Firms' Resilience to Supply Chain Disruptions

Milad Baghersad

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Christopher W. Zobel (Chair)
Lara Khansa
Roberta S. Russell
Onur Şeref
Marcus Wiens

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ABSTRACT

This dissertation consists of three papers related to firms' resiliency to supply chain disruptions. The first paper seeks to evaluate the effects of supply chain disruptions on firms' performance by using a recent dataset of supply chain disruptions. To this end, we analyzed operating and stock market performances of over 300 firms that experienced a supply chain disruption during 2005 to the end of 2014. The results show that supply chain disruptions are still associated with a significant decrease in operating income, return on sales, return on assets, sales, and a negative performance in total assets. Supply chain disruptions are also associated with a significant negative abnormal stock return on the day of the supply chain disruption announcements. These results are in line with previous findings in the literature.

In the second paper, in order to provide a more detailed characterization of negative impacts of disruptions on firms' performance, we develop three complementary measures of system loss: the initial loss due to the disruption, the maximum loss, and the total loss over time. Then, we utilize the contingent resource-based view to evaluate the moderating effects of operational slack and operational scope on the relationship between the severity of supply chain disruptions and the three complementary measures of system loss. We find that maintaining certain aspects of operational slack and broadening business scope can affect these different measures of loss in different ways, although these effects are contingent on the disruptions' severity.

The third paper examines relationships between the origin of supply chain disruptions, firms' past experience, and the negative impacts of supply chain disruptions on firms' performance. This third study shows that the impact of external and internal supply chain disruptions on firms' performance can be different when firms do and do not have past experience with similar events. For example, the results show that past experience significantly decreases initial loss, recovery time, and total loss over time experienced by firms after internal disruptions, although past experience may not decrease initial loss, recovery time, and total loss over time in the case of external disruptions.

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GENERAL AUDIENCE ABSTRACT

Supply chain disruptions occur frequently in today’s complex and interdependent business environment. The Kumamoto earthquakes, Hanjin Shipping’s bankruptcy, and Hurricanes Harvey and Irma, are just a few events that led to major supply chain disruptions in the U.S. and other parts of the world in 2016 and 2017 alone. In this dissertation, we first use a recent dataset of supply chain disruptions to evaluate the effects of supply chain disruptions on firms' performance. The results show that supply chain disruptions are still associated with significant negative impacts on firms’ performance as they have been shown to be in previous studies of earlier datasets.

Next, we provide a broader assessment of supply chain disruptions’ impacts on firms’ performance. To accomplish this, we specifically consider the negative impacts with respect to three complementary metrics borrowed from the systems resilience literature: the initial loss, the maximum loss, and the total loss over time. The initial loss and maximum loss metrics evaluate different characteristics of the magnitude of a disruption’s impact on a firm’s performance, whereas total loss over time gives a broader measure of the overall effect of that disruption on that firm, over time. By adopting a more comprehensive view of firms’ performance through the use of such systems resilience concepts, we develop new and expanded inferences about how and when maintaining operational slack and broadening operational scope can benefit firms by helping to reduce the negative impacts of disruptions.

Finally, we study the relationships between the negative impacts of supply chain disruptions on firms’ performance, the origin of supply chain disruptions, and firms’ prior experience. The results show that the impact of internal and external supply chain disruptions on firms’ performance can be different when firms do and do not have past experience with similar events. In particular, the results show that past experience significantly decreases initial loss, recovery time, and total loss over time experienced by firms after internal disruptions. However, past experience may not decrease initial loss, recovery time, and total loss over time in the case of external disruptions.

DEDICATION

I would like to dedicate this dissertation to:

- My dear and loving wife **Leila**, my brothers **Mehdi** and **Mostafa**, and my sister, **Maryam**. Thank you for all of your love and support.
- Three people who changed my life with their endless support: **Mr. Hasan Hosseini**, **Mr. Naser Kakavand**, and last but not least, **Dr. Christopher Zobel**. I can not be more grateful for what they have done for me.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1: Introduction

1.1. Introduction

Supply chain disruptions are unexpected and unplanned events that interrupt the normal flow of materials and goods within a firm's supply chain (Craighead et al., 2007). Although these events are unpredicted, they are very common in the current business environment. According to the 2015 Supply Chain Resilience Survey, 74% of 537 firms surveyed across 67 different countries announced that they experienced at least one supply chain disruption over the last year (Business Continuity Institute, 2015). Similar surveys in 2013 and 2014 had revealed almost the same percentage (Business Continuity Institute, 2013 and 2014).

The economic consequences of supply chain disruptions on disrupted firms can be devastating. According to Allianz Global Corporate & Specialty (AGCS), the average amount of large business interruption claims[1] between 2010 and 2014 was more than $2 million and increasing every year, which is 36% higher than the equivalent average loss due to property damage (AGCS, 2015, p.4). AGCS highlights the increasing interdependency in supply chains as one of the main reasons for the growing trend in the size and number of business interruption claims: "The Tohoku earthquake and tsunami alone led to some 150 claims notifications for AGCS. Reflecting the growth of interdependencies, the vast majority of notifications were from companies located outside Japan that were not directly impacted by the disaster" (AGCS, 2015, p. 28).

Examples of supply chain disruptions, and their negative impacts on firms, are also abundant in the popular media. For example, after the 2016 Kumamoto earthquake, Toyota halted

[1] Claims over €20,000

26 of its car assembly lines in Japan, due not to direct physical damage caused by the earthquake but instead to production halts by a supplier (Kubota, 2016). It was the second time in three months that Toyota stopped its production in several plants across Japan due to supplier troubles (Kubota, 2016). This same event also disrupted Sony's production of image sensors used in Apple's iPhones (Yamazaki & Saoshiro, 2016). As another example, Chipotle Mexican Grill Inc., known for its organic and locally sourced ingredients, experienced a 44% decline in its 2015 fourth quarter profit after increasing concerns about the Chipotle's supply chain due to an E. Coli outbreak (Dulaney, 2016; Nordrum, 2015).

Considering that supply chain disruptions are very common and have devastating impacts on firms' performance, it is not surprising to find that a majority of firms have significant concerns about their resilience to supply chain disruptions (World Economic Forum, 2013), i.e., their ability to resist the effects of a disruption and to recover an acceptable level of functionality after it occurs (Melnyk, Closs, Griffis, Zobel, & Macdonald, 2014; Pettit, Fiksel, & Croxton, 2010; Ponomarov & Holcomb, 2009; A. J. Schmitt & Singh, 2012). In response to firms' concerns to supply chain disruptions, researchers have begun to study possible approaches to make firms more resilient against such disruptions. Consequently, different resilience strategies and tactics have been developed and recommended in the literature over the past two decades, such as maintaining a flexible supply base (Chopra and Sodhi, 2004; Hu and Kostamis, 2015; Tomlin, 2006), establishing strategic stockpiles (DeCroix, 2013; Liu et al., 2016; Qi et al., 2009), supporting supplier process improvement (Bakshi and Kleindorfer, 2009; Hu et al., 2013; Wang et al., 2009), and purchasing business interruption insurance (Dong and Tomlin, 2012).

1.2. Research objectives and contributions

Although supply chain disruptions and firms' resilience to the disruptions have received a lot of attention from researchers over past years, little is known about how and when different factors and operational strategies actually affect firms' resiliency to supply chain disruptions. Part of this disconnect is due to a lack of established metrics for quantifying firms' resilience and the fact that most of the available literature about supply chain resilience is conceptual (Scholten, Stevenson, & Van Donk, 2017). This dissertation aims to fill this gap by establishing new metrics to evaluate firms' resiliency to supply chain disruptions and to analyze relationships between the developed resilience metrics and a number of factors and strategies.

To this end, we first collect and analyze operating and stock market performances of over 300 U.S. publicly traded firms that experienced a supply chain disruption during 2005 to the end of 2014. Despite growing attention to supply chain disruptions in the literature, to our best knowledge this is the first time that the impacts of supply chain disruptions on firms' operating performance have been empirically evaluated in recent years. Our results show that supply chain disruptions are still associated with a significant decrease in operating income, return on sales, return on assets, sales, and a negative performance in total assets. Supply chain disruptions are also associated with a significant negative abnormal stock return on the day of the supply chain disruption announcements. We also show that that larger firms are more resilient to supply chain disruptions than smaller firms.

In our next contribution, to better evaluate impact of operational strategies on firms' resiliency to supply chain disruptions, we develop three complementary metrics borrowed from the systems resilience literature: the initial loss, the maximum loss, and the total loss over time. The initial loss and maximum loss metrics evaluate different characteristics of the magnitude of a disruption's impact on a firm's performance, whereas total loss over time gives a broader measure of the overall effect of that disruption, on that firm, over time. This is the first time that such metrics have explicitly been used to characterize the impacts of supply chain disruptions on firms' performance.

Using the developed metrics, we investigate how and when two recommended types of operational strategies (i.e. maintaining operational slack and broadening operational scope) improve firms' resiliency against supply chain disruptions. By adopting a more comprehensive view of firms' performance through the use of such systems resilience concepts, and by utilizing a contingent resource-based view, we are able to develop new and expanded inferences about how and when maintaining operational slack and broadening operational scope can benefit firms by helping to reduce the negative impacts of disruptions.

In our third contribution to the literature, we provide insights about the effects of two other important factors that have received little attention in previous studies on firms' performance after supply chain disruptions: the origin of the disruptions and the experience of firms with similar disruptive events in the past. The origin of a supply chain disruption event can be either inside or outside of a firm (Bode, Kemmerling, & Wagner, 2013; Schmidt & Raman, 2012; Wagner & Bode, 2008). An internal disruption refers to a disruptive event that happens inside the firm's boundaries, such as a strike by the firm's workers or a machine breakdown. On the contrary, an external disruption refers to a disruptive event that happens outside the firm's boundaries, such as a supplier failure. Since firms have more control over events inside their boundaries, they may respond differently to internal disruptions than they do to external disruptions. At the same time, whether an event is internal or external, we might expect that firms that have experienced a similar disruptive event in the past may be better prepared to face such a disruption again.

To clarify the different ways in which both the disruptions' origins and the firms' experience may impact the firms' performance, we explicitly consider four different output measures to characterize the firms' response to the disruptions: the initial performance loss due to the disruption, the maximum amount of loss due to the disruption, the subsequent amount of time needed to recover to an appropriate level of performance, and the overall amount of loss that is suffered over time. With considering different types of impacts, we provide new insights about how and when past experience can benefit firms by helping to reduce the negative impacts of supply chain disruptions.

1.3. Structure of the dissertation

The remainder of this dissertation is organized as follows:

- Chapter 2 evaluates impacts of supply chain disruptions on more than 300 U.S. publicly traded firms disrupted from 2005 to 2014.
- Chapter 3 utilizes the contingent resource-based view to evaluate the moderating effects of operational slack and operational scope on the relationship between the severity of supply chain disruptions and the actual impacts of those disruptions on firms' performance. In order to provide a more detailed characterization of these impacts, three complementary measures of system loss are introduced in the third chapter.
- Chapter 4 evaluates the effects of the origin of disruptions and past experience on four measures of system loss: the initial loss, the maximum loss, the time to recovery, and the total loss over time.
- Finally, Chapter 5 summarizes the results and implications, and discusses the limitations of this study and possible future directions.

Chapter 2: An empirical investigation of impacts of supply chain disruptions on firms

2.1. Introduction

In the present business environment, every business organization faces different types of risk that can disrupt the flow of material and information, or in other words, disrupt that organization's supply chain. Negative impacts of supply chain disruptions on businesses are not limited to a single time financial loss, however, such as a lost sale. Disruptions may increase customer complaints, tarnish firms' reputation and brand, decrease stock value of firms, and open the door for competitors to increase their share of the market.

