Organizational Resilience to Disruption Risks: Developing Metrics and Testing Effectiveness of Operational Strategies

Milad Baghersad,[1*] Christopher W. Zobel[2]

[1] Department of Information Technology & Operations Management, College of Business, Florida Atlantic University, Boca Raton, FL, 33431, USA

[2] Department of Business Information Technology, Pamplin College of Business, Virginia Tech, Blacksburg, VA, 24061, USA

* Address correspondence to Milad Baghersad, Department of Information Technology & Operations Management, College of Business, Fleming Hall, Room 215, Florida Atlantic University, Boca Raton, FL, 33431, USA; Tel: +1 (561)297-3179; fax: +1(561)297-3043; mbaghersad@fau.edu.

ABSTRACT

This study draws from the system resilience literature to propose three different metrics for evaluating the resilience performance of organizations against disruptions: the initial loss due to the disruption, the maximum loss, and the total loss over time. In order to show the usefulness of the developed metrics in practice, we deploy these metrics to study the effectiveness of two resilience strategies: maintaining operational slack and broadening operational scope, by empirically analyzing the performance of manufacturing firms that experienced a disruption during the period from 2005 to the end of 2014. The results show that maintaining certain aspects of operational slack and broadening business scope and geographic scope can affect these different metrics in different ways. Our results help decision makers in risk management to gain a better understanding of the conditions under which the recommended strategies actually improve organizations' resilience, as well as the ways in which they may do so.

Keywords: System Resilience; Disruptions; Resilience Strategies; Risk Management

Summary for social media

The results of this study provide a better understanding of the conditions under which maintaining operational slack and broadening operational scope improve organizations' resilience. @czobel

1. INTRODUCTION

Disruptive events, such as earthquakes, flood, and work stoppages, occur frequently in today's complex and interdependent business environment. These events have devastating impacts on the disrupted organization and can propagate across its entire network of organizations, both immediately and over longer time periods (Thekdi & Santos, 2016). Recent global disruptions due to the COVID-19 crisis highlight the importance of preparedness for facing such events.

Over the past two decades, a variety of strategies have been recommended in the risk management literature to attempt to improve organizations' resilience against disruptions. However, how and when such strategies can actually reduce the negative impact of disruptions and improve the resilience of organizations is less well known. Part of this disconnect is due to a lack of established metrics for evaluating organizations' resilience.

Gaining a better understanding of resilience behavior is important from both a theoretical and a practical perspective. From a theoretical viewpoint, it is critical for researchers to understand how operational strategies improve resilience and how they affect the relationship between disruptions and the negative impacts of those disruptions on performance over time. The recommended strategies can be very costly for organizations, however, so from a practitioner's viewpoint it is important to gain a better understanding of the conditions under which the recommended strategies actually improve organizations' resilience, as well as the ways in which they may do so.

In this research effort, therefore, we build upon the system resilience literature to develop and quantify three different metrics that indicate the resilience of organizations against disruptions: initial loss, maximum loss, and total loss over time (which provides a combined measure of both loss and recovery). These three indicators of resilience, named resilience metrics, are quantified with respect to the long-term operating performance of organizations and selected so that they represent both the robustness capabilities and the recoverability capabilities of firms. We argue that organizations with lower initial loss, maximum loss, and total loss over time aftermath of a disruption are more resilience. The metrics then can be employed to evaluate the effectiveness of different resilience strategies for improving the performance of organizations after disruptions.

To demonstrate the applicability of the new resilience metrics, we specifically investigate the complex relationship between operational strategies and disruption impacts. We do so by focusing on the effects of two types of operational strategies: maintaining operational slack and broadening operational scope. Although these strategies have been recommended for improving organizations' resilience to disruptions, previous empirical studies suggest that they may not always be effective at protecting against disruptions (Hendricks, Singhal, & Zhang, 2009; Kathryn, Peter, & James, 2014). Our study helps to explain this disconnect by arguing that the effectiveness of maintaining operational slack and broadening operational scope is highly dependent on the severity of the disruption events and on the different types of resilience metrics that are applied. Adopting a more comprehensive view of disruptions' impacts through the use of disaster resilience concepts and utilizing the resource-based view allows us to develop new and expanded inferences about how and when maintaining operational slack and broadening operational scope can benefit organizations by helping to reduce the negative impacts of disruptions.

The remainder of our discussion proceeds as follows. Section 2 describes the three resilience metrics from the system resilience literature used in this study. Section 3 posits three hypotheses about the relationship between the operational slack and operational scope and the three metrics. Section 4 outlines the data collection procedures. Section 5 explains how the three metrics of interest based on the system resilience literature are calculated and describes the methods used to conduct the results. Section 6 then summarizes the results. Finally, Section 7 discusses the findings and provides future research directions.

2. ORGANIZATIONAL RESILIENCE

The concept of strengthening resilience to disruptions has received an increasing amount of attention among both academics and practitioners over the past few decades (Aven, 2019; Baroud, Ramirez-Marquez, Barker, & Rocco, 2014; Hosseini & Ivanov, 2020; Najarian & Lim, 2019). Despite this growing focus, however, there is still inconsistency among interpretations of the concept of resilience to disruptions within different academic disciplines (Hosseini, Barker, & Ramirez-Marquez, 2016; Hosseini, Ivanov, & Dolgui, 2019; Linkov et al., 2018). For example, a number of existing research efforts focus primarily on the recovery capability of organizations and define resilience as the ability of an organization to return to an desirable performance level following a disruption (Christopher & Peck, 2004; Zsidisin & Wagner, 2010). A number of other studies consider resilience to include both the ability of an organization or a system to withstand a disruption and the ability for that organization to recover to its previous state or to a more desirable state (Haimes, 2009; Mackenzie & Zobel, 2016; Melnyk, Closs, Griffis, Zobel, & Macdonald, 2014; Schmitt & Singh, 2012; Zobel, 2014).

This latter view of resilience involves two different but interconnected capacities of organizations: robustness and recoverability. Robustness refers to the extent to which an organization is prepared to cope with disruptions, whereas recoverability refers to the ability of an organization to recover to an acceptable level. In this paper, we consider the latter view of resilience and define the resilience of an organization to a given disruption to be the ability of the organization both to withstand the disruption and to recover its operational capability after the disruption occurs (Haimes, 2009; Mackenzie & Zobel, 2016; Melnyk et al., 2014).

Although different metrics have been provided to quantify resilience to disruptions in other fields such as systems engineering (see Hosseini, Barker, et al. (2016) for a comprehensive review), relatively little attention has been paid to *operationalizing* organizations' responses to improve resilience to supply chain disruptions (Hosseini & Ivanov, 2020; Kamalahmadi & Parast, 2016; Torabi, Baghersad, & Mansouri, 2015). As highlighted in a systematic literature review by Hosseini, Ivanov, & Dolgui (2019) available metrics to quantify resilience in the supply chain management context can be divided two distinct groups. The first group of studies attempt to directly quantify resilience as a single metric, usually with a value between zero and one. Torabi et al. (2015), for example, measured the resilience of a manufacturer's supply base as a function of the total amount of shortage after a disruption. Similarly, Ojha, Ghadge, Tiwari, & Bititci (2018) measured resilience as a function of service loss after a disruption. Hosseini, Al Khaled, & Sarder (2016) used Bayesian networks to assess the resilience of a manufacturer. They first identified the key drivers of resilience in supply chain networks based on absorptive, adaptive, and restorative capacities, and then calculated the resilience of the manufacturer as the ratio of recovered lost production to the lost production capacity. More recently, Behzadi, O'Sullivan, & Olsen (2020) also proposed using the net present value of the loss of performance as a measure of resilience.

The second group of studies, on the other hand, measure indicators and/or drivers of resilience to evaluate the performance of supply chains against possible disruptions (Hosseini, Ivanov, et al., 2019). For instance, Rajesh (2016) argued that a firm's supply chain resilience to disruptions can be evaluated based on a set of multiple measures and proposed five types of indicators of resilience: flexibility indicators, responsiveness indicators, quality indicators, productivity indicators, and accessibility indicators. Their flexibility indicators, for example, include four measures: stock out rate, inventory accuracy rate, number of small disruptions managed through flexibility, and percentage increase in sales from design flexibility. Hosseini, Morshedlou, et al. (2019) argued that geographic diversification of suppliers is a critical strategy to improve resilience of firms and proposed using a measure of supplier segregation as an indicator of firms' resilience. Li & Zobel (2020) also considered three indicators for measuring resilience of a supply chain network, which include robustness, recovery time, and average functionality.

Resilience is inherently a multi-dimensional concept (Pant, Barker, & Zobel, 2014; Zobel, 2010, 2011, 2014). Therefore, considering different dimensions of an organization's behavior against a disruption, similar to the second group of studies, is very beneficial in evaluating resilience. An important perspective on this is provided by the seminal paper of Sheffi and Rice (2005), in which they characterize the dynamics of an organization's response to a disruption using a response curve, referred to as a "disruption profile". Such a response curve illustrates the transient change in performance of a system over time, and as a result, it captures both the impact of a disruption on the system and the response behavior of the system as it subsequently recovers. Fig. 1 provides an illustration of a corresponding disruption profile. Sheffi and Rice (2005) similarly argue that any serious disruption will affect an organization's performance over time, and they propose eight distinct phases to characterize the organizations' responses to disruptions: preparation, the disruptive event, first response, initial impact, full impact, preparation for recovery, recovery, and long-term impact. They did not, however, define a unit of performance or discuss how to measure each of these phases based on such a performance measure.

