of Disrupted Firms: Number of Competitors**

| Number of Competitors | Number of Disrupted Firms |
|-----------------------|---------------------------|
| 1-10                  | 59                        |
| 11-50                 | 17                        |
| 50+                   | 7                         |

**Table A2. Distribution of Disruption Events: Number of Competitors to Disrupted Firms**

| Number of Competitors | Number of Events |
|-----------------------|------------------|
| 1-10                  | 98               |
| 11-25                 | 18               |
| 26-50                 | 14               |
| 50+                   | 5                |

**Table A3: Categories of Man-Made Disruptions**

|                         |
|-------------------------|
| Bankruptcy              |
| Business Sale           |
| Business Spin-off       |
| Chemical Spill          |
| Company Split           |
| Corporate Restructuring |
| Cyber Attack            |
| Factory Disruption      |
| Factory Fire            |
| FDA/EMA/OSHA            |
| Action                  |
| Force Majeure           |
| Human Health            |
| Labor Disruption        |

Labor Violation  
 Leadership Transition  
 Legal Action  
 Merger & Acquisition  
 Power Outage  
 Protest/Riot  
 Recall  
 Supply Shortage

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**Table A4: BCP, CMP, and ERP questionnaire**

|                | <b>Business Continuity Planning</b>                                                                                                                                        | <b>Crisis Management Planning</b>                                                                       | <b>Emergency Response Planning</b>                                                                               |
|----------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|
| Identification | Have you identified and trained critical resources in performing duties essential to operations                                                                            | Is there a procedure for recording vital information about incidents, actions taken, and decisions made | Are set procedures established to communicate with emergency responders and other authorities during an incident |
| Planning       | Has an analysis of the threats and opportunities that may impact the implementation of the Business Continuity Management Program been conducted within the past 12 months | Is there a procedure for issuing alerts and warnings                                                    | Does your company have an emergency response team established and documented                                     |
| Training       | Do you conduct audits/tests to ensure the BCP provided is functional                                                                                                       | Does your company have a crisis management team trained                                                 | Are they trained to activate the triggers and implement the recovery plans                                       |

**Table A5: Supplier Orientation Questionnaire**

|                                                                        |
|------------------------------------------------------------------------|
| Is there a listing of suppliers documented in a supplier repository    |
| Do you collect BCPs from your suppliers                                |
| Have you collected BCP from all single sourced suppliers, at a minimum |

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