Examples of supply chain disruption events and their destructive effects on firms' performance are abundant in the literature. For instance, Japan's 2011 earthquake and tsunami caused delays in deliveries of Apple's iPad2 (Revilla & Sáenz, 2014) and disrupted automotive sector and retail supply chains in different parts of the world such as the United Kingdom (U.K.) (Todo, Nakajima, & Matous, 2015; Torabi, Baghersad, & Mansouri, 2015). Similarly, Hurricane Sandy in 2012 disrupted fuel supply chains - one of the most critical infrastructures - along the East coast of the United States, and interrupted the service of transportation firms such as CSX and Norfolk Southern (Joseph Fiksel, 2015).

Hendricks and Singhal (2005a, 2005b, 2003) studied more than 500 firms that experienced a supply chain disruption during the 1990s and empirically showed that supply chain disruptions significantly affect firms' operating and stock market performances in both the short-run and the long-run. This was followed by a number of other studies that were conducted to better understand firms' resilience to supply chain disruptions (e.g., Ambulkar et al., 2015; Kim et al., 2015; Knemeyer et al., 2009; Wagner and Bode, 2006). In practice, as well, a number of firms have incorporated resilience strategies into their supply chain risk management frameworks. For example, Procter & Gamble has embedded supply chain risk management within its corporate risk management since 2000, including regular auditing of its suppliers' business continuity plans (Babcock, 2014). Despite such initiatives, however, there is, as of yet, no empirical evidence in the literature that shows firms' performance against supply chain disruptions has improved in recent years.

With this in mind, this research effort aims to build on previous studies by evaluating impacts of supply chain disruptions on firms' performance in recent years. To this end, the performance of a set of firms disrupted during the period 2005 to 2014 is analyzed. The results show that supply chain disruptions still have negative impacts on firms. This study also contributes to the literature by empirically validating several additional insights about overall firm performance in the presence of supply chain disruptions. By analyzing the resilience performance of disrupted firms in recent years, we are able to show that larger firms are more resilient to supply chain disruptions than smaller firms. We also demonstrate that firms in some industry sectors are more resilient to supply chain disruptions than firms in other sectors.

The rest of this chapter is organized as follows. Section 2.2 reviews related research about the effects of supply chain disruptions on firms and system resilience, and it introduces the formal hypotheses. Section 2.3 outlines the data collection procedures, Section 2.4 describes the methodology used to conduct the results, and Section 2.5 provides the results. Finally, Section 2.6 discusses the findings and provides future research directions.

2.2. Background and hypotheses development

2.2.1. Effects of supply chain disruptions

Supply chain disruptions may affect firms' performance both in the short-run and in the long-run. The short-run negative effects of supply chain disruptions on firms, in particular, are well documented in the literature. For example, based on a large sample of supply chain disruptions announced during 1989 to 2000, Hendricks and Singhal (2003) found that supply chain disruptions significantly decrease shareholders value (measured by abnormal stock returns) during a two-day trading time period, from one day before to the day of an announcement. They also observed that stock market reaction after disruptions is more negative for firms with higher growth prospects. However, Hendricks and Singhal (2003) also found that the abnormal returns were not significant over a longer 60-day time period after the disruption announcements.

Zsidisin et al. (2016) calculated the same abnormal return behavior as Hendricks and Singhal (2003), but based their analysis on a new empirical set of supply chain disruptions that occurred between 2000 and 2012. They also reported a significant negative stock market reaction during the actual day of the announcement. In contrast to Hendricks and Singhal (2003), however, Zsidisin et al. (2016) found that growth prospects have no negative impact on the stock market reaction, although the debt-equity ratio does have a significant negative influence on that reaction. Hendricks et al. (2009) further found that firms with higher operational slack and a higher degree of vertical relatedness (i.e. a low level of outsourcing) experience less of a negative stock market reaction after disruption announcements. They observed that the degree of business diversification has no impact on the reaction of stock market and that the reaction of stock market is more negative for firms that are more geographically diversified. Schmidt and Raman (2012) also reported that when supply chain disruptions are attributed to factors within the authority of the focal firm, the short-run stock market reaction is more negative.

Investigating the long-run effects of supply chain disruptions is more difficult than the short-run effects, because of availability of data and controlling for other events that may affect long-run performance of firms. We have only found a few papers in the literature that have empirically investigated the long-run effects of supply chain disruptions on firms. Hendricks and Singhal (2005a) used supply chain disruptions announced during the period from 1989 to 2000 to report that the average cumulative abnormal stock return of disrupted firms was negative during the period from one year before to two years after a disruption announcement. They also observed that supply chain disruption announcements have a negative impact on the firms' long-run equity risk.

Using almost the same dataset (firms disrupted in 1990s), Hendricks and Singhal (2005b) analyzed the effects of supply chain disruptions on firms' operating performance. They reported that supply chain disruption announcements are associated with a decrease in profitability measures (operating income, return on sales, and return on assets) and net sales, with negative assets and inventory performances, and with an increase in costs. They observed that disrupted firms did not recover from negative consequences of disruptions even two years after the supply chain disruption announcements. Finally, Hendricks and Singhal (2014) showed that the announcement of demand-supply mismatches (production disruptions, excess inventory, and product introduction delays) increases the equity volatility of firms over a two-year period around the announcement date (one year before to one year after the announcement).

Table 2.1 summarizes the existing empirical research on the effects of supply chain disruptions, as discussed above. The combined results suggest that supply chain disruptions have destructive effects on firms' performance in both the short-run and the long-run. It is important, however, to recognize that the majority of the supply chain disruption datasets used in this literature, especially for the research on the long-run effects, belong to the 1990s and to the beginning years of the 2000s. With this in mind, the initial contribution of this paper is to re-evaluate the reported effects of supply chain disruptions on firms' performance by using a new

Table 2.1. Summary of previous empirical research on effects of supply chain disruptions

References	Performance measure (short/long-run impact)	Sampling time (N. of samples)	Main moderator factors	Main findings
Hendricks and Singhal (2003)	Stock returns (short-run)	1989-2000 (519)	• Size of firm (-) • Growth prospects (+) • Debt-equity ratio (0)	• Announcements of disruption are associated with a negative abnormal stock return in short-run (during 2-day event period) • Long-run abnormal return after the disruption announcement is not statistically different from zero
Hendricks and Singhal (2005a)	Stock returns and equity risk (long-run)	1989-2000 (827)		• The abnormal stock return is negative between one year before to two years after disruption announcement
Hendricks and Singhal (2005b)	Operating performance (long-run)	1992-1999 (885)	• Size of firm (-)	• Supply chain disruptions are associated with a decrease in profitability measures (operating income, return on sales, and return on assets) and net sales • Supply chain disruptions are associated with a negative asset and inventory performance and an increase in costs • Disrupted firms do not recover from negative consequences of disruption even 2 years after announcements
Hendricks et al. (2009)	Stock returns (short-run)	1987-1998 (307)	• Operational slack (-) • Business diversification (0) • Geographically diversification (+) • Vertical relatedness (-) • Size of firm (-) • Growth prospects (+) • Debt-equity ratio (0)	• Abnormal stock return of firms with higher degree of vertical relatedness and higher operational slack is less negative • Abnormal stock return of higher geographically diversified firms is significantly more negative.
Schmidt and Raman (2012)	Stock returns (short-run)	1998-2011 (517)	• Rates of operating performance improvement (+) for internal disruptions and (0) for external disruptions	• Internal disruptions are associated with a more negative stock market reaction • Stock market reaction to internal disruptions is more negative for firms with a higher prior rate of operating performance improvement
Hendricks and Singhal (2014)	Equity volatility (long-run)	1987-2003	• Information asymmetry among investors (+)	• Excess inventory, production disruptions, and product introduction delays increase the equity volatility of firms in long-run • The equity volatility increases related to excess inventory are higher than the volatility increases related to introduction delays and production disruptions
Zsidisin et al. (2016)	Stock returns (short-run)	2000-2012 (116)	• Size of firm (-) • Growth prospects (0) • Debt-equity ratio (-)	• Disruption announcements are associated with a negative abnormal stock return in short-run • Reason of supply chain disruptions has impact on stock market reaction

Note: (-) shows that the variable decreases magnitude of the negative impact, (+) shows that the variable increases magnitude of the negative impact, and (0) shows that the researchers did not find a significant impact of the variable on magnitude of the negative impact.

dataset of supply chain disruptions that occurred between 2005 and 2014. Our corresponding first hypothesis is as follows:

H1a. *Supply chain disruptions are (still) associated with negative operating performance.*

H1b. *Supply chain disruptions are (still) associated with negative stock market performance.*

2.2.2. Impacts of supply chain disruptions on firms with different sizes

The ability of different firms to face supply chain disruptions can vary depending on the characteristics of the firms. Hendricks and Singhal (2003) and Zsidisin et al., (2016) found that larger firms experience less of a negative market reaction than do smaller firms. Similarly, Hendricks and Singhal (2005b) reported that larger firms experience less negative initial impact on their operating performance than do smaller firms after supply chain disruptions. However, there is no empirical evidence in the literature about the difference in resilience of firms of different sizes after supply chain disruptions.

It is more likely for larger firms to have documented risk management plans, specific business continuity teams, and more resources to face unplanned events. Larger firms usually are more geographically diverse, which can help them when one of their facilities in one area is disrupted. Larger firms are also more likely to have disaster and/or business interruption insurance. Therefore, it seems larger firms have more ability to absorb negative impacts of supply chain disruptions and to recover more quickly after the disruptions; in other words, more ability to be resilient. Based on this argument, Hypothesis 2 formalizes our argument about the resilience of firms of different sizes.

H2. *Larger firms are more resilient to supply chain disruptions than smaller firms.*

Finally, in addition to these two main sets of hypotheses, the following discussion also evaluates the relative impacts of supply chain disruptions on different industry sectors with respect to the performance of firms.

2.3. Data collection and sample description

PR Newswire and Business Wire include the vast majority of press releases from publicly traded U.S. firms (Schmidt & Raman, 2012), and they previously have been used by other researchers to obtain such press releases for analysis (e.g. Liu et al., 2014 and Mitra and Singhal 2008). With this in mind, we searched PR Newswire and Business Wire in the Factiva database to find supply disruption announcements of firms. The search was limited to North American companies and restricted to the time period from 2005 to the end of 2014. The keywords used to search the headline or lead paragraph of news articles were as follows: delay, disruption, interruption, shortage, or problem, paired together with other words like: delivery, component, or operations. Around 12000 news items were collected and the full text of each item was reviewed to extract supply chain disruption announcements. A number of the news items were not included because they were about delays in filling annual financial reports or delays in meeting with investors, which are not supply chain disruptions. We also deleted disruption announcements that were not related to U.S. publicly traded firms. Since we are evaluating the performance of disrupted firms from the quarter of the disruption announcement to eight quarters after the quarter of the disruption announcement, we deleted disruption announcements that happened to the same firms within the first two years of another disruption, which is the same approach taken by Hendricks and Singhal (2005b).

Figure 2.1 presents the distribution of the collected supply chain disruption announcements per year. The number of disruptions announced in 2005 and 2008 is higher than other years, which agrees with the intuition that Hurricane Katrina (2005) and the global financial crisis (2008) had a widespread impact on supply chain operations. We also collected firms' quarterly performance and stock return data through the COMPUSTAT and CRSP databases available from WRDS (Wharton Research Data Services, University of Pennsylvania).

Descriptive statistics of the sample firms for different quarters around the disruption announcements quarter are presented in Table 2.2. The mean (median) of sales, total assets, and operating income of sample firms at one quarter before the announcement quarter are 3127.97 (423.22), 19823.54 (2120.47), and 480.97 (56.38) million U.S. dollars, accordingly. Table 2.3 presents the distribution of sample firms' total assets for a quarter before the announcements quarter. This table shows that the sample firms include a diverse range of firms from very small to large firms.