---Insert Fig. 1 Approximately Here---------------------------

The idea of using a response curve to characterize the performance of a system in response to a disruption is well known in the system resilience literature (Barker, Ramirez-Marquez, & Rocco, 2013; Baroud et al., 2014; Curt & Tacnet, 2018; Kong, Simonovic, & Zhang, 2019; Zhang, Mahadevan, & Goebel, 2019). Bruneau et al. (2003) initially proposed the idea of using the area above such a response curve as a measure of the *loss of resilience* in a system, or the total loss experienced by the system over time, with a larger area corresponding to a less resilient system. Similar ideas are used to evaluate the resilience of systems across a number of different contexts (Adams, Bekkem, & Toledo-Durán, 2012; Giahi, MacKenzie, & Hu, 2020; Mackenzie & Zobel, 2016; Sahebjamnia, Torabi, & Mansouri, 2015; Thekdi & Santos, 2019).

Zobel (2010, 2011, 2014) specifically argues that a single measure for resilience cannot sufficiently capture the tradeoffs between the actual loss of performance due to the impact of a disruption and the subsequent length of time needed for the system to recover. Since a large initial impact followed by a quick recovery could result in the same area above the response curve as would a much smaller impact with a much longer recovery time, he argues that multiple characteristics of the system's response should be measured simultaneously, in order to better reflect system performance and to more effectively characterize resilient behavior (Zobel, 2010; 2011). The robustness and resilience performance measures of Brandon-Jones et al. (2014) also echo this perspective by directly considering both the amount of loss and the ability to return to normal operating performance after a disruption. Mackenzie and Zobel (2016) also leverage this idea to find optimal allocations of resources to increase an organization's resilience to disruptions.

With this in mind, this current study seeks to provide a more complete characterization of the impacts of disruptions on organizations' performance by using three complementary metrics. As illustrated in Fig. 2, the first metric reflects the initial impact of the disruption, whereas the second metric reflects the subsequent maximum impact of the event, measured at the time when recovery begins. The third metric then provides a combined measure of both robustness and recoverability, similar to the original measure of *loss of resilience* provided by Bruneau et al. (2003). If the maximum impact is equal to the initial impact then this implies that the organization is able to resist increasing (or cascading) losses over time. Similarly, an organization with less total loss over time is generally able either to maintain more functionality overall, or to recover more quickly, than one with more total loss. Together, these performance metrics thus help to characterize not just the immediate impacts of a disruption on an organization, but also the longer-term impacts and the relative extent to which the organization is able to recover over time. These three metrics are calculated using financial performance of firms in Section 5.

--Insert Fig. 2 Approximately Here--------------------------

With these three measures in mind, the following hypotheses serve to conceptualize the relationship between operational strategies and the different characteristics of the organization's subsequent performance response.

3. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

We ground our conceptual model in the resource-based view (RBV) of the organization. Known as one of the most powerful theories for understanding organizations (Barney, Ketchen, & Wright, 2011), the RBV relates the competitive advantage of an organization to strategic resources that are heterogeneously distributed across that organization (Barney, 1991; Wernerfelt, 1984). According to the RBV, valuable, rare, unique, and non-substitutable resources enable an organization’s competitive advantage (Barney, 1991). The RBV has been widely utilized by researchers to explain differences in organizations’ performance outcomes.

3.1. Operational Slack

Organizational slack has been defined as the pool of resources in excess of what an organization needs to execute its normal level of activities during a given planning cycle (Nohria and Gulati, 1996; Voss et al., 2008; Azadegan et al., 2013). Although lean production theory suggests that eliminating slack resources enhances competitiveness and performance (Kinney & Wempe, 2002; Modi & Mishra, 2011), several studies have found that having organizational slack actually enhances organizations' performance in specific business environments (Kovach, Hora, Manikas, & Patel, 2015; Tan & Peng, 2003; Wan & Yiu, 2009) such as in highly unstable markets.

Organizations can carry slack resources in four different forms: operational, financial, customer relational, and human resources (Voss et al., 2008). In our first set of hypotheses, we evaluate the impacts of the first type of organizational slack, i.e. operational slack, on organizations' performance in the presence of disruptions. Operational slack is unused or underutilized operational resources (Tan and Peng, 2003; Voss et al., 2008). Inventory slack (raw materials, work-in-process, and finished products), supply chain slack (overall slack in a firm's supply chain), and capacity slack (such as backup utilities, extra production capacity, and excess labor) are three common types of such operational slack (Kovach et al., 2015).

Operational slack can be considered as a strategic resource for organizations in case of disruptions. Based on the resource-based view, therefore, organizations maintaining operational slack have a competitive advantage over organizations that do not have enough operational slack. These critical extra resources can be used to avoid significant losses after disruptions. Some of these types of operational slack (such as inventory slack) can allow organizations, such as manufacturing firms, to absorb the shock of disruptions (i.e. they can improve robustness), and therefore help them to experience less initial loss and less maximum loss of performance.

However, other types of operational slack (such as capacity slack) may instead help organizations recover to a desirable service level after a disruption.

The existing literature thus suggests that having operational slack benefits organizations in their efforts to respond to disruptions. The extent of such benefits, however, is not necessarily clear. We argue that the benefits of operational slack depend on the level of severity of the disruption. When disruptions are severe and can potentially cause significant losses, operational slack helps organizations to reduce the actual amount of such losses. However, the benefits of having operational slack in the case of minor disruptions are not as much as for severe disruptions. Hypotheses 1a to 1c formalize this expectation about the impacts of operational slack on the resilience metrics in the presence of disruptions:

Hypothesis 1a (1b and 1c). Operational slack moderates the relationship between the severity of a disruption and resilience metrics (the initial loss, the maximum loss, and the total loss over time) of an organization such that an organization with higher operational slack will be more resilient to disruptions.

3.2. Operational Scope

The next two subsections discuss the impacts of two different types of operational scope on the performance of organizations after disruptions: business scope and geographic scope.

3.2.1. Business Scope

Business scope refers to the breadth of an organization's business portfolio. There are at least two reasons why we would expect broadening business scope to improve organizations' performance in the case of a disruption. First of all, we would expect the operational impacts of a disruption on a line of business to be less destructive for organizations with a large number of different businesses than for organizations that are focused only on a few businesses (Hendricks et al., 2009). This suggests that organizations with larger business scope would be more robust to disruptions than less diversified organizations. Secondly, diversified organizations have competitive advantages over their more focused counterparts through strategic resources, such as flexibility in capital and labor markets, that diversification provides (Caves, 1981; Palich, Cardinal, & Miller, 2000). "*It [i.e. a diversified organization] can also shift capital (and other critical resources, for that matter) between businesses within its portfolio*" (Palich et al., 2000 p. 157). The resource-based view suggests that these additional critical resources derived from business diversification provide a competitive advantage to organizations, especially in the case of disruptions. Therefore, we expect managers in the more diversified organizations to have more flexibility to accelerate the recovery process by shifting funds and resources from undisrupted businesses to the disrupted businesses. We also expect the benefits of business scope for organizations to be higher when organizations experience a more severe disruption.

Hypotheses 2a to 2c therefore formalize these expectations:

Hypothesis 2a (2b and 2c). Business scope moderates the relationship between the severity of a disruption and resilience metrics (the initial loss, the maximum loss, and the total loss over time) of an organization such that an organization with higher business scope will be more resilient to disruptions.

3.2.2. Geographic Scope

In contrast to business scope, geographic scope involves the establishment of manufacturing facilities in different countries and regions (Kovach et al., 2015); in other words, regionalizing production. Geographic scope has been recommended as a strategy to decrease the impacts of disruptions for organizations. Chopra and Sodhi (2014), for example, argue that regionalizing operations avoids disruption of the entire organization by isolating a disruption in its region. From a resource-based view, geographic diversification provides resource flexibility which enables organizations to relocate resources from undisrupted locations to disrupted locations. This flexibility provides a critical advantage for organizations during recovery after disruptions. More geographically diversified organizations also have access to higher number of suppliers as they operate in different locations and can use these suppliers to offset impacts of a disruption in other regions. Similar to business scope and operational slack, we expect the benefits of geographic scope to also be contingent on the level of severity of the disruption, i.e. the benefits of geographic scope for organizations will be greater in case of a more severe disruption.

Hypotheses 3a to 3c formalize this expectation.

Hypothesis 3a (3b and 3c). Geographic scope moderates the relationship between the severity of a disruption and resilience metrics (the initial loss, the maximum loss, and the total loss over time) of an organization such that an organization with higher geographic scope will be more resilient to disruptions.

Given these three sets of hypotheses, Fig. 3 presents the relationships of interest in this study.