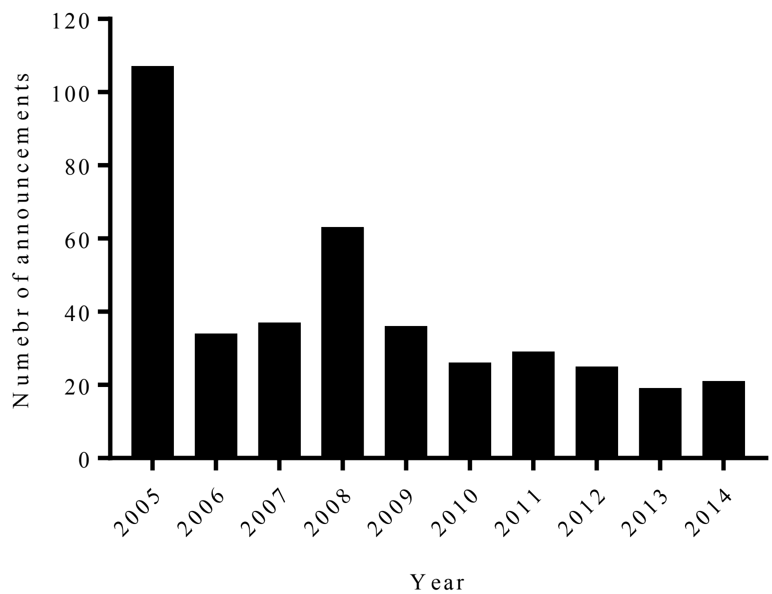

Figure 2.1. Distribution of the disruption announcements per year

Table 2.2. Descriptive statistics of sample firms (*N*=397)

Measure	Four quarters before the announcement quarter			Quarter before the announcement quarter			Four quarters after the announcement quarter		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Sales (million $)	3055.67	400.17	7964.38	3127.97	423.22	8587.38	3456.80	411.73	9952.19
Total assets (million $)	19158.37	2214.20	84230.23	19823.54	2120.47	87734.85	21516.49	2421.83	94489.33
Operating income (million $)	462.96	67.25	1395.07	480.97	56.38	1464.29	551.62	69.11	1588.32
Return on sales (%)	-547.82	14.86	5505.88	-836.57	14.19	8256.78	-481.36	13.71	7043.46
Return on assets (%)	2.09	2.93	6.55	1.99	2.71	6.03	1.78	2.65	5.87
Total costs (million $)	2623.07	313.42	6886.45	2681.54	342.91	7476.34	2959.64	325.50	8796.91
Total inventory (million $)	1090.03	127.84	3522.95	1162.38	143.70	3818.58	1193.23	137.94	3390.81

Table 2.3. Distribution of sample firms based on total assets for a quarter before the announcement quarter

Range	Number	Percentage	
Total assets ≤ $500M	101	25.44	
Total assets > $500M and ≤ $2B	86	21.66	Minimum: $0.363M
Total assets > $2B and ≤ $10B	88	22.17	Maximum: $1,422.968B
Total assets > $10B and ≤ $40B	76	19.14	
Total assets > $40B	34	8.56	
Total assets unknown	12	3.02	
Total	397	100	

Table 2.4 presents the distribution of sample firms per industry sectors and provides the reason for the disruptions. The industry sector groups are defined according to firms' Standard Industrial Classification (SIC) code. The sample firms include all types of industry sectors, except the public administration sector. The manufacturing sector with 46% of the total number of firms, the transportation and utilities (transportation, communications, electric, gas and sanitary service) sector with 17%, and the mining sector with 15% are the most common industry sectors between the sample firms.

Table 2.4. Distribution of sample firms per industry sectors

Industry sector	Range of SIC code	Number of firms	Percentage
Agriculture, Forestry and Fishing	0100-0999	3	0.76
Mining	1000-1499	61	15.37
Construction	1500-1799	2	0.50
Manufacturing	2000-3999	184	46.35
Transportation, Communications, Electric, Gas and Sanitary service	4000-4999	68	17.13
Wholesale Trade	5000-5199	11	2.77
Retail Trade	5200-5999	15	3.78
Finance, Insurance and Real Estate	6000-6799	20	5.04
Services	7000-8999	30	7.56
Public Administration	9100-9729	0	0.00
Non-classifiable	9900-9999	3	0.76
Total		397	100

2.4. Methodology

Sections 2.4.1 and 2.4.2 describe the methods applied to estimate the impacts of disruptions on the firms' operating performance and stock price, respectively. Section 4.3 describes the method used to calculate the total resilience.

2.4.1. Impact of supply chain disruptions on firms' operating performance

We compare the operating performance of each sample firm with the operating performance of a control firm that is similar to the sample firm in terms of size and industry sector. The control firms are selected using the method developed by Hendricks and Singhal (2005b). The method is as follows (Hendricks & Singhal, 2005b):

Step 1. List a set of all possible firms from the COMPUSTAT database.

Step 2. Remove the sample firms from the set of possible control firms.

Step 3. Match each existing sample firm with the best possible control firm using model 1:

Model 1:

$$Min\ \frac{|sales\ of\ sample - sales\ of control|}{\max(sales\ of\ sample, sales\ of control)} + \frac{|assets\ of\ sample - \ assets\ of control|}{\max(assets\ of\ sample, assets\ of control)}$$

Subject to:

- The amount of available data for control firm must be same as the sample firm.
- The control firm must have same quarter-ending month as the sample firm.
- The control firm and the sample must have at least same three-digit SIC code.
- The sales and total assets of the control firm must be within a factor of 3-digit of the sample firm's sales and total assets.

Step 4. Record the best match between the sample and the control firms and remove the recorded sample and control firms from the next steps.

Step 5. Repeat steps 3 and 4 until all sample firms are matched with a control firm or no more feasible matches exist.

Using this method, we were able to match 313 (79%) of the 397 sample firms to the control firms. We named this set of matched firms the *size-matched control group*. To increase the number of matched pairs, similar to Hendricks and Singhal (2005b), we then relaxed the last constraint (the sales and assets constraint) in Model 1 and generated a new set of paired firms named the *most-matched control group*. We were able to match 378 (95%) of the 397 sample firms to the control firms by using this second approach.

Following Hendricks and Singhal (2005b), we use the control-adjusted change in performance measures to quantify the impacts of supply chain disruptions. The control-adjusted change in a performance measure, such as sales at quarter *t*, can be calculated from formula 2-1:

$$\frac{Sales_t^s - Sales_{t-4}^s}{|Sales_{t-4}^s|} - \frac{Sales_t^c - Sales_{t-4}^c}{|Sales_{t-4}^c|} \tag{2-1}$$

where $Sales_k^s$ ($Sales_k^c$) shows the sales of the sample (control) firm at quarter *k*. Note that the calendar quarters of all firms are measured relative to their disruption event. Accordingly, quarters -4, 0, and 4 present four quarters before the announcement quarter, the quarter of the announcement, and four quarters after the announcement quarter, accordingly.

2.4.2. Impact of supply chain disruptions on firms' stock price

In the following analysis, we use the abnormal stock returns as a proxy of the impact of supply chain disruptions on firms' stock price. The event study methodology is the common method for calculating the abnormal returns of firms after an event (Corrado, 2011). Four different models of the event study methodology are applied to calculate the daily abnormal returns: (a) market model (Brown & Warner, 1985), (b) market-adjusted model (Brown & Warner, 1985), (c) Fama-French three factor model (Fama & French, 1996), and (d) Fama-French plus momentum model (Carhart, 1997). For more details about these four methods, we refer the interested readers to the cited references. We also use the Buy-Hold Abnormal Return (BHAR) method to calculate the long-run impact of disruptions on firms' stock price. Equation (2-2) shows BHAR formulas for stock *i* from day 1 to day *T*.

$$BHAR_{iT} = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{mt}) \tag{2-2}$$

Where R_{it} is the rate of return of stock *i* on day *t*, and R_{mt} is the rate of return for the benchmark of stock *i* on day *t*.

2.4.3. Resilience

A response curve, which captures both the initial impact of the disruption event on a system and the response of the system as it subsequently recovers, can be used as the basis for estimating a system's resilience. Bruneau et al. (2003) introduced the idea of measuring the area above a response curve to represent the loss of resilience in a system. Others have subsequently extended this work by considering the area beneath such a response curve as the basis for a direct measure of the system's ability to resist and recover from a disruptive event (Chang & Shinozuka, 2004; Cimellaro et al., 2010; Zobel & Khansa, 2012; Zobel, 2014).

Zobel's (2010, 2011) concept of "predicted resilience" is based upon measuring this area beneath the response curve as a ratio of the larger area expected in the absence of a disruption. The predicted resilience measure provides an overall measure of the system's relative ability to resist and recover from a disruption over time. As a measure of the normalized area under a given response curve *Q(t)*, subject to a disruption at time t_0, the predicted resilience of a system is provided by the following formula:

$$PR = \frac{\int_{t=t_0}^{t=t_0+T^*} Q(t)}{T^*} \tag{2-3}$$

where T^* is a user-defined upper bound on the length of recovery time that is used to normalize the result. As illustrated by the simple example given in Figure 2.2, $Q(t_0)$ can be interpreted as the initial loss due to the sudden impact of a disruption, and 1-$Q(t_0)$ thus can be used to represent the system's robustness.

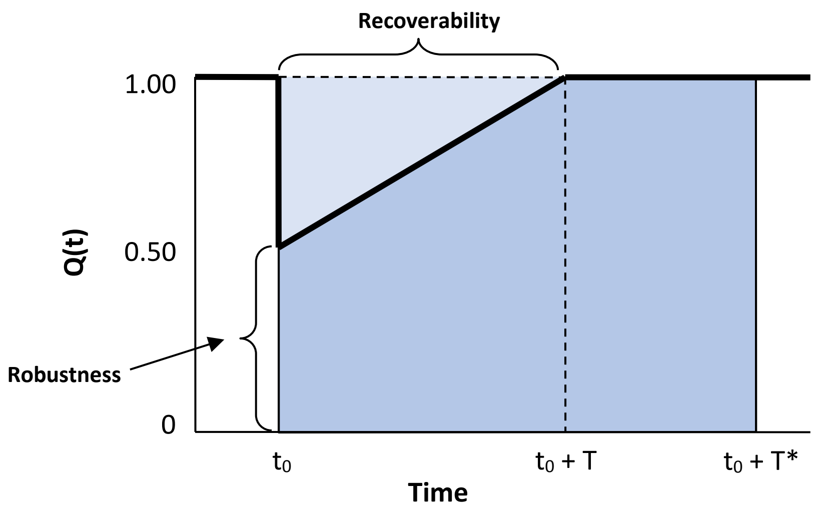

Figure 2.2. Predicted resilience (adapted from Zobel, 2011)

In order to adapt this resilience formula for the supply chain performance measures considered in this paper, however, it is necessary to make a few adjustments. First of all, because equation 2-3, as presented, assumes a continuous response function, it must be generalized in order to represent the resilience of a discrete time process by instead incorporating the sum of discrete deviations over time. Secondly, because the control-adjusted change of performance measures in this paper can take on either positive or negative values, the formula must be extended to allow for positive deviations also. For some of the performance measures, such as inventory and assets, both negative and positive deviations of control-adjusted changes are considered disruptive. For operating income, return on sales, return on assets, and sales only the negative deviations are disruptive. On the contrary, for control-adjusted change of cost, only positive deviations are disruptive. To account for these issues, therefore, we present a new formula to calculate total resilience (TR) in our current context:

$$TR = 1 - \frac{\sum_{t=t_0}^{t=t_0+T^*} \left|d_t^{\pm}\right|}{d_{max} \times T^*} \tag{2-4}$$

where d_t is the deviation of a performance measure from the normal level at quarter t, d_{max} is the magnitude of the maximum possible deviation, and $d_{t_0}^{\pm}$ can be calculated from formula 2-5, as follows:

$$d_{t_0}^{\pm} = |d_t| \quad \text{if both negative and positive deviations are destructive,}$$

$$d_{t_0}^{\pm} = \begin{cases} 0 \ if \ d_t \geq 0 \\ d_t \ if \ d_t < 0 \end{cases} \quad \text{if only negative deviation is destructive, and} \tag{2-5}$$

$$d_{t_0}^{\pm} = \begin{cases} d_t \ if \ d_t \geq 0 \\ 0 \ if \ d_t < 0 \end{cases} \quad \text{if only positive deviation is destructive.}$$

2.5. Results

2.5.1. Impacts of supply chain disruptions on firms disrupted from 2005 to 2014

In order to test the impacts of supply chain disruptions on the operating performance of firms, we calculate the control-adjusted change in profitability measures (operating income, return on sales, and return on assets), sales, assets, cost, and inventory at the quarter of the disruption announcements. Table 2.5 provides the control-adjusted change in operating performance measures for both the size-matched and most-matched control groups. In order to eliminate the impact of outliers, 2.5 percent of all data is trimmed symmetrically from each tail and then the results are reported.