---Insert Fig. 3 Approximately Here**---------------------------**

4. DISRUPTION DATA

PR Newswire and Business Wire in the Factiva database are our sources for finding disruption announcements released by U.S. publicly traded firms. These two outlets are both reliable sources for obtaining the vast majority of press releases from U.S. publicly traded firms (W. Schmidt &

Raman, 2012). We limit our search to the time period from 2005 to the end of 2013. We use the following sets of terms to search the headlines and lead paragraphs of the news articles: delay, disruption, interruption, shortage, or problem, paired together with: component, delivery, parts, shipment, manufacturing, production, or operations. Similar terms have been used by other researchers to identify disruption announcements (Hendricks & Singhal, 2003; C. G. Schmidt, Wuttke, Ball, & Heese, 2020). Out of more than 11,000 news articles that are retrieved and reviewed one by one by the research team, we initially record more than 400 disruptions reported by U.S. publicly traded firms. We then remove any explicit dependencies between announcements by deleting each disruption announcement that relates to the same firm within the first two years of another disruption; this is the same approach taken by Hendricks and Singhal in their study (2005b), which decreases the number of sample firms to 397 firms. To be sure that the financial impacts are purely driven by the disruptions, one of the authors spent more than one hundred hours reviewing the announcements to ensure that the disruptions are relevant. We also removed firms that experienced other significant events, such as a merger, within a two-year period after each recorded disruption.

As a result of removing firms with insufficient data, we end up with a final sample of 316 distinct disruption announcements. Within this sample, several firms have missing data after the quarter of the disruption announcement – these firms are included only in the context of calculating the initial loss metric. Since the resilience strategies that we are considering may have different effects on firms in different industry sectors (for example, managing inventory slack is more relevant in the manufacturing sector than in the services sector), we focus our analyses on manufacturing firms, i.e., firms with a Standard Industrial Classification (SIC) code from 2000 to 3999. Narrowing our focus in this way subsequently decreases our sample to 150 firms.

5. MEASURES AND DESCRIPTIVE STATISTICS

5.1. Resilience Metrics

In this particular study, we choose to use return on assets (ROA) as a measure of organizations' performance. "From an operations management perspective, ROA proxies for both profitability and efficiency in utilization of assets" (Kovach et al., 2015, p. 6). To calculate the impact of disruptions on the ROA of disrupted firms, we first match each sample firm with control firms that are similar to the sample firm, using the *performance-industry-matched* method as presented in Hendricks and Singhal (2008).

We calculate the abnormal performance of a sample firm at quarter t (Δ_t) using the difference between its actual and expected ROA value:

$$\Delta_t = \text{Actual ROA of the sample firm at quarter } t \\ - \text{ expected ROA of the sample firm at quarter } t \quad (1)$$

In normal conditions (without experiencing disruptions), sample firms are expected to grow at a similar rate as their matched control firms. Therefore, we can find the expected ROA of a sample firm from the change in ROA of its matched control group (Hendricks and Singhal 2008). When $0 \leq t < 4$, the expected ROA of the sample firm at quarter t is estimated from the firm's ROA value at quarter t-4 plus the change in the median ROA value of the set of matched control firms between quarter t-4 and quarter t. As in Hendricks and Singhal (2008), we use the change in the median of the control firms' ROA to calculate the expected ROA of the sample firms in order to avoid the possible influence of outliers on the mean value. Similarly when $4 \leq t \leq 8$, the expected ROA of the sample firm at quarter t is estimated from the firm's *estimated* ROA value from four quarters before (i.e., quarter t-4) plus the change in the median ROA value of the set of matched control firms between quarter t-4 and quarter t.

A negative value of Δ_t indicates that the sample firm's growth is less than the control firms' growth, and that the sample firm experiences a relative loss in quarter *t*. Note that, for the sake of analyses in the following sections, the calendar quarters of firms are transformed to their event quarters. For example, quarters -4, 0, 4 represent four quarters before the disruption quarter, the quarter of the disruption, and four quarters after the disruption quarter, accordingly.

In order to evaluate the total loss in performance over time in response to a disruption, the firm's performance should be considered during an appropriate time period after the disruption has occurred. In this study, therefore, we consider the firm's performance from the quarter of the disruption announcement to eight quarters after the quarter of the disruption announcement. In order to calculate this metric we also need the performance data of firms from four quarters *before* the quarter of the disruption announcement. Therefore, the performance data of each sample firm used in this study consists, in total, of 13 consecutive quarters. Our adoption of a two year time frame echoes that of Hendricks and Singhal (2005b), who also use this same relative time frame to evaluate the long-term impacts of disruptions on firms.

Although some disruptions, such as quality issues, may become known prior to the quarter of the official announcement, in this study we simply define the initial loss to be that which occurs in the actual quarter of the disruption announcement. Therefore, following the suggestion of Zobel (2010, 2011, 2014), we calculate the amount of initial loss (L_0) to be:

$$L_0 = -\Delta_0 \qquad (2)$$

where Δ_0 is the abnormal performance of the sample form at time t=0, and where the loss suffered in quarter t is given by $L_t = -\Delta_t$. Since Δ_0 will be negative if the actual ROA is less than expected, then a larger positive value of L_0 indicates more initial loss.

We also calculate the maximum loss for a given sample firm, beginning with the quarter of the announcement of a disruption and ending eight quarters after that announcement, as follows:

$$L_{max} = \max_{t=0\ to\ 8}\{-\Delta_t\} = \max_{t=0\ to\ 8}\{L_t\} \tag{3}$$

As with the measure of initial loss, a positive and higher value of L_{max} represents a larger maximum loss value.

In order to calculate the total loss suffered by a sample firm over the first two years after a disruption, we then simply consider the sum of the positive loss values over that given time period:

$$Total\ loss\ over\ time = \sum_{t=0}^{8} \max(0, L_t) \tag{4}$$

5.2. Independent Variables

5.2.1. Severity of Event

Most existing research characterizes the severity of a disruptive event only in terms of the strength of its observed impacts on the organization (Ambulkar, Blackhurst, & Grawe, 2015; Bode & Wagner, 2015; T. G. Schmitt, Kumar, Stecke, Glover, & Ehlen, 2017). It thus is often measured by considering outcomes such as how much of a delay was introduced into the delivery of a particular product and the amount by which a firm's revenue was decreased as a result. In our current context, we may specifically measure such impacts by using the three performance outcome measures introduced above. Given two organization affected by exactly the same disruptive event, the differences in such measures could provide an indication of the relative resilience of each organization. If two different events affect the two organizations, however, then it can be difficult to compare the resulting behaviors by looking only at performance outcomes. This is because an inherently resilient organization that is subjected to an extremely disruptive event (such as a natural disaster) might suffer much more loss over time than would a much less resilient firm subjected to a very minor disruptive event (such as the temporary failure of a supplier that provides a non-critical component).

Even the same disruptive event, however, could lead either to a negligible impact on production or to a significant long-term impact on firm performance, depending on the type of event, the location of the event, the timing of the event, and the importance of the facilities or resources that are impacted. For example, the same small fire that causes minimal damage to an empty warehouse will have dramatically greater impacts, and cause a much more severe disruption, if it occurs in a clean room facility and affects a critical component (Mukherjee, 2008).

In order to characterize the relative severity of the disruptive event itself, therefore, we need to be able to capture some indication of both the event and the specific context in which it occurs. To accomplish this, we asked a panel of experts in operations management to evaluate the actual severity of the events. For each event, we provided the disruption announcement and basic information about the company, including a summary of the company's description, total assets, annual sales, and number of employees. Table I shows one example of such a disruption announcement and the basic information that was provided to experts. Given this information, we then asked experts to evaluate the severity of the event based on a 5-point Likert scale adapted from a risk assessment framework developed by the Committee of Sponsoring Organizations of the Treadway Commission (Curtis & Carey, 2012). Table II shows the scale that was provided to the experts. As some announcements may not provide enough information to rate the severity of disruptions, experts could choose "not enough information is provided".

--Insert Table I Approximately Here---------------------------

---Insert Table II Approximately Here---------------------------

We recruited experts with operations and supply chain management experience using the Amazon Mechanical Turk service (MTurk) and an on-line survey instrument. MTurk has been used in similar studies to study the behavior of experts in the context of disruptions (see for example, Cantor et al. (2014) and Mena et al. (2019)). Similar to Cantor et al. (2014), we required that the participants have supply chain experience and a current supply chain role. To ensure this, we also conducted a prescreening test before the main survey, and the respondents were required to answer all prescreening questions correctly to enter the main survey. Each survey was limited to 10 events, which resulted in 15 different surveys. We collected 91 acceptable responses in total (6 responses for each survey on average). We removed 9 events out of 150, which had more than two experts selecting "not enough information is provided," and this reduced the total number of events to 141.

5.2.2. Operational Slack

In line with previous studies (Azadegan et al., 2013; Hendricks et al., 2009; Kovach et al., 2015), we consider three different metrics for operational slack: inventory slack, supply chain slack, and capacity slack, and we apply similar methods to those used in these studies to calculate the three measures.