Table 2.5. Control-adjusted change in operating performance measures at quarter 0

Performance measure	Size-matched control group				Most-matched control group			
	N.	Mean	Median	% Neg.	N.	Mean	Median	% Neg.
Change in operating income (%)	256	-25.40 (-2.48***)	-7.31 (-2829**)	58.98 (-23***)	293	-26.50 (-2.62***)	-8.33 (-3936.5***)	60.07 (-29.5***)
Change in return on sales (%)	243	-13.07 (-2.22*)	-4.16 (2231*)	57.20 (-17.5*)	271	-12.70 (-2.43**)	-4.55 (-2704*)	56.09 (-16.5*)
Change in return on assets (%)	243	-13.88 (-2.16*)	-7.45 (-3039***)	59.50 (-22.5***)	282	-16.11 (-2.28**)	-10.72 (-4014.5***)	59.79 (-27***)
Change in sales (%)	277	-4.82 (-2.11*)	-3.26 (-2731*)	57.76 (-22***)	319	-4.40 (-1.83)	-2.94 (-3054.5)	56.43 (-21**)
Change in total assets (%)	279	6.27 (2.25**)	2.38 (3132**)	41.94 (22.5***)	322	6.41 (2.66***)	2.36 (4004.5**)	42.86 (23**)
Change in total costs (%)	206	4.91 (1.98*)	-0.28 (809.5)	50.49 (-1)	244	8.27 (2.37**)	-0.10 (1231)	50.41 (-1)
Change in total inventory (%)	219	7.04 (2.17**)	1.79 (1108.5)	46.58 (7)	249	7.01 (2.29**)	0.72 (1106)	48.19 (4)

Table 2.5 shows a negative association between supply chain disruption announcements and profitability measures at the quarter of the disruption announcements. Based on the most-matched control group, the mean of control-adjusted change in operating income, return on sales, and return on assets are, respectively, -26.5%, -12.70%, and -16.11%, all of them significantly different from zero (p-values ≤ 0.025). The median of control-adjusted change in operating income, return on sales, and return on assets for most-matched control group are, respectively, -8.33%, -4.55%, and -10.72%, significantly different from zero (p-values ≤ 0.05). Also, the percentage of firms that experience a negative control-adjusted change in operating income, return on sales, and return on assets after announcements is more than 50% (p-values ≤ 0.05). Results of non-parametric tests show that the results of the t-test are not biased by outliers and skewness of data.

Supply chain disruption announcements are also associated with a negative change in sales at the quarter of the disruption announcements. Based on the size-matched control group, the mean (median) of control-adjusted change in sales is -2.11% (-3.26%), which is significantly different from zero (p-value ≤ 0.05). However, the mean and median of control-adjusted change in sales for the most-matched control group are not statistically significant (p-values > 0.05). For additional insight, therefore, we calculated the control-change in sales at quarter 1 and all test results for both control groups indicate that supply chain disruption announcements are associated with a negative change in sales (p-values ≤ 0.025). This delay in the impact of supply chain disruptions on sales is perhaps because of having enough inventory in quarter 0.

Table 2.5 also reveals that supply chain disruptions are associated with a positive change in total assets. Based on the most-matched control group, the mean (median) of control-adjusted change in assets is 6.41% (2.36%), which is significantly different from zero (p-values ≤ 0.05). Also, the percentage of firms that experience a positive control-adjusted change in assets after announcements is more than 50% (p-values ≤ 0.025). Hendricks and Singhal (2005b) also observed a similar increase in assets after supply chain disruptions. They argued that although an increase in the assets can be a positive sign for firms, while the sales are decreased it indicates lower turnover which is destructive for firms.

Based on the most-matched control group, the mean of control-adjusted change in cost and inventory at the quarter of the announcements are, respectively, 8.27%, and 7.21%, both of which are significantly different from zero (p-values ≤ 0.025). However, the signed rank test and sign test results do not show a significant change in cost and inventory measures in both the size-matched and the most-matched control groups. There thus is only weak evidence that that supply chain disruption announcements are associated with an increase in cost and inventory. These results contrast with Hendricks and Singhal's (2005b) observation that reported a strong increase in total cost and inventory after supply chain disruption announcements.

Supply chain disruption announcements are also associated with a negative abnormal return in the short-run. Figure 2.3 shows average abnormal returns of sample firms from the market model for 10 trading days before (day -10) to 10 trading days after the announcement day (day +10). We calculated abnormal returns of sample firms for same period of time from three other models and the reaction of the stock market to disruption announcements was almost the same, so other figures are not reported.

Table 2.6 provides descriptive statistics and test results of average abnormal returns calculated from the four different models on the day of the announcements. Based on the market model, the mean abnormal returns on day zero is -1.64%, which is significantly different from zero (p-value ≤ 0.001). The median of abnormal returns on day zero from the market model is -1.12%, which also is significantly different from zero (p-value ≤ 0.001). Also, the percentage of firms that experience a negative abnormal return on day 0 is more than 50% (p-values ≤ 0.001). The statistical test results from the market-adjusted, Fama-French three factor, and Fama-French plus momentum models are also similar to the results of the market model. In summary, hypothesis 1 is supported.

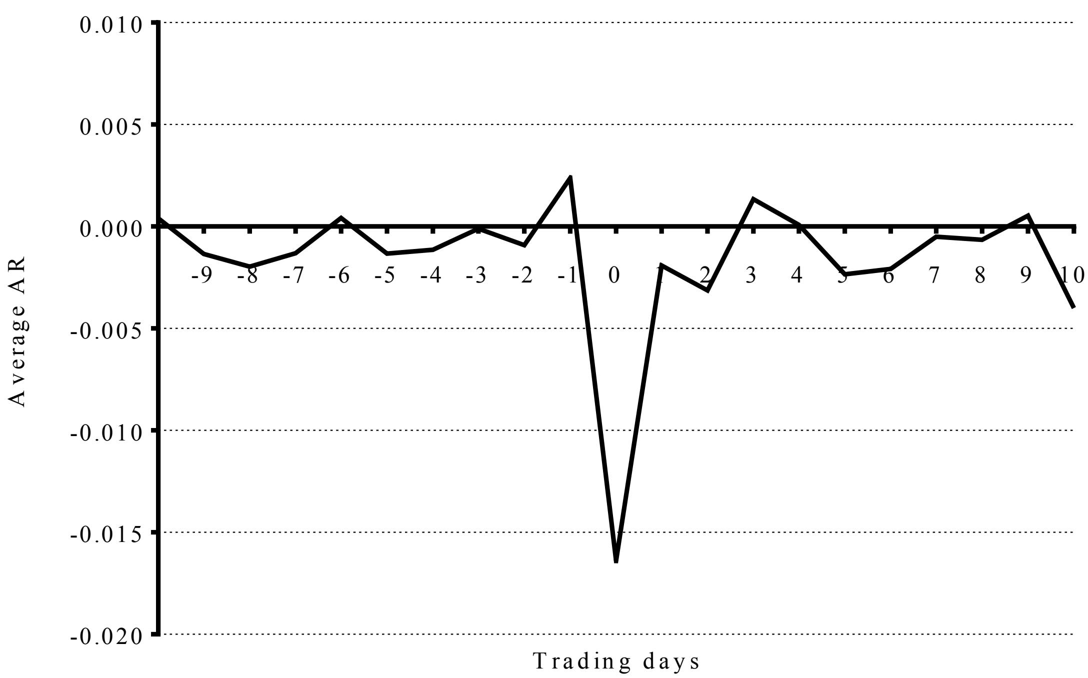

Figure 2.3. Average abnormal returns from market model from day -10 to day +10

Table 2.6. Average abnormal returns from four different models on the day of the announcements

Abnormal returns	N.	Mean	Median	% Neg.
Market model	328	-1.64% (-10.82***)	-1.12% (-17192.5***)	72.56 (-75.5***)
Market-adjusted model	328	-1.53% (-10.39***)	-1.04% (-16409.5***)	71.95 (-73.5***)
Fama-French three factor model	328	-1.59% (-10.78***)	-0.92% (-16752.5***)	70.43 (-68.5***)
Fama-French plus momentum	328	-1.57% (-10.69***)	0.93% (-16712.5***)	70.73 (-69.5***)

The student's t value for the mean, sign rank test's S value for the median, and sign test's M value for the percentage negative are reported in the parentheses. $* \ p \le 0.05$, $** \ p \le 0.025$, and $*** \ p \le 0.01$ for two-tailed tests.

2.5.2. Relation between size of firms and resilience

The next part of the analysis focuses on examining the impact of firms' size on the resilience metric. To support this, we divided the firms into two groups: smaller firms with total assets less than or equal to \$2B, and larger firms with total assets more than \$2B. Table 2.7 shows descriptive statistics and test results for the difference between the total resilience of the smaller and the larger sample firms. In order to calculate the total resilience, we considered the sample firms that have available data for calculating control-adjusted changes during quarter 0 to quarter 8 (9 quarters). We consider T^* equal to 9 and d_{max} equal to the maximum magnitude of the control-adjusted change of the given performance measure. The results show that larger firms are more resilient than smaller firms considering all operating performance measures (p-values < 0.05), except for total costs and inventory (p-values > 0.05).

Table 2.7. Test results for the difference between the total resilience of the smaller and the larger sample firms

Unit of total resilience	Group 1 (smaller firms)			Group 2 (larger firms)			Two-sample t-test value for difference between group 1 and 2
	N.	Mean	S.D.	N.	Mean	S.D.	
Operating income (%)	99	98.5	2.12	119	99.23	1.34	-3.06*** (9117***)
Return on sales (%)	81	98.80	1.78	118	99.30	1.22	-2.34** (6745***)
Return on assets (%)	93	98.38	2.29	113	99.29	1.22	-3.64*** (7936.5***)
Sales (%)	109	97.42	2.34	153	98.03	2.10	-2.21* (12926***)
Total assets (%)	118	97.69	2.53	148	98.46	2.15	-2.66*** (14055.5***)
Total costs (%)	91	98.34	1.95	94	98.65	1.62	-1.18 (8087.5)
Total inventory (%)	78	97.58	2.57	126	98.17	2.07	-1.78 (7519)

The statistic values of Wilcoxon two-sample test for the means are reported in the parentheses. $* \ p \le 0.05$, $** \ p \le 0.025$, and $*** \ p \le 0.01$ for two-tailed tests.

To offer deeper insight on response behavior of smaller and larger firms, we compared control-adjusted change in operating performance of the smaller and the larger firms in quarter 1.

The results are reported in Table 2.8. Supply chain disruptions have more negative impact on the smaller firms one quarter after the quarter of the announcements considering all performance measures (p-values < 0.05) but sales, cost, and inventory. These results are almost the same at quarters 2 and 3. However, there is no significant difference between performance of two groups after quarter 4 (p-values > 0.05), except for the control-adjusted change of returns on sales in quarter 7.

Table 2.8. Control-adjusted change in operating performance measures of the smaller and the larger sample firms at quarter 1.

Unit of initial loss	Group 1 (smaller firms)			Group 2 (larger firms)			Two-sample t-test value for difference between group 1 and 2
	N.	Mean	S.D.	N.	Mean	S.D.	
Operating income (%)	141	-80.71	248.3	154	-17.58	185.3	-2.49*** (19242*)
Return on sales (%)	120	-54.21	154.2	152	-18.41	133.8	-2.05* (14787***)
Return on assets (%)	139	-80.21	248.5	150	-18.70	147.8	-2.58*** (18737*)
Sales (%)	141	-12.68	61.92	186	-3.71	31.29	-1.71 (22901)
Total assets (%)	159	11.26	41.70	179	2.93	27.47	2.19** (28902*)
Total costs (%)	125	3.50	53.84	120	2.15	37.05	0.23 (14235)
Total inventory (%)	104	2.20	52.37	161	1.61	34.64	0.11 (14448)

The statistic values of Wilcoxon two-sample test for the means are reported in the parentheses. * $p \leq 0.05$, ** $p \leq 0.025$, and *** $p \leq 0.01$ for two-tailed tests.

2.5.3. Additional results

2.5.3.1. Comparing industry sectors

One might expect different industry sectors to be prepared differently against supply chain disruptions. To estimate the difference between the total resilience and the robustness of firms facing supply chain disruptions from different industry sectors, we ran a series of ANOVA tests considering different operating performance measures of the sample firms. We only considered industry sectors with a sample number in our dataset of more than 30, i.e. the manufacturing sector, the transportation and utilities sectors (transportation, communications, electric, gas and sanitary service), and the mining sectors.

Table 2.9 presents the ANOVA and Tukey's studentized range test results for the impact of industry sectors on the robustness and on the total resilience of firms considering only operating income. Panel A shows that the total resilience of firms from different sectors differs significantly (p-value < 0.01). However, panel B shows that the initial loss of firms from different sectors does not differ significantly (p-value > 0.10). The result of Tukey's test in panel C shows that firms from the transportation and utilities sector are more resilient than firms from the manufacturing and the mining sectors, which agrees with the intuition that firms in the transportation, communications, electric, gas and sanitary sectors provide essential services to the communities and need to restore their services as soon as possible.

We also ran similar tests considering other operating performance measures than operating income. The results are not reported, but are available upon request. In general, the results are consistent with the results reported here considering operating income, with one exception that the total resilience of firms does not differ for different industry sectors considering the total inventory measure (p-values > 0.10).

Table 2.9. Impact of industry sectors on the total resilience and robustness of the sample firms considering operating income

Panel A: ANOVA results for the total resilience of firms in different sectors

Source	DF	Sum of Squares	Mean Square	F Value
Between industry sectors	2	29.82	14.91	5.07***
Within industry sectors	177	520.13	2.94	
Total	179	549.95		

Panel B: ANOVA results for the initial loss of firms in different sectors

Source	DF	Sum of Squares	Mean Square	F Value
Between industry sectors	2	125346.95	62673.47	1.99
Within industry sectors	238	7496698.90	31498.74	
Total	240	7622045.85		

Panel C: Tukey's studentized range test for the total resilience (the Type I experimentwise error rate =0.05)

Comparison of sectors	Simultaneous 95% confidence limits		Difference Between Means
Transportation and Utilities - Manufacturing	0.19	1.68	0.94*
Transportation and Utilities - Mining	0.11	2.01	1.06*
Manufacturing - Mining	-0.69	0.93	012

$*$ $p \leq 0.05$, $**$ $p \leq 0.025$, and $***$ $p \leq 0.01$ for two-tailed tests.

2.5.3.2. Improvement of resilience capacity

In order to find possible trends in the improvement of firms' resilience capacities between 2005 and 2014, we compared the operating performance of firms during two separate five-year time periods: 2005-2009 and 2010-2014. Both the two-sample t-test and the Wilcoxon sum rank test show no significant difference between the initial loss of operating performance measures during the two time periods (p-values > 0.10).

Table 2.10 presents descriptive statistics of the total resilience of sample firms during the two time periods. The last column of Table 2.10 compares the total resilience of these two groups. The results of the two-sample t-test and the Wilcoxon two-sample test in this case show that there is not enough evidence that the total resilience of firms has improved from 2005-2009 to 2010-2014 (p-values > 0.05).

Table 2.10. Test results for difference between the total resilience of the sample firms during 2005-2009 and 2010-2014

	Group 1 (sample firms from 2005 to 2009)			Group 2 (sample firms from 2010 to 2014)			Two-sample t-test value for difference between group 1 and 2
Unit of total resilience	N.	Mean	S.D.	N.	Mean	S.D.	
Operating income (%)	160	98.83	1.87	58	99.12	1.46	-1.07 (6860)
Return on sales (%)	146	99.02	1.60	53	99.33	1.12	-1.32 (5972)
Return on assets (%)	153	98.77	1.97	53	99.18	1.36	-1.40 (5894.5)
Sales (%)	193	97.70	2.32	69	98.00	1.92	-0.96 (9304)
Total assets (%)	199	98.07	2.39	67	98.24	2.25	-0.49 (9309)
Total costs (%)	142	98.48	1.90	43	98.55	1.37	-0.25 (37.24.5)
Total inventory (%)	149	97.91	2.37	55	98.04	2.07	-0.35 (5609)

The statistic values of Wilcoxon two-sample test for the means are reported in the parentheses. * $p \leq 0.05$, ** $p \leq 0.025$, and *** $p \leq 0.01$ for two-tailed tests.

2.6. Discussion

2.6.1. Academic contributions

This study makes several contributions to the academic literature. First, it re-evaluates the effects of supply chain disruptions on firms' operating and stock market performances using a new set of supply chain disruptions announced during 2005 to 2014. The results show that supply chain disruptions are still associated with a significant decrease in operating income, return on sales, return on assets, sales, and a negative performance in total assets. Supply chain disruptions are also associated with a significant negative abnormal stock return at the day of the supply chain disruption announcements. These results are in line with Hendricks and Singhal (2005b and 2003).

Unlike Hendricks and Singhal (2005b), however, we only found a weak association between supply chain disruptions and a negative performance in total cost and inventory.

Next, we empirically showed for the first time that size of firms is associated with resilience. Larger firms are more resilient than smaller firms considering profitability measures, sales, and total assets. We observed that larger firms are better than smaller firms in terms of their ability to recover quickly after the supply chain disruption announcements. Finally, we found that some industry sectors are more prepared against disruptions and therefore they are more resilient than other sectors. The results reveal that firms from the transportation and utilities sector are more resilient than firms in the manufacturing and mining sectors.

2.6.2. Managerial contributions

This paper has several implications for practitioners in the field of supply chain risk management. In spite of increasing knowledge about supply chain disruptions and recent recommendations from scholars for reducing the effects of disruptions, supply chain disruptions still negatively affect performance of firms in the short-run and the long-run. This finding indicates that firms should consider investing more resources into their robustness and recovery capacities. MacKenzie and Zobel (2016) introduced a framework that can help managers decide how to allocate limited resources between reducing the initial loss and the recovery time. Explicitly considering the tradeoffs between investing in robustness and investing in reducing recovery time can help managers to build more resilient firms in the presence of supply chain disruptions.

Our study reveals that firms from the transportation and utilities sector are more resilient than firms in the manufacturing and mining sectors. This is perhaps because firms from the transportation, communications, electric, gas, and sanitary sector provide essential services to the communities and based on their past experience know how to response quickly to supply chain disruptions. This finding indicates that managers from other industry sectors can learn from firms in the transportation and utilities sector to make their firms more resilient to supply chain disruptions.

2.6.3. Limitations and future directions

This study has several limitations. First, we only considered U.S. publicly traded firms in the process of collecting data. Supply chain disruptions may have different effects on firms in other countries. Therefore, we are not able to generalize our inferences about the effects of supply chain disruptions to firms from other countries. This limitation also exists in other empirical research efforts mentioned in the paper. Firms outside of the U.S. may present different resilience behavior with respect to supply chain disruptions. For example, we expect firms located in developing countries to be less resilient. Analyzing the resilience behavior of firms outside of the U.S. and comparing it with resilience of U.S. firms is an interesting direction for future research.

The second limitation is that we collected supply chain disruption announcements through searching PR Newswire and Business Wire, which are different news agencies than what Hendricks and Singhal (2005b and 2003) used. Part of the motivation for this was that Hendricks and Singhal (2005b and 2003) used the Wall Street Journal, which is a tertiary source of news, as a source. As discussed by Schmidt and Raman (2012) and Zsidisin et al. (2016), the Wall Street Journal publishes only news that they think they is important, and not all news stories. Hendricks and Singhal (2005b and 2003) also used the Dow Jones News Service, which merged into Dow Jones Institutional News in 2013. After searching that service using the same terms chosen for this paper, we found fewer relevant news items in the Dow Jones News Service and the Dow Jones Institutional News than what we found from PR Newswire and Business Wire. We therefore used PR Newswire and Business Wire as our news sources.

Chapter 3: Negative impacts of Supply Chain Disruptions on Firms' performance: Role of Operational Slack and Operational Scope

3.1. Introduction

Supply chain disruptions are unplanned and unexpected events that disrupt the normal flow of materials, goods, or information within a firm's supply chains (Craighead et al., 2007). Such events occur frequently in today's complex and interdependent business environment, and they affect both small and large companies to the extent that 65% of 408 firms surveyed across 64 different countries announced that they experienced at least one supply chain disruption in the previous year (Business Continuity Institute, 2017). The results of similar surveys in 2015 and 2016 revealed almost the same percentage (Business Continuity Institute, 2015 and 2016). The Kumamoto earthquakes (Tajitsu & Yamazaki, 2016), Hanjin Shipping's bankruptcy (Quittner, 2016), and Hurricanes Harvey (MH&L News, 2017) and Irma (Henson, 2017), are just a few events that led to major global supply chain disruptions in 2016 and 2017 alone.

Whether initiated by a ten minute-long fire in a semiconductor plant in Albuquerque (Latour, 2001), or by a catastrophic earthquake and tsunami in Japan (Clark & Takahashi, 2011), supply chain disruptions can have devastating impacts on the disrupted firms (Christopher & Lee, 2004), both immediately and over longer time periods. For example, not only did Ericsson experience a loss of approximately $200 million during the first year after its supplier failure in 2000, but the disruption also had a significant impact on the firm's decision to outsource cell phone manufacturing to Flextronics and to form a strategic joint venture with Sony in 2001 (Mukherjee, 2008). Furthermore, although the firm had effectively returned to health in 2004, its revenues fell by 52% compared to what they had been in 2000 (Mukherjee, 2008).

According to Allianz Global Corporate & Specialty (AGCS), the average amount of large business interruption claims[2] between 2010 and 2014 was more than $2 million and increasing every year, which is 36% higher than the equivalent average loss due to property damage (AGCS, 2015, p.4). AGCS highlights the increasing interdependency in supply chains as one of the main reasons for the growing trend in the size and number of business interruption claims: "The Tohoku earthquake and tsunami alone led to some 150 claims notifications for AGCS. Reflecting the growth of interdependencies, the vast majority of notifications were from companies located outside Japan that were not directly impacted by the disaster" (AGCS, 2015, p. 28). A majority of firms thus have significant concerns about their resilience to supply chain disruptions (World Economic Forum, 2013), i.e., their ability to resist the effects of a disruption and to recover an acceptable level of functionality after it occurs (Melnyk et al., 2014; Pettit et al., 2010; Ponomarov & Holcomb, 2009; A. J. Schmitt & Singh, 2012). Resilience to supply chain disruptions therefore incorporates readiness to events, the ability to provide efficient responses, and the ability to recover to a desired level of performance (Ponomarov & Holcomb, 2009).