Inventory slack of a firm is measured as the firm's days of inventory, which is calculated as 365 times the ratio of average inventory to cost of goods sold. To account for differences in days of inventory across different industries, we calculate industry-adjusted days of inventory of each firm by first subtracting the average days of inventory for its industry from the firm's days of inventory and then dividing the result by this same industry average. Firms with higher days of inventory are better able to react to disruptions, by utilizing finished goods, compared to firms with lower days of inventory (Kovach et al., 2015).

Supply chain slack is measured by cash-to-cash cycle, which is equal to the sum of days of inventory and days of account receivables, minus days of account payables. Days of account receivables is equal to 365 times the ratio of average account receivables to annual sales, and days of account payables is equal to 365 times the ratio of average account payables to cost of goods sold. To account for potential differences of cash-to-cash cycle across different industries, we use the industry-adjusted cash-to-cash cycle, which is the cash-to-cash cycle of each firm minus the average cash-to-cash cycle of its industry divided by 100. The cash-to-cash cycle includes the inventory level of the focal firm, accounts receivables from customers, and accounts payable to suppliers, and it is commonly used as a measure of leanness of firms' supply chains, where a higher cash-to-cash cycle means lower slack in the supply chain network (Hendricks et al., 2009; Kovach et al., 2015).

The last form of operational slack, capacity slack, is measured as the ratio of net property, plant, and equipment to sales. Similar to what is done for the other measures, we calculate the industry-adjusted capacity slack for each firm, which is the capacity slack of the firm minus the average capacity slack of its industry. When the ratio of net property, plant, and equipment to sales is higher, it means that the firm has higher resources compared to other firms.

5.2.3. Business Scope

According to Statement 131 of the Financial Accounting Standards Board (FASB), firms are required to disclose their major business segments (FASB, 1997). Based on firms' business segment information available from COMPUSTAT Historical Segments, therefore, business scope is calculated to be 1 minus the Herfindahl index of sales (Hendricks et al., 2009):

$$B_{Hrf} = 1 - \sum_{i} \left(\frac{S_i^b}{S} \right)^2 \qquad (5)$$

where S_i^b is the annual sales of business segment i and S is the total sales of the firm. When no business segment is reported, B_{Hrf} is assumed to be zero. A higher value of the business scope measure indicates a higher degree of business diversification.

5.2.4. Geographic Scope

Firms are also required to disclose information about their major operating segments by geographic area (FASB, 1997). As indicated in Statement No. 131 of the Financial Accounting Standards, this can help firms better understand how their risk is concentrated. Similar to what was done with business diversification, therefore, we may calculate a value for geographic scope based on the firms' geographic segment information available from the COMPUSTAT Historical Segments database. This segment information includes, as follows (Hendricks et al., 2009):

$$G_{Hrf} = 1 - \sum_{i} \left(\frac{S_i^g}{S} \right)^2 \qquad (6)$$

where S_i^g is annual sales associated with their actual operations in geographic segment i and S is total sales of the firm. The result therefore provides a measure of the extent to which the firm's operations are distributed across different geographic segments. When no geographic segment is reported, G_{Hrf} is assumed to be zero. Similar to the business scope measure, higher values of the geographic scope measure (G_{Hrf}) indicate a higher degree of geographic diversification.

5.2.5. Control Variables

We consider several control variables that may have significant impact on loss experienced by firms after disruptions. First, we control for firms' size. Larger firms typically have more resources available with which to face unplanned events, and therefore we would expect larger firms to withstand a disruption more easily and to recover more quickly after the disruption. We thus include size of firm, calculated as the natural logarithm of the total assets, as one of the control variables. Older firms may have more experience in response to disruptions. Therefore, we include the firm's age as a second control variable, with a value based on the difference between the year of the disruption announcement and the first year that the firm was listed in the COMPUSTAT database. We consider book to market value ratio as a third control variable. This ratio controls the firms' growth expectations and risk characteristics (Kim, Sambharya, & Yang, 2016). Next, since we expect that disruptions have a different impact on firms operating in highly intense industries, we also consider an additional variable: industry growth rate. Industry growth rate is calculated to be the average sales growth rate of firms with the same two-digit SIC code as the sample firm.

6. RESULTS

Table III provides zero-order correlations, means, and standard deviations for the dependent, independent, and control variables. We used the student's t-test for the mean and sign rank for the median to test if the initial loss, the maximum loss, and the total loss over time are greater than zero. The results of the statistical tests show that disruptions are associated with significant negative impacts on firm performance for all three of the resilience metrics (α= 0.01).

--Insert Table III Approximately Here--------------------------

Given these initial results, we use Ordinary Least Squares (OLS) regression to test the hypotheses given in Section 2. We also evaluate variance inflation factors (VIF) for the variables in each of our models. The VIFs in our models are lower than or equal to 5, which is less than the recommended cut-off in the literature (i.e. 10), and therefore we do not expect multicollinearity issues in our analyses.

Table IV provides the results of the regression analyses for the three dependent variables: initial loss, maximum loss, and total loss. Models 1, 4, and 7 only include the control variables, the direct effects for each dependent variable are included in Models 2, 5, 8, and the interaction terms are introduced in Models 3, 6, and 9. Considering initial loss, the results of Model 1 indicate that firm size is negatively associated with initial loss (p-value ≤ 0.01). Model 2 shows that the severity of the event is positively associated with initial loss (p-values ≤ 0.01). Model 3, in turn, shows that inventory slack and business scope have significant interaction terms with severity (p-values ≤ 0.10). This suggests that inventory slack and business scope negatively moderate the relationship between severity of event and initial loss due to the disruption (supporting H1a and H2a). On the other hand, the moderating effect of geographic scope on the relationship between the severity of an event and the initial loss is not supported (H3a is not supported).

Model 4 shows that firm size and book to market ratio are both negatively associated with maximum loss (p-values ≤ 0.05). The results of Model 5 indicate that the severity of the event is positively associated and inventory slack and geographic scope are negatively associated with maximum loss (p-value ≤ 0.05). The results from adding the interaction terms between severity and each of the other factors suggest that inventory slack negatively, and supply chain slack positively, moderate the relationship between severity of event and maximum loss (H1b is partially supported). At the same time, although the interaction of geographic scope with severity is not also statistically significant (p-value > 0.10), the results show that geographic scope does have a direct negative effect on maximum loss.

Finally, the last three columns of Table IV provide the results of regression analyses considering total loss over time as the dependent variable. Similar to the results for maximum loss, the results of Model 7 show that firm size and book to market ratio are both negatively associated with total loss over time (p-values ≤ 0.05). The results of Model 8 indicate that severity of the event is positively associated and inventory slack and geographic scope are negatively associated with total loss over time (p-value ≤ 0.10). Model 9 then suggests that inventory slack and business scope negatively, and supply chain slack positively, moderate the relationship between the severity of the event and the total loss over time (p-values ≤ 0.10), which supports H1c and H2c. At the same time, however, the interaction between severity and geographic scope is not statistically significant (p-value > 0.10), although geographic scope is directly and negatively associated with total loss (p-value ≤ 0.05).

Overall, all the models presented in Table IV have F-values greater than or equal to 2.482, and all of the models are statistically significant at the 1% level. The R^2 values of all models are between 11.6% and 56.5%.

--Insert Table IV Approximately Here--------------------------

To further analyze the significant interactions between different strategies and disruption severity, the associated relationships are plotted at one standard deviation below and one standard deviation above the mean values of the moderator variables. The resulting interaction plots are provided in Fig. 4.

Fig. 4a and Fig. 4b show that inventory slack and business scope decrease the initial loss when the disruption severity is high. Surprisingly, the results show that inventory slack and business scope actually increase initial loss experienced by firms when severity is low. Fig. 4a and Fig. 4b thus confirm our hypotheses that operational slack (H1a) and business scope (H2a) moderate the relationship between the severity and initial loss.

Fig. 4c shows that inventory slack is negatively associated with maximum loss when severity is high, whereas it does not have a significant effect on maximum loss when severity is low. Fig. 4d surprisingly shows that supply chain slack has a negative effect on maximum loss when severity is low, but it has a positive effect on maximum loss when severity is high. The similar effect of supply chain slack is observed considering total loss over time (Fig. 4f). Furthermore, Fig. 4e and Fig. 4g show that operational slack (expressed as inventory slack) and business scope each have a negative effect on total loss over time when severity is high, but they may increase total loss over time when severity is low.

--Insert Fig. 4 Approximately Here--------------------------

7. CONCLUSION, LIMITATIONS, AND FURTHER RESEARCH

This study makes a general contribution to the disruption management literature and has several important implications for risk managers. Our study is the first to explicitly consider and operationalize three new metrics drawn from the disruption profile introduced by Sheffi and Rice (2005) to evaluate organizations' operating performance against disruptions. Using the three resilience metrics, our study shows that different types of operational slack and operational scope may have different effects on these three metrics and therefore that they may benefit organizations in different ways. In particular, our study shows that inventory slack does negatively moderate the relationship between the severity of disruptions and the resilience metrics, in terms of the initial loss, the maximum loss, and the total loss over time. The results also show that if the severity of a disruption is high then firms with higher business scope are significantly more resilient to disruptions, but if the disruption's severity is low then business scope may not be beneficial to firms. These results indicate that it may be the added complexity associated with more business diversity that leads to negative impacts on performance. This aligns well with the results of Craighead, Blackhurst, Rungtusanatham, & Handfield (2007), who showed that complexity can increase the negative impact of disruptions on organizations.