Over the past two decades, a variety of strategies have been recommended in the supply chain risk management literature to attempt to improve firms' resilience, such as maintaining operational slack (DeCroix, 2013; F. Liu et al., 2016; Qi et al., 2009; Stecke & Kumar, 2009), and diversifying resources (Chopra and Sodhi, 2004; Hu and Kostamis, 2015; Tomlin, 2006). However, how and when such operational strategies can actually reduce the negative impact of supply chain disruptions is less well known. The answers to these questions are important from both a theoretical and a practical perspective. From a theoretical viewpoint, it is critical for researchers to understand how operational strategies affect the relationship between disruptions and the negative impacts of

[2] Claims over €20,000

those disruptions on firms' performance over time. From a practitioner's viewpoint, in order to support investments in resilience strategies it is important to gain a better understanding of the conditions under which the recommended strategies actually improve firms' resilience and the ways in which they may do so.

Building on the contingent resource-based view, this current research effort investigates the effects of two such types of operational strategy, i.e. maintaining operational slack and broadening operational scope, for managing the negative impacts of supply chain disruptions on firms' performance. In the context of this evaluation, our study seeks also to present a broader assessment of supply chain disruptions' impacts on firms' performance. To accomplish this, it specifically considers these impacts with respect to three complementary metrics borrowed from the systems resilience literature: the initial loss, the maximum loss, and the total loss over time. The initial loss and maximum loss metrics evaluate different characteristics of the magnitude of a disruption's impact on a firm's performance, whereas total loss over time gives a broader measure of the overall effect of that disruption, on that firm, over time. This is the first time that such metrics have explicitly been used to characterize the impacts of supply chain disruptions on firms' performance.

By adopting a more comprehensive view of firms' performance through the use of such systems resilience concepts, and by utilizing a contingent resource-based view, we are able to develop new and expanded inferences about how and when maintaining operational slack and broadening operational scope can benefit firms by helping to reduce the negative impacts of disruptions. The results of our study show that the benefits of operational slack, expressed in terms of inventory slack, supply chain slack, and capacity slack, and the benefits of operational scope, expressed in terms of business scope, are highly dependent on the severity of a disruption. The results also show, however, that the benefits of these strategies differ based on the type of negative impact suffered by the firm. For example, we find that although maintaining inventory slack reduces maximum loss and total loss in the case of a severe disruption, such a strategy has no significant effect on initial loss, regardless of the severity of the event.

The benefits of maintaining operational slack and broadening operational scope, as indicated in our study, differ significantly from previous findings that are based on post-disruption stock market reactions. For example, Hendricks et al. (2009) find that inventory slack and business scope have no significant effect on the stock market reaction after disruptions and that geographic scope increases the negative impact of supply chain disruptions on stock returns. Our results show a significant relationship between both inventory slack and business scope and the negative impacts of disruptions on firms' performance. Our results also indicate that although the amount of geographic scope has no significant effect on immediate loss of firms, it actually decreases both the maximum loss and the total loss over time, when it is firms' performance that is being considered.

The remainder of our discussion proceeds as follows. Section 3.2 reviews the related literature and posits three hypotheses about the relationship between the operational slack and operational scope and the impacts of supply chain disruptions on firms' performance. Section 3.3 outlines the data collection procedures. Section 3.4 develops the three metrics of interest based on the system resilience literature and describes the methods used to conduct the results. Section 3.5 then summarizes the results and Section 3.6 provides robustness tests. Finally, Section 3.7 discusses the findings and provides future research directions.

3.2. Theoretical background and hypotheses development

3.2.1. Contingent resource-based view

We ground our conceptual model in the contingent resource-based view of the firm, which is based on combining contingency theory with a resource-based view (RBV) perspective (Brush & Artz, 1999). Known as one of the most powerful theories for understanding organizations (J. B. Barney, David J. Ketchen, & Wright, 2011), the RBV relates the competitive advantage of a firm to strategic resources that are heterogeneously distributed across that firm (J. Barney, 1991; Wernerfelt, 1984). According to the RBV, valuable, rare, unique, and non-substitutable resources enable a firm's competitive advantage (J. Barney, 1991), and these resources can be classified within six categories: physical resources, financial resources, technological resources, reputation, human resources, and organizational resources (Grant, 1991). The RBV has been widely utilized by researchers to explain differences in firms' performance outcomes, and it is becoming increasingly popular in the operations and supply chain management literature (for a review, see Hitt et al., 2016). Despite its relative popularity, however, the RBV has been criticized because its static nature ignores the operating environment of firms, thus making it insensitive to context (Bromiley & Rau, 2016; Brush & Artz, 1999; Ling-yee, 2007). Furthermore, it has been shown that possession of strategic resources, in and of themselves, is not sufficient enough for a firm to gain competitive advantage (Autry & Sanders, 2009; Blome, Schoenherr, & Rexhausen, 2013; Eisenhardt & Martin, 2000).

The dynamic capabilities perspective, which extends the RBV, suggests that it is a firm's ability to build, reconfigure, and integrate resources in response to rapidly changing environments that helps to create its competitive advantage (Allred, Fawcett, Wallin, & Magnan, 2011; Blome et al., 2013; Eisenhardt & Martin, 2000; Teece, Pisano, & Shuen, 1997). The use of the term "capabilities" emphasizes that management takes an active role in integrating, building, and reconfiguring skills, resources, and competencies in order to effectively adapt the organization to changes in its environment (Teece et al., 1997). Given this emphasis, the dynamic capabilities view is able to explain why firms with equivalent resources may nevertheless have very different performance outcomes.

Similar to the RBV, however, the dynamic capabilities perspective still falls short in explaining why some resources are valuable in some contexts and not in others, as reflected in the mixed findings about the impact of organizational slack on firm performance (Daniel, Lohrke, Fornaciari, & Turner, 2004; Modi & Mishra, 2011). With this in mind, a further extension to the theory, the contingent resource-based view, argues that "firms' existing resources" and "environmental conditions" both play an important role in "conditioning the effect of the firm's acquired resources on performance" (Ling-yee, 2007, p. 361). This leads to the assertion that the value of resources is contingent upon the context within which they are utilized (Aragon-Correa & Sharma, 2003; Sedera, Lokuge, Grover, Sarker, & Sarker, 2016).

The contingent resource-based view has thus been used in the literature to understand the relationship between specific resources and the corresponding performance of firms under different conditions. For example, Brandon-Jones et al. (2014) studied the moderating impact of supply base complexity on the relationship between supply chain visibility and two particular "performance outcomes" after a disruption: *resilience*, which the authors define as the ability of the "supply chain to return to normal operating performance within an acceptable period of time", and *robustness*, which they define as the ability of the supply chain to maintain its functionality in spite of the disruption. The authors show that the beneficial effects of visibility on resilience and robustness increase as the supply base complexity also increases, and therefore that the benefit is contingent upon complexity (Brandon-Jones et al., 2014). Our study also considers performance in response to a supply chain disruption, but it instead uses the severity of the disruption as the contingent factor. We thus use the contingent resource-based view to evaluate the moderating effects of operational slack and operational scope on the relationship between the severity of the disruption and the different ways in which that disruption subsequently impacts firm performance.

3.2.2. Characterizing firms' performance in response to disruptions

Hendricks and Singhal (2003, 2005a, and 2005b) empirically analyze the effects of supply chain disruptions on firms' operating performance metrics (such as return on assets, return on sales, and operating income), and on stock returns, using a large number of firms that experienced supply chain disruptions. They show that supply chain disruptions are significantly associated with negative operating and stock market performance, not only in the short-term but also in the long-term, with some disrupted firms not fully recovering from the negative operating impacts of a supply chain disruption even two years after the disruption occurs. This is reaffirmed in a recent study by Zsidisin et al. (2016), in which the authors assess the impacts of supply chain disruptions on shareholder wealth for a more recent time period and show that supply chain disruptions still have a significant negative impact on shareholder wealth.

The notion of a firm's resilience to supply chain disruptions has received an increasing amount of attention among both academics and practitioners over the past few decades (Zsidisin et al. 2016). Despite this growing focus, however, relatively little attention has been paid to *operationalizing* firms' performance to improve resilience to such disruptions. An important perspective on this is provided by the seminal paper of Sheffi and Rice (2005), in which they characterize the dynamics of a firm'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. Sheffi and Rice (2005) argue that any serious disruption will affect a firm's performance in similar ways and they propose eight distinct phases to characterize the firms' responses to disruptions: preparation, the disruptive event, first response, initial impact, full impact, preparation for recovery, recovery, and long-term impact. Figure 3.1 provides an illustration of a corresponding disruption profile.

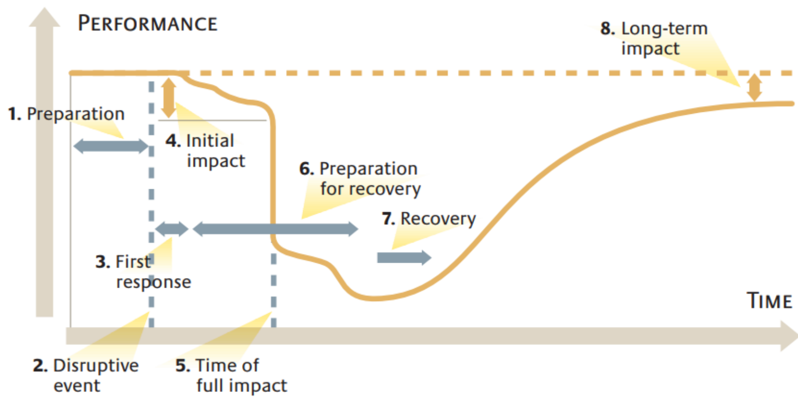

Figure 3.1. The disruption profile introduced by Sheffi and Rice (2005)

The idea of using a response curve to characterize the performance of a system in response to a disruption is also well known in the system resilience literature. 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. This use of the response curve as an analytical tool has since been widely extended and utilized to evaluate a system's performance against disruptions in different contexts, such as interdependent industry sectors and infrastructure systems (Francis & Bekera, 2014; Ouyang, Dueñas-Osorio, & Min, 2012; Pant, Barker, & Zobel, 2014), urban communities (Cimellaro, Reinhorn, & Bruneau, 2010), transportation systems (Adams, Bekkem, & Toledo-Durán, 2012; Adjetey-Bahun, Birregah, Châtelet, & Planchet, 2016; Henry & Ramirez-Marquez, 2012), and supply chains and organizations (Sahebjamnia, Torabi, & Mansouri, 2015; Spiegler, Naim, & Wikner, 2012; Torabi et al., 2015).

In this same context, 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) 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) further demonstrate the importance of this, in the context of increasing the resilience of an electric power network following Superstorm Sandy, by showing that investing in certain resilience strategies may have a larger impact on reducing loss whereas investing in others may have more of an effect on the length of time until recovery. As illustrated by the disruption profile in Figure 3.1, such an approach easily could be extended to consider other characteristics of a system's response to a disruption.

With this in mind, this current study seeks to provide a more complete characterization of the impacts of supply chain disruptions on firms' performance by using three complementary metrics derived from the resilience literature: the initial loss, the maximum loss, and the total loss over time. The first two metrics (initial loss and maximum loss) provide different measures of robustness, or resistance to loss of performance. As illustrated in Figure 3.2, the initial loss reflects the initial impact of the disruption, whereas the maximum loss reflects the subsequent maximum impact of the event, measured at the time when recovery begins. The total loss observed over time 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 supply chain is able to resist increasing (or cascading) losses over time. Similarly, a supply chain 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 measures thus help to characterize not just the immediate impacts of a disruption on a firm, but also the longer-term impacts and the relative extent to which the firm is able to recover over time.

Figure 3.2 illustrates the three chosen measures with a simple example of a performance response curve for a firm in which $Q(t)$ is some measure of firm performance (or functionality) at time t, such as return on assets (ROA). $1\text{-}Q(t_0)$ then represents the initial loss in performance due to a disruption, $1\text{-}Q(t_{max})$ represents the maximum loss in performance, and the shaded area above the response curve represents the total loss experienced by the firm over time.

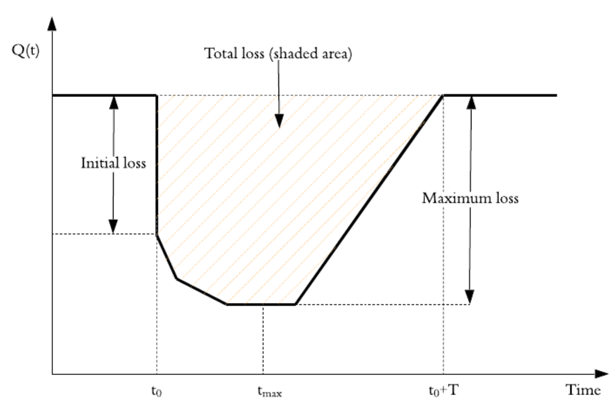

Figure 3.2. Selected components of measuring resilience.

With these three measures in mind, the following hypotheses serve to conceptualize the relationship between operational slack and operational scope, as strategies for reducing the impacts of supply chain disruptions, with respect to their ability to moderate the relationship between the severity of a supply chain disruption and different characteristics of the firm's subsequent performance response.

3.2.3. Operational slack

Organizational slack has been defined as the pool of resources in excess of what a firm 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 (Fullerton et al., 2003; Kinney and Wempe, 2002; Modi and Mishra, 2011; Womack et al., 1990), several studies have found that having organizational slack actually enhances firms' performance in specific business environments such as in highly unstable markets (Tan and Peng, 2003; Daniel et al., 2004; George, 2005; Wan and Yiu, 2009; Wefald et al., 2010; Kovach et al., 2015), which agrees with the contingent resource-based view.

Firms 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 firms' performance in the presence of supply chain disruptions. Operational slack is firms' 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). Some of these types of operational slack (such as inventory slack) can allow firms, 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 firms recover to a desirable service level after a supply chain disruption. For example, in the wake of the 2016 Kumamoto earthquakes, Toyota was criticized for its tight production system which did not hold enough inventory to absorb the shock of a supplier disruption (Kubota, 2016). However, Toyota's disrupted supplier announced that it would ramp up productions in its other unaffected facilities, in order to utilize extra production capacity to resolve the shortages (Tajitsu and Yamazaki, 2016).

Accordingly, operational slack has been recommended as one of the main strategies to make firms more resilient against supply chain disruptions (Chopra & Sodhi, 2004; J. Fiksel, Polyviou, Croxton, & Pettit, 2015; F. Liu et al., 2016; Melnyk et al., 2014; Qi et al., 2009; Stecke & Kumar, 2009; Tang, 2006; Tomlin, 2006). For instance, Sheffi and Rice (2005) argue that "companies can bolster their resilience by either building in redundancy or building in flexibility." They define redundancy as resources in reserve to be used in case of a disruption. Similarly, Kleindorfer and Saad (2005) consider maintaining operational slack as one of their recommended principles to decrease supply chain disruption risk, and they mention that "establishing backup systems, contingency plans, and maintaining reasonable slack, can increase the level of readiness in managing risk." Fiksel et al. (2015) further identify capacity slack as one of the main factors that help a firm to anticipate and overcome supply chain disruptions.

The existing literature thus suggests that having operational slack benefits firms in their efforts to respond to supply chain disruptions. The extent of such benefits, however, is not necessarily clear. According to the contingent resource-based view, we argue that the benefits of operational slack are contingent on the level of severity of the disruption; for example, the benefit of maintaining operational slack will be greater in the case of a more severe disruption.

Hypotheses 1a to 1c formalize this expectation about the impacts of operational slack on the performance of firms, in the presence of supply chain disruptions and in the context of the three different characteristics of firm performance defined above:

H1a. *Operational slack negatively moderates the relationship between the severity of a supply chain disruption and the initial loss of performance by a firm: the higher the severity, the greater the effects of operational slack on reducing the initial loss.*

H1b. *Operational slack negatively moderates the relationship between the severity of a supply chain disruption and the maximum loss of performance by a firm: the higher the severity, the greater the effects of operational slack on reducing the maximum loss.*

H1c. *Operational slack negatively moderates the relationship between the severity of a supply chain disruption and the total loss of performance over time by a firm: the higher the severity, the greater the effects of operational slack on reducing the total loss of performance.*

3.2.4. Operational Scope

Managing the scope of a firm's activities, i.e. its operational scope, is a critical element in achieving a competitive advantage (Kovach et al., 2015; Porter & Advantage, 1985). The next two subsections discuss the impacts of two different types of operational scope on the performance of firms after supply chain disruptions: business scope and geographic scope.

3.2.4.1. Business Scope

Business scope refers to the breadth of a firm's business portfolio. There have been several studies that have looked at the effects of such business scope on the performance of firms, but there is some inconsistency in the findings. For example, using a meta-analysis of 55 studies published during 1971 and 1998, Palich et al. (2000) find an inverted U-association between business scope and firms' performance. However, Bausch and Pils (2009), also using a meta-analysis methodology, find that “there is no such thing as a universally valid nature of the [business] diversification strategy–performance linkage”. Kovach et al. (2015) argue that benefits of business scope depends on the firms’ dynamic environment (contingency). They subsequently show that business scope is positively associated with performance when firms are operating in unpredictable markets.

There are at least two reasons why we would expect broadening business scope to improve firms’ performance in the case of a supply chain disruption. First of all, we would expect the operational impacts of a disruption on a line of business to be less destructive for firms with a large number of different businesses than for firms that are focused only on a few businesses (Hendricks et al., 2009). This suggests that firms with larger business scope would be more robust to supply chain disruptions than less diversified firms. Secondly, we would expect managers in the more diversified firms to have more flexibility to accelerate the recovery process by shifting funds and resources from undisrupted businesses to the disrupted businesses. Consequently, we would expect them also to experience faster recovery. We also expect that the benefits of business scope for firms is contingent on the severity of the disruption, i.e. that business scope has a greater effect on the relationship between the disruption and the firm's performance when the severity of the disruption is higher.

Hypotheses 2a to 2c therefore formalize these expectations about the relationship between business scope and the impacts of supply chain disruptions on firms’ performance.

H2a. *Business scope negatively moderates the relationship between the severity of a supply chain disruption and the initial loss of performance by a firm: the higher the severity, the greater the effects of business scope on reducing the initial loss of performance.*

H2b. *Business scope negatively moderates the relationship between the severity of a supply chain disruption and the maximum loss of performance by a firm: the higher the severity, the greater the effects of business scope on reducing the maximum loss of performance.*

H2c. *Business scope negatively moderates the relationship between the severity of a supply chain disruption and the total loss of performance over time by a firm: the higher the severity, the greater the effects of business scope on reducing the total loss of performance.*

3.2.4.2. 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 increases firms' responsiveness to demand fluctuation, but it also can result in loss of efficiency due to increasing organizational slack. Studies suggest different types of relationship between geographic scope and firms' performance: from a positive linear relationship (Kirca et al., 2011; Kumar, 2009; Marano et al., 2016), to a negative linear relationship (Denis et al., 2002; Kovach et al., 2015), to a variety of curvilinear relationships (Berry and Kaul, 2016; Lampel and Giachetti, 2013; Park and Jang, 2012).

Despite these differences in opinion about the relationship between geographic scope and firms' performance, however, geographic scope has been recommended as a strategy to decrease the impacts of supply chain disruptions. Chopra and Sodhi (2014), for example, argue that regionalizing operations avoids disruption of the entire organization by isolating a disruption in its region. The authors highlight the importance of this by emphasizing Japanese automakers' disruptions after the 2011 Japan earthquake and tsunami when their worldwide production was affected by a shortage of a part that could be sourced only from the disrupted region. Similarly, Craighead et al. (2007) argue that a supply chain disruption event would have more negative effects on highly dense supply chains relative to less dense supply chains, with "supply chain density being inversely related to geographical spacing". Therefore, firms with a large number of distributed manufacturing facilities have a greater ability to absorb the shock of a facility disruption than do firms with only a few manufacturing facilities. Geographic diversification also enables firms to relocate resources from undisrupted locations to disrupted locations, which facilitates the recovery process. 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 firms will be greater in case of a more severe disruption.

Hypotheses 3a to 3c formalize this expectation.

H3a. *Geographic scope negatively moderates the relationship between the severity of a supply chain disruption and the initial loss of performance by a firm: the higher the severity, the greater the effects of geographic scope on reducing the initial loss of performance.*

H3b. *Geographic scope negatively moderates the relationship between the severity of a supply chain disruption and the maximum loss of performance by a firm: the higher the severity, the greater the effects of Geographic scope on reducing the maximum loss of performance.*

H3c. *Geographic scope negatively moderates the relationship between the severity of a supply chain disruption and the total loss of performance over time by a firm: the higher the severity, the greater the effects of Geographic scope on reducing the total loss of performance.*

Given these three sets of hypotheses, Figure 3.3 presents the relationships of interest in this study.

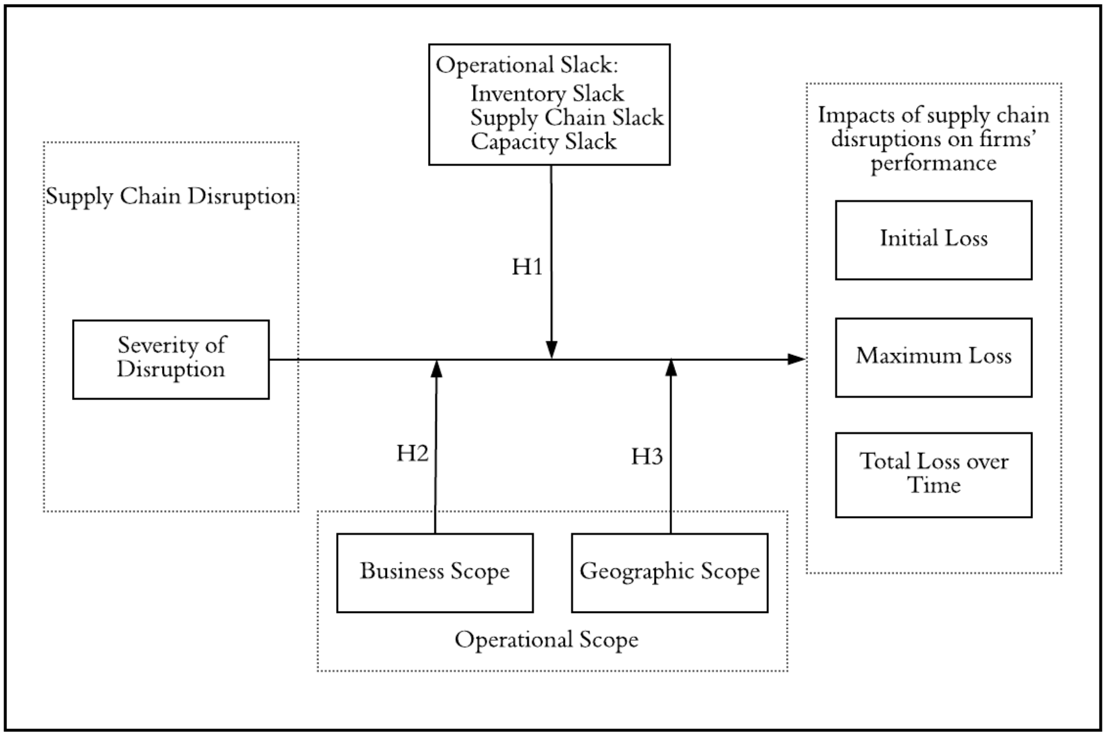

Figure 3.3. Research model

3.3. Supply chain disruption data

PR Newswire and Business Wire in the Factiva database are our sources for finding supply chain 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 (Schmidt & Raman, 2012), and they have been used by other researchers to find such press releases (Liu et al., 2014; Mitra & Singhal, 2008). We limit our search to the time period from 2005 to the end of 2013 in order to coincide with the increase in attention to supply chain disruptions that began between 2001 and 2005 (see for example, Chopra & Sodhi, 2004; Christopher & Peck, 2004; Sheffi & Rice, 2005). Most of the resilience strategies being considered in this paper were recommended during this time period.