Our findings also show that different types of operational slack and operational scope may affect resilience abilities of organizations differently in the short-term versus the long-term. This makes it important, for example, to recognize that investing resources in increasing geographic scope may not have immediate effects but could be beneficial in the long run, regardless of the size of any future potential disruption. Investing resources into building supply chain slack may also have little to no effect on the initial impacts of a disruption, but if the disruption is not very severe then having increased slack may help to significantly reduce both the total loss and the maximum amount of loss suffered (see Fig. 4d and Fig. 4f). In contrast to geographic scope and supply chain slack, which had no significant effect on the initial loss due to a disruption, investing in inventory slack can help to significantly reduce the initial performance loss that can result from a high severity disruption. Furthermore, given a severe disruption, such an investment can also have a significant negative effect on both maximum loss and total loss over time by providing firms with the time to find other sources of supply. The results of the study also show that broadening business scope can be a good strategy to allow a manager to reduce initial loss, and total loss over time, in the case of high severity disruptions.

This study has several important implications for supply chain risk managers. First of all, our findings show that different types of operational slack and operational scope may affect supply chain disruptions differently in the short-term versus the long-term. This makes it important, for example, to recognize that establishing manufacturing facilities in different regions to increase the geographic scope may not have immediate effects in reducing the negative impacts of disruptions but could be beneficial in the long run, regardless of the size of any potential future disruption.

In contrast to geographic scope and supply chain slack, which had no significant effect on the initial loss due to a disruption, investing in strategies related to inventory slack, such as maintaining a higher level of raw materials, work-in-process, and finished products, can help to significantly reduce the initial performance loss that can result from a high severity disruption. Furthermore, given a severe disruption, such an investment can also have a significant negative effect on both maximum loss and total loss over time by providing firms with the time to find other sources of supply. As an example of this, BioMarin Pharmaceutical Inc. experienced only minor effects when its main supplier experienced a major disruption:

"*BioMarin Pharmaceutical Inc. (Nasdaq: BMRN) announced today that the temporary interruption of bulk production at Genzyme's Allston Landing manufacturing facility is not expected to have any impact on Aldurazyme supply or revenue to BioMarin or Genzyme. ... BioMarin has a total of approximately ten months of vialed inventory on hand, utilizes a second fill finish supplier and a third is expected to be qualified later this year*" (PR Newswire, 2009).

The results of the study also show that broadening business scope, such as increasing the number of different businesses a firm is involved in, can be a good strategy to allow managers to reduce initial loss and total loss over time, in the case of high severity disruptions.

Taken together, these results imply that managers should invest available resources into inventory slack and business scope, in order to decrease the impacts of a severe supply chain disruption on a firm's performance, and they should invest in strategies related to supply chain slack, such as maintaining a higher level of inventory alongside supply chain networks, if they wish to reduce their losses in the case of low severity supply chain disruptions. On the other hand, geographic diversification can be a good strategy for reducing the long-term impacts of both high and low severity supply chain disruptions. In either case, however, it is important to recognize that decisions about making such investments also need to consider additional factors before they are implemented, such as their relative cost and their impacts on operational efficiency.

In this study, we consider the performance of firms over the first two years (8 quarters beyond the quarter of the disruption) after the disruptions occurred. It is important to acknowledge that it may take more than two years for a firm to recover from a disruption, or the firm simply may not recover at all. Future research may therefore consider a longer timeframe to calculate the values for the maximum loss and the total loss over time. It is also important to note that the OLS regression method used in this study shows the correlation between our independent variables and resilience metrics but does not necessarily imply causation. Although showing a positive relationship between business factors and resilience metrics is very important, establishing causality can provide more benefits to decision-makers. Future studies should consider alternative methods, such as Bayesian networks (Hosseini and Ivanov, 2020), to establish causality between business factors and the resilience metrics studied in this paper. Furthermore, in this study, we did not evaluate recovery time of organizations after disruptions. Recovery time has been considered as an important measure of resilience in the literature, however it is more challenging to calculate in our context since some organizations may never recover to their original level. Future research may develop methods to calculate the recovery time of organizations after disruptions using operating performance.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant Nos. 1952792 and 1735139.

REFERENCES

Adams, T. M., Bekkem, K. R., & Toledo-Durán, E. J. (2012). Freight resilience measures. *Journal of Transportation Engineering*, *138*(11), 1403–1409. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000415

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, *33–34*, 111–122. https://doi.org/10.1016/j.jom.2014.11.002

Aven, T. (2019). The Call for a Shift from Risk to Resilience: What Does it Mean? *Risk Analysis*, *39*(6), 1196–1203. https://doi.org/10.1111/risa.13247

Azadegan, A., Patel, P. C., & Parida, V. (2013). Operational Slack and Venture Survival. *Production and Operations Management*, *22*(1), 1–18. https://doi.org/10.1111/j.1937-5956.2012.01361.x

Barker, K., Ramirez-Marquez, J. E., & Rocco, C. M. (2013). Resilience-based network component importance measures. *Reliability Engineering & System Safety*, *117*, 89–97. https://doi.org/https://doi.org/10.1016/j.ress.2013.03.012

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J. B., Ketchen, D. J., & Wright, M. (2011). The future of resource-based theory: Revitalization or decline? *Journal of Management*, *37*(5), 1299–1315. https://doi.org/10.1177/0149206310391805

Baroud, H., Ramirez-Marquez, J. E., Barker, K., & Rocco, C. M. (2014). Stochastic Measures of Network Resilience: Applications to Waterway Commodity Flows. *Risk Analysis*, *34*(7), 1317–1335. https://doi.org/10.1111/risa.12175

Behzadi, G., O'Sullivan, M. J., & Olsen, T. L. (2020). On metrics for supply chain resilience. *European Journal of Operational Research*, *287*(1), 145–158.

Bode, C., & Wagner, S. M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. *Journal of Operations Management*, *36*, 215–228. https://doi.org/10.1016/j.jom.2014.12.004

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, *50*(3), 55–73. https://doi.org/10.1111/jscm.12050

Bruneau, M., Chang, S., Eguchi, R., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., … von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, *19*(4), 733–752. Retrieved from http://earthquakespectra.org/doi/abs/10.1193/1.1623497

Cantor, D. E., Blackhurst, J. V, & Cortes, J. D. (2014). The clock is ticking: The role of uncertainty, regulatory focus, and level of risk on supply chain disruption decision making behavior. *Transportation Research Part E: Logistics and Transportation Review*, *72*, 159–172. https://doi.org/https://doi.org/10.1016/j.tre.2014.10.007

Caves, R. E. (1981). Diversification and Seller Concentration: Evidence From Changes, 1963-72. *The Review of Economics and Statistics*, *63*(2), 289. https://doi.org/10.2307/1924100

Chopra, S., & Sodhi, M. (2014). Reducing the risk of supply chain disruptions. *MIT Sloan Management Review*, *55*(3), 73–80. Retrieved from http://search.proquest.com/openview/1a05ebdc973a88cec6b9d2ba18011685/1?pq-origsite=gscholar

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, *15*(2), 1–14. https://doi.org/10.1108/09574090410700275

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: Design characteristics and mitigation capabilities. *Decision Sciences*, *38*(1), 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x

Curt, C., & Tacnet, J.-M. (2018). Resilience of Critical Infrastructures: Review and Analysis of Current Approaches. *Risk Analysis*, *38*(11), 2441–2458. https://doi.org/10.1111/risa.13166

Curtis, P., & Carey, M. (2012). *Risk assessment in practice*. Retrieved from https://www.coso.org/Documents/COSO-ERM-Risk-Assessment-in-Practice-Thought-Paper-October-2012.pdf

Financial Accounting Standards Board (FASB). (1997). Disclosures about Segments of an Enterprise and Related Information. Statement of Financial Accounting Standards No. 131. *Norwalk, CT: FASB*, (131).

Giahi, R., MacKenzie, C. A., & Hu, C. (2020). Design optimization for resilience for risk-averse firms. *Computers & Industrial Engineering*, *139*, 106122. https://doi.org/https://doi.org/10.1016/j.cie.2019.106122

Haimes, Y. Y. (2009). On the Definition of Resilience in Systems. *Risk Analysis*, *29*(4), 498–501. https://doi.org/10.1111/j.1539-6924.2009.01216.x

Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501–522. https://doi.org/10.1016/j.jom.2003.02.003

Hendricks, K. B., & Singhal, V. R. (2008). The effect of product introduction delays on operating performance. *Management Science*, *54*(5), 878–892. https://doi.org/10.1287/mnsc.1070.0805

Hendricks, K. B., Singhal, V. R., & Zhang, R. (2009). The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of Operations Management*, *27*(3), 233–246. https://doi.org/10.1016/j.jom.2008.09.001

Hosseini, S., Al Khaled, A., & Sarder, M. D. (2016). A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer. *Journal of Manufacturing Systems*, *41*, 211–227.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering and System Safety*, *145*, 47–61. https://doi.org/10.1016/j.ress.2015.08.006

Hosseini, S., & Ivanov, D. (2020). Bayesian networks for supply chain risk, resilience and ripple effect analysis: A literature review. *Expert Systems with Applications*, *161*, 113649.

Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, *125*, 285–307. https://doi.org/https://doi.org/10.1016/j.tre.2019.03.001

Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M. D., Barker, K., & Al Khaled, A. (2019). Resilient supplier selection and optimal order allocation under disruption risks. *International Journal of Production Economics*, *213*, 124–137.

Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, *171*, 116–133.

Kathryn, A. M., Peter, T. W., & James, A. H. (2014). Mitigating supply chain disruptions – a normal accident perspective. *Supply Chain Management: An International Journal*, *19*(2), 142–152. https://doi.org/10.1108/SCM-03-2013-0083

Kim, S., Sambharya, R. B., & Yang, J. S. (2016). Do CEOs exercise managerial discretion to save their jobs? *Journal of Management & Governance*, *20*(1), 179–200. https://doi.org/10.1007/s10997-014-9300-2

Kinney, M. R., & Wempe, W. F. (2002). Further Evidence on the Extent and Origins of JIT's Profitability Effects. *The Accounting Review*, *77*(1), 203–225. Retrieved from http://www.jstor.org/stable/3068862

Kong, J., Simonovic, S. P., & Zhang, C. (2019). Sequential Hazards Resilience of Interdependent Infrastructure System: A Case Study of Greater Toronto Area Energy Infrastructure System. *Risk Analysis*, *39*(5), 1141–1168. https://doi.org/10.1111/risa.13222

Kovach, J. J., Hora, M., Manikas, A., & Patel, P. C. (2015). Firm performance in dynamic environments: The role of operational slack and operational scope. *Journal of Operations Management*, *37*, 1–12. https://doi.org/10.1016/j.jom.2015.04.002

Li, Y., & Zobel, C. W. (2020). Exploring supply chain network resilience in the presence of the ripple effect. *International Journal of Production Economics*, *228*, 107693. https://doi.org/https://doi.org/10.1016/j.ijpe.2020.107693

Linkov, I., Fox-Lent, C., Read, L., Allen, C. R., Arnott, J. C., Bellini, E., … Woods, D. (2018). Tiered Approach to Resilience Assessment. *Risk Analysis*, *38*(9), 1772–1780. https://doi.org/10.1111/risa.12991

Mackenzie, C. A., & Zobel, C. W. (2016). Allocating resources to enhance resilience, with application to superstorm Sandy and an electric utility. *Risk Analysis*, *36*(4), 847–862. https://doi.org/10.1111/risa.12479

Melnyk, S. A., Closs, D. J., Griffis, tanley E., Zobel, C. W., & Macdonald, J. R. (2014). Understanding supply chain resilience. *Supply Chain Management Review*, *18*(1), 34–41. Retrieved from http://trid.trb.org/view.aspx?id=1304353

Mena, C., Melnyk, S. A., Baghersad, M., & Zobel, C. W. (2019). Sourcing Decisions under Conditions of Risk and Resilience: A Behavioral Study. *Decision Sciences*, *n/a*(n/a).

https://doi.org/10.1111/deci.12403
Modi, S. B., & Mishra, S. (2011). What drives financial performance-resource efficiency or resource slack?: Evidence from U.S. based manufacturing firms from 1991 to 2006. *Journal of Operations Management*, *29*(3), 254–273. https://doi.org/10.1016/j.jom.2011.01.002
Mukherjee, A. S. (2008). *The spider's strategy: creating netowrks to avert crisis, create change and really get ahead*. Upper Saddle River, New Jersey: Pearson Education, Inc. Retrieved from http://www.ftpress.com/articles/article.aspx?p=1244469
Najarian, M., & Lim, G. J. (2019). Design and Assessment Methodology for System Resilience Metrics. *Risk Analysis*, *39*(9), 1885–1898. https://doi.org/10.1111/risa.13274
Nohria, N., & GULATI, R. (1996). Is slack good or bad for innovation? *Academy of Management Journal*, *39*(5), 1245–1264. https://doi.org/10.2307/256998
Ojha, R., Ghadge, A., Tiwari, M. K., & Bititci, U. S. (2018). Bayesian network modelling for supply chain risk propagation. *International Journal of Production Research*, *56*(17), 5795–5819.
Palich, L. E., Cardinal, L. B., & Miller, C. C. (2000). Curvilinearity in the diversification-performance linkage: An examination of over three decades of research. *Strategic Management Journal*, *21*(2), 155–174. Retrieved from http://www.jstor.org/stable/pdf/3094038.pdf
Pant, R., Barker, K., & Zobel, C. W. (2014). Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. *Reliability Engineering & System Safety*, *125*, 92–102. https://doi.org/10.1016/j.ress.2013.09.007
PR Newswire. (2009), "Temporary Production Interruption at Allston Landing Manufacturing Facility Has No Impact on Aldurazyme", *PR Newswire*, 16 June.
Rajesh, R. (2016). Forecasting supply chain resilience performance using grey prediction. *Electronic Commerce Research and Applications*, *20*, 42–58.
Sahebjamnia, N., Torabi, S. A., & Mansouri, S. A. (2015). Integrated business continuity and disaster recovery planning: Towards organizational resilience. *European Journal of Operational Research*, *242*(1), 261–273. https://doi.org/10.1016/j.ejor.2014.09.055
Schmidt, C. G., Wuttke, D. A., Ball, G. P., & Heese, H. S. (2020). Does social media elevate supply chain importance? An empirical examination of supply chain glitches, Twitter reactions, and stock market returns. *Journal of Operations Management*, *n/a*(n/a). https://doi.org/10.1002/joom.1087
Schmidt, W., & Raman, A. (2012). When supply-chain disruptions matter. *Harvard Business School, Cambridge, MA*, 34. Retrieved from http://www.hbs.edu/faculty/Publication Files/13-006_cff75cd2-952d-493d-89e7-d7043385eb64.pdf
Schmitt, A. J., & Singh, M. (2012). A quantitative analysis of disruption risk in a multi-echelon supply chain. *International Journal of Production Economics*, *139*(1), 22–32. https://doi.org/10.1016/j.ijpe.2012.01.004
Schmitt, T. G., Kumar, S., Stecke, K. E., Glover, F. W., & Ehlen, M. A. (2017). Mitigating disruptions in a multi-echelon supply chain using adaptive ordering. *Omega*, *68*, 185–198. https://doi.org/10.1016/j.omega.2016.07.004
Sheffi, Y., & Rice, J. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review*, *47*(1), 41–48.
Tan, J., & Peng, M. W. (2003). Organizational slack and firm performance during economic transitions: two studies from an emerging economy. *Strategic Management Journal*, *24*(13), 1249–1263. https://doi.org/10.1002/smj.351

Thekdi, S. A., & Santos, J. (2019). Decision-Making Analytics Using Plural Resilience Parameters for Adaptive Management of Complex Systems. *Risk Analysis*, *39*(4), 871–889. https://doi.org/10.1111/risa.13209

Thekdi, S. A., & Santos, J. R. (2016). Supply Chain Vulnerability Analysis Using Scenario-Based Input-Output Modeling: Application to Port Operations. *Risk Analysis*, *36*(5), 1025–1039. https://doi.org/10.1111/risa.12473

Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation Research Part E: Logistics and Transportation Review*, *79*, 22–48. https://doi.org/10.1016/j.tre.2015.03.005

Voss, G. B., Sirdeshmukh, D., & Voss, Z. G. (2008). The effects of slack resources and environmental threat on product exploration and exploitation. *Academy of Management Journal*, *51*(1), 147–164. https://doi.org/10.5465/AMJ.2008.30767373

Wan, W. P., & Yiu, D. W. (2009). From crisis to opportunity: environmental jolt, corporate acquisitions, and firm performance. *Strategic Management Journal*, *30*(7), 791–801. https://doi.org/10.1002/smj.744

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180. https://doi.org/10.1002/smj.4250050207

Zhang, X., Mahadevan, S., & Goebel, K. (2019). Network Reconfiguration for Increasing Transportation System Resilience Under Extreme Events. *Risk Analysis*, *39*(9), 2054–2075. https://doi.org/10.1111/risa.13320

Zobel, C. (2010). Comparative visualization of predicted disaster resilience. *Proceedings of the 7th International ISCRAM Conference*, (May), 1–6. Retrieved from http://www.iscram.org/ISCRAM2010/Papers/191-Zobel.pdf

Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. *Decision Support Systems*, *50*(2), 394–403. Retrieved from http://www.sciencedirect.com/science/article/pii/S0167923610001764

Zobel, C. W. C. (2010). Comparative visualization of predicted disaster resilience. *Proceedings of the 7th International ISCRAM Conference*, (May), 1–6. Retrieved from http://www.iscram.org/ISCRAM2010/Papers/191-Zobel.pdf

Zobel, Christopher W. (2014). Quantitatively representing nonlinear disaster recovery. *Decision Sciences*, *45*(6), 1053–1082. https://doi.org/10.1111/deci.12103

Zsidisin, G. A., & Wagner, S. M. (2010). Do perceptions become reality? The moderating role of supply chain resiliency on disruption occurrence. *Journal of Business Logistics*, *31*(2), 1–20. https://doi.org/10.1002/j.2158-1592.2010.tb00140.x

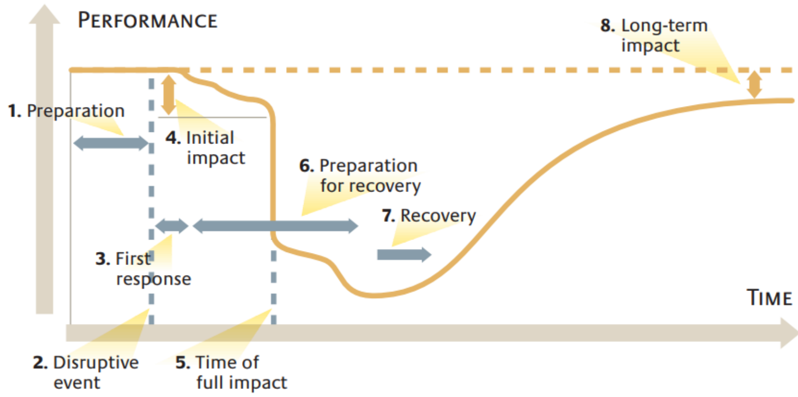

Fig. 1. The disruption profile introduced by Sheffi and Rice (2005)

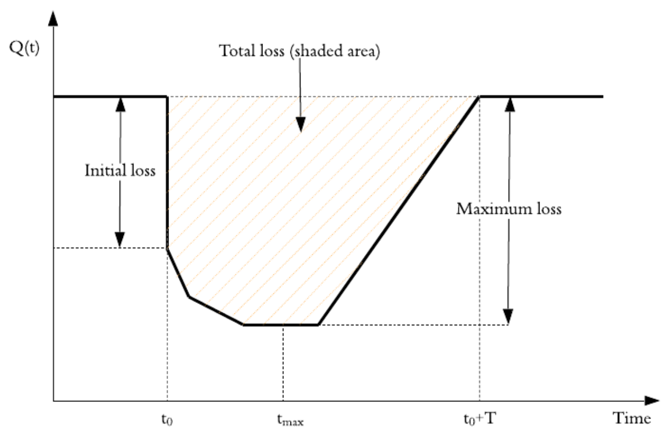

Fig. 2. Selected components of measuring resilience.

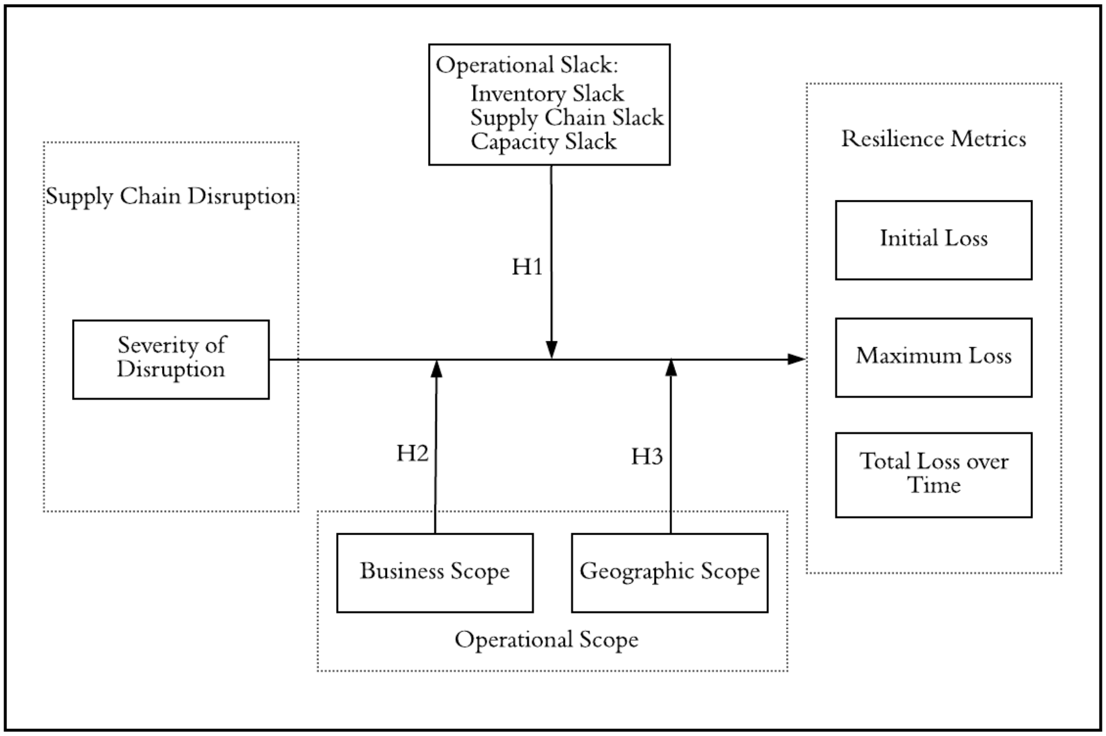

Fig. 3. Research Model

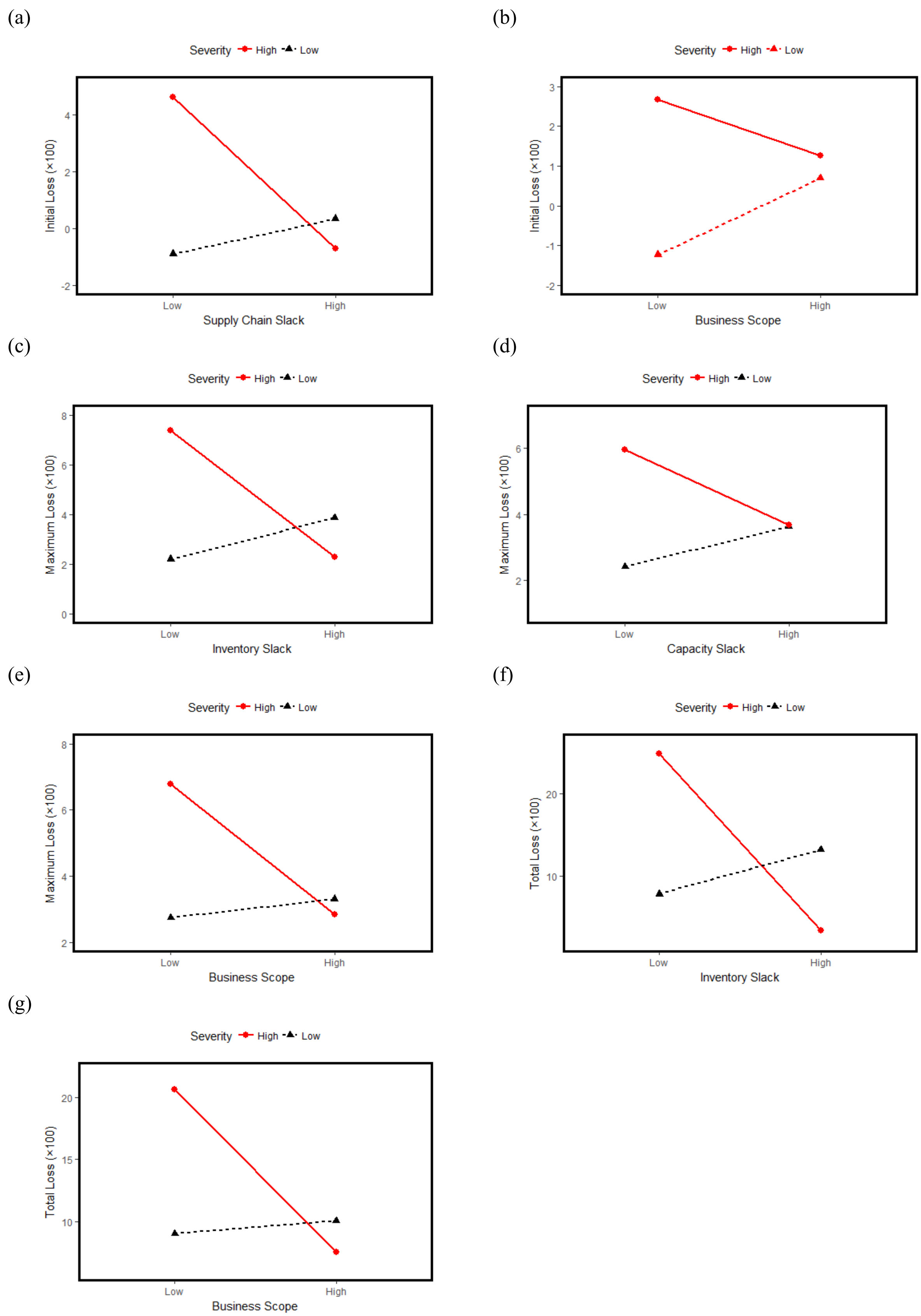

Fig. 4. Interaction plots

Table I. An example of disruption announcement provided to experts

Announcement	**Corning's Taichung LCD Glass Production Disrupted; Fourth-quarter glass volume to be impacted** 19 October 2009 CORNING, N.Y. - (BUSINESS WIRE) - Corning Incorporated (NYSE: GLW) announced today that its LCD glass manufacturing facility in Taichung, Taiwan, experienced a power disruption over the weekend that affected some of its glass-making operations. The company said that although it will be several days before the full extent is known, the disruption is expected to have a material impact on glass volume in the fourth quarter. "The majority of our Taichung glass production continues to operate normally," James B. Flaws, vice chairman and chief financial officer, said. "However the power disruption caused the shutdown of several of our glass melting tanks. We are in the process of determining how much glass melting capacity was affected, the time to repair the tanks, and the impact on our glass volume available for customers." Corning said its preliminary assessment of the impact is that fourth-quarter glass volume now could be flat to down slightly sequentially. Without the power disruption, the company said it believes quarterly glass volume would have increased by as much as 5%. Flaws said, "We are doing everything possible to accelerate repairs and leverage our worldwide supply chain to secure additional glass supply.
Company information	**About Corning Incorporated** Corning Incorporated is the world leader in specialty glass and ceramics. Drawing on more than 150 years of materials science and process engineering knowledge, Corning creates and makes keystone components that enable high-technology systems for consumer electronics, mobile emissions control, telecommunications and life sciences. Our products include glass substrates for LCD televisions, computer monitors and laptops; ceramic substrates and filters for mobile emission control systems; optical fiber, cable, hardware & equipment for telecommunications networks; optical biosensors for drug discovery; and other advanced optics and specialty glass solutions for a number of industries including semiconductor, aerospace, defense, astronomy and metrology. Total assets (million): $19256 Annual sales (million): $5948 Number of employees (thousand): 27
Question	**How do you rate the severity of the above event?** 1 (Incidental) 2 (Minor) 3 (Moderate) 4 (Major) 5 (Extreme) Not enough information is provided.

Table II. Severity scale adapted from risk assessment framework (Curtis & Carey, 2012)

Rating*	Descriptor	Potential consequence
5	Extreme	Extreme financial loss International long-term negative media coverage Game-changing loss of market share Significant prosecution and fines, litigation including class actions, incarceration of leadership Significant injuries or fatalities to employees or third parties, such as customers or vendors Multiple senior leaders leave
4	Major	Major financial loss National long-term negative media coverage; significant loss of market share Report to regulator requiring major project for corrective action Limited in-patient care required for employees or third parties, such as customers or vendors Some senior managers leave, high turnover of experienced staff, not perceived as employer of choice
3	Moderate	Moderate financial loss National short-term negative media coverage Report of breach to regulator with immediate correction to be implemented Out-patient medical treatment required for employees or third parties, such as customers or vendors Widespread staff morale problems and high turnover
2	Minor	Minor financial loss Local reputational damage Reportable incident to regulator, no follow up No or minor injuries to employees or third parties, such as customers or vendors General staff morale problems and increase in turnover
1	Incidental	Very minor financial loss Local media attention quickly remedied Not reportable to regulator No injuries to employees or third parties, such as customers or vendors Isolated staff dissatisfaction

* Assign the rating for the highest consequence anticipated. For example, if any one of the criteria for a rating of 5 is met, then the impact rating assigned is 5 even though other criteria may fall lower in the scale.

Table III. Means, standard deviations, and correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Initial loss (×100)	1.00												
2. Maximum loss (×100)	0.67	1.00											
3. Total loss (×100)	0.59	0.92	1.00										
4. Firm size	-0.32	-0.50	-0.46	1.00									
5. Firm age	-0.21	-0.28	-0.26	0.52	1.00								
6. Book to market ratio	-0.13	-0.29	-0.29	0.13	0.02	1.00							
7. Growth rate	0.02	-0.07	-0.06	-0.01	0.10	-0.01	1.00						
8. Severity of event	0.25	0.46	0.46	-0.14	-0.08	-0.09	-0.05	1.00					
9. Inventory slack	-0.07	-0.23	-0.24	0.03	-0.05	0.07	0.00	-0.17	1.00				
10.Supply chain slack	0.00	0.04	0.06	-0.15	-0.10	0.03	-0.01	0.01	0.17	1.00			
11.Capacity slack	0.02	-0.03	-0.01	0.03	-0.02	-0.27	0.10	-0.17	0.03	-0.36	1.00		
12.Business diversification	-0.14	-0.30	-0.30	0.41	0.24	0.07	-0.04	-0.16	0.00	-0.08	0.10	1.00	
13.Geographic diversification	-0.16	-0.45	-0.42	0.49	0.40	-0.03	0.09	-0.26	0.11	-0.13	0.26	0.38	1.00
Sample size	141	119	119	141	141	141	141	141	141	141	141	141	141
Mean	1.12	4.38	11.20	7.35	29.13	0.48	0.12	2.99	-0.25	0.98	0.18	0.33	0.34
Standard deviation	3.68	5.10	16.48	1.99	18.84	0.42	0.20	0.94	0.50	5.03	0.59	0.32	0.30

Table IV. Results of regression analyses.

	Initial Loss (×100)			Maximum Loss (×100)			Total Loss (×100)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	5.61 ***	2.84 *	2.92 *	14.45 ***	7.52 ***	7.91 ***	40.66 ***	16.87 ***	18.79 ***
	(1.17)	(1.70) ***	(1.72)	(1.59)	(2.01)	(2.00)	(5.31)	(6.67)	(6.40)
Firm size	-0.51 ***	-0.51	-0.52 ***	-1.13 ***	-0.82 ***	-0.85 ***	-3.20 ***	-2.16 ***	-2.39 ***
	(0.18)	(0.20)	(0.20)	(0.24)	(0.23)	(0.23)	(0.81)	(0.77)	(0.73)
Firm age	-0.01	-0.01	-0.01	-0.01	0.00	0.00	-0.04	-0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.07)	(0.07)
Book to market	-0.86	-0.63	-0.67	-2.51 **	-1.83 *	-2.24 **	-8.54 **	-5.72 *	-6.99 **
	(0.72)	(0.76)	(0.77)	(1.08)	(1.00)	(0.99)	(3.58)	(3.33)	(3.18)
Growth rate	0.38	0.51	0.61	-1.56	-0.99	-0.20	-3.92	-2.52	0.05
	(1.49)	(1.50)	(1.50)	(2.07)	(1.83)	(1.78)	(6.88)	(6.06)	(5.71)
Severity of event		0.81 ***	0.67 **		1.57 ***	1.43 ***		5.23 ***	4.62 ***
		(0.33)	(0.33)		(0.40)	(0.38)		(1.31)	(1.22)
Inventory slack		-0.22	0.28		-2.14 ***	-1.33 *		-8.10 ***	-4.47 *
		(0.62)	(0.64)		(0.82)	(0.71)		(2.71)	(2.63)
Supply chain slack		-0.02	-0.03		0.09	-0.08		0.46	-0.13
		(0.07)	(0.07)		(0.12)	(0.13)		(0.40)	(0.42)
Capacity slack		0.07	0.07		0.51	0.13		2.68	0.58
		(0.60)	(0.64)		(0.83)	(0.86)		(2.76)	(2.75)
Business scope		0.17	0.49		-0.90	-0.15		-4.55	-1.94
		(1.03)	(1.05)		(1.24)	(1.23)		(4.13)	(3.95)
Geographic scope		0.57	0.23		-3.16 **	-3.55 **		-8.95 *	-9.86 **
		(1.25)	(1.26)		(1.56)	(1.52)		(5.19)	(4.87)
Severity of event ×			-1.57 **			-2.43 ***			-9.19***
Inventory slack			(0.75)			(0.93)			(2.98)
Severity of event ×			0.05			0.41 ***			1.42 ***
Supply chain slack			(0.09)			(0.15)			(0.49)
Severity of event ×			-0.10			0.47			2.97
Capacity slack			(0.69)			(0.81)			(2.59)
Severity of event ×			-1.73 *			-0.70			-7.34 *
Business scope			(0.89)			(0.81)			(4.07)
Severity of event ×			-1.03			-1.84			-7.69
Geographic scope			(1.28)			(1.54)			(4.93)
Model F statistic	4.469 ***	2.482 ***	2.339 ***	11.814 ***	10.314 ***	8.653 ***	9.478 ***	9.229 ***	8.925 ***
N	141	141	141	119	119	119	119	119	119
R^2	0.116	0.160	0.219	0.293	0.488	0.558	0.250	0.461	0.565
Adjusted R^2	0.090	0.096	0.125	0.268	0.441	0.493	0.223	0.411	0.502
ΔR^2		0.044	0.059		0.195	0.070		0.211	0.104

Note: two-tailed tests, ***, **, * indicates significance at 0.01,0.05,0.1 levels, standard errors in parentheses