We use the following sets of terms to search the headlines and lead paragraphs of the news articles published in PR Newswire and Business Wire: delay, disruption, interruption, shortage, or problem, paired together with: component, delivery, parts, shipment, manufacturing, production, or operations. 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 supply chain 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.

In order to calculate the initial loss metric (which needs the least amount of data), each firm needs to have performance data available in the COMPUSTAT database for at least four quarters prior to the quarter of the disruption announcement as well as for the quarter of the disruption announcement (35 firms from the sample do not satisfy this condition). For performing the regression analysis, the sample firms also need to have data available for each independent variable in the model for the year before the announcement year. As a result of removing firms with insufficient data, we end up with a final sample of 316 distinct supply chain 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, and Figure 3.4 presents the resulting distribution of the supply chain disruption announcements per year. As Figure 4 shows, the number of supply chain disruption announcements is higher in 2005, which agrees with the expectation that Hurricane Katrina (2005) had significant impacts on supply chain operations.

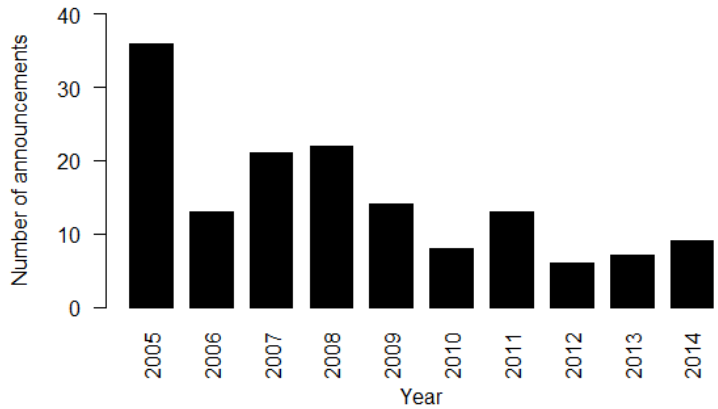

Figure 3.4. Distribution of the disruption announcements per year.

3.4. Measures and descriptive statistics

3.4.1. Dependent variables

In this particular study, we choose to use a firm's return on assets (ROA) as a measure of firms' performance, as done previously in the literature (Craighead et al. 2009; Hendricks & Singhal 2005b; Wagner et al. 2012). "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 supply chain 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). Appendix A provides the details of this matching technique.

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

$$\Delta_t = \textit{Actual ROA of the sample firm at quarter } t \\ \quad - \textit{expected ROA of the sample firm at quarter } t \qquad (3\text{-}1)$$

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 supply chain 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. As described in Appendix A, 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 supply chain disruptions on firms.

Although some supply chain 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:

$$L_0 = -\Delta_0 \tag{3-2}$$

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:

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

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 supply chain disruption, we then simply consider the sum of the positive loss values over that given time period:

$$total\ loss\ over\ time = \sum_{t=0}^{8} \max(0, L_t) \tag{3-4}$$

3.4.2. Independent variables

3.4.2.1. 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 firm (Ambulkar et al., 2015; Christoph 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 firms affected by exactly the same disruptive event, the differences in such measures could provide an indication of the relative resilience of each firm. If two different events affect the two firms, however, then it can be difficult to compare the resulting behaviors by looking only at performance outcomes. This is because an inherently resilient firm 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 in a supply chain

(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. In this study, we accomplish this by assessing the initial reaction of the stock market to the announcement of the disruption, as a proxy variable for the complex combination of factors that determines the actual underlying severity of the event. Proxy variables are easy to measure variables that are commonly used in applied work in place of difficult to observe or measure variables (Teece et al., 1997).

Using the stock market reaction allows us to provide an indication of the *expected severity* of a disruption, based on the shareholders' assessment of how much effect the disruption will have on the firm. By considering only the immediate response of the market to the announcement, we may further avoid dependence on any operational decisions subsequently made by the firm in response to the disruption. As an alternative, a panel of experts could instead be used to evaluate the intensity and scope of the event. For example, Bharadwaj et al. (2009) used such a panel to divide the severity of information technology failures into low, medium, or high severity based on the scope and duration of each failure. In our context, such an expert panel assessment would also need to be made without regard to the actual response of the organization to the disruptive event in order to maintain its independence from any such actions.

The Buy and Hold Abnormal Return (BHAR) method is used in this study to calculate the immediate response of the market to the announcement from one day before the day of the announcement to one day after the day of the announcement. Equation (3-5) shows the BHAR formula for stock *i* from day -1 to day 1.

$$BHAR_i = \prod_{t=-1}^{1}(1 + R_{it}) - \prod_{t=-1}^{1}(1 + R_{mt}) \tag{3-5}$$

where R_{it} is the rate of return of stock *i* on day *t*, and R_{mt} is the rate of return for the benchmark of stock *i* on day *t*. We use the *Event Study by WRDS* tool to calculate the BHAR value for each event and then the calculated value is multiplied by -1 to generate the event's severity.

3.4.2.2. Operational slack

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 Hendricks et al. (2009) and Kovach et al. (2015) to calculate these three measures. Please note that we calculate all of the following independent variables (operational slack, operational scope, and any control variables) based on the fiscal year prior to the year of the disruption announcement.

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. We consider firms with same three-digit SIC code to be in the same industry.

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. Cash-to-cash cycle is a measure of a supply chain's leanness, where a smaller cash-to-cash cycle means the supply chain is more lean (Hendricks et al., 2009). 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 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.

3.4.2.3. 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):

$$B_{Hrf} = 1 - \sum_{i} \left(\frac{S_i^b}{S} \right)^2 \tag{3-6}$$

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.

3.4.2.4. 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):

$$G_{Hrf} = 1 - \sum_{i} \left(\frac{S_i^g}{S} \right)^2 \tag{3-7}$$

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.

3.4.2.5. 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 (S. Kim, Sambharya, & Yang, 2016). Next, since we expect that supply chain 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.

3.5. Results

Table 3.1 provides zero-order correlations, means, and standard deviations for the dependent, independent, and control variables. Table 3.2 then reports the summary of statistical tests for the initial loss, the maximum loss, and the total loss over time. The results of the different statistical tests in Table 3.2 show that supply chain disruptions are associated with significant negative impacts on firm performance for all three of the loss metrics (initial loss, maximum loss, and total loss over time).

Table 3.1. 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)	0.69	1.00											
3. Total loss (×100)	0.60	0.93	1.00										
4. Firm size	-0.36	-0.46	-0.42	1.00									
5. Firm age	-0.22	-0.28	-0.27	0.52	1.00								
6. Book to market ratio	-0.01	-0.28	-0.26	-0.02	0.01	1.00							
7. Growth rate	0.03	-0.01	-0.02	-0.02	0.09	0.00	1.00						
8. Severity of event	0.36	0.39	0.42	-0.25	-0.17	0.09	-0.12	1.00					
9. Inventory slack	0.33	-0.23	-0.22	-0.07	-0.09	0.01	0.00	-0.32	1.00				
10. Supply chain slack	-0.26	0.01	0.05	-0.07	-0.04	0.03	-0.02	0.01	-0.10	1.00			
11. Capacity slack	0.03	-0.01	0.02	0.00	-0.05	-0.02	0.11	0.15	0.03	-0.34	1.00		
12. Business diversification	-0.15	-0.31	-0.31	0.42	0.25	0.10	-0.03	-0.11	-0.04	-0.04	0.08	1.00	
13. Geographic diversification	-0.19	-0.39	-0.34	0.47	0.35	0.03	0.07	-0.07	0.03	-0.08	0.26	0.34	1.00
Sample size	149	125	125	149	149	149	149	136	149	149	149	149	149
Mean	1.306	4.375	13.956	7.379	28.658	0.341	0.114	0.032	-0.212	0.768	0.177	0.325	0.342
Standard deviation	4.736	5.844	22.762	2.005	18.908	1.685	0.197	0.092	0.604	5.346	0.577	0.324	0.303

Table 3.2. Summary of statistics tests for the three performance metrics.

	Performance-industry-matched		
Performance measure	N.	Mean	Median
Initial loss (×100)	149	1.306*** (3.37)	0.40*** (1723.5)
Maximum loss (×100)	125	4.37*** (8.37)	2.75*** (3837.5)
Total loss (×100)	125	13.96*** (6.85)	6.60*** (3923.5)

The student's t value for the mean, and sign rank test's S value for the median are reported in the parentheses. ***, **, * indicates significance at 0.01,0.05,0.1 levels for two-tailed tests.

Given these initial results, we use Ordinary Least Squares (OLS) regression to test the hypotheses given in Section 3.2. We exclude one observation from our models because of it having a high residual by predicted value. 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 3.3 provides the results of the regression analyses for the three dependent variables: initial loss, maximum loss, and total loss. Model 1 only includes the control variables, the direct effects for each dependent variable are included in Model 2, and the interaction terms are introduced in Model 3. Considering initial loss, the results of Model 1 indicate that firm size is negatively associated with initial loss (p-value ≤ 0.01). Model 2 for initial loss shows that capacity slack is negatively associated and the severity of the event is positively associated with initial loss (p-values ≤ 0.05). This suggests that firms with higher capacity slack experience less initial loss and, as expected, that a more severe event results in a higher amount of initial loss. Model 3, in turn, shows that supply chain slack and business scope have significant interaction terms with severity (p-values ≤ 0.10). This suggests that supply chain slack and business scope negatively moderate the relationship between severity of event and initial loss due to the disruption (supporting H1a and H2a). The results also show that capacity slack has a direct negative effect on initial loss experienced after disruptions. 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 1 for maximum loss shows that firm size and book to market ratio are both negatively associated with maximum loss (p-values ≤ 0.05). The results of Model 2 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, capacity slack, and business scope negatively moderate the relationship between severity of event and maximum loss (H1b and H2b are 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 two columns of Table 3.3 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 1 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 2 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 3 then suggests that inventory slack and business scope negatively 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 3.3 have F-values greater than or equal to 2.645, and all of the models are statistically significant at the 1% level. The R^2 values of all models are between 13.5% and 52.6%, which is greater than, or comparable to, the values reported in several previous studies using cross-sectional data (see, for example, Mitra and Singhal, 2008; Shockley et al., 2015; Flammer, 2015).

Table 3.3. Results of regression analyses.

	Initial Loss (×100)			Maximum Loss (×100)			Total Loss (×100)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	7.513 ***	3.210 **	3.549 ***	14.921 ***	10.041 ***	7.116 ***	51.342 ***	33.648 ***	23.213 ***
	(1.435)	(1.311)	(1.331)	(1.855)	(2.117)	(2.117)	(7.414)	(8.407)	(8.273)
Firm size	-0.802 ***	-0.292	-0.338 *	-1.120 ***	-0.507 *	-0.058	-3.838 ***	-1.946	-0.301
	(0.215)	(0.193)	(0.192)	(0.276)	(0.310)	(0.300)	(1.102)	(1.230)	(1.173)
Firm age	-0.012	-0.011	-0.008	-0.029	-0.013	-0.026	-0.125	-0.031	-0.084
	(0.023)	(0.017)	(0.017)	(0.028)	(0.027)	(0.025)	(0.112)	(0.107)	(0.096)
Book to market	-0.056	-0.727	-0.479	-2.906 **	-1.046	-0.332	-10.682 **	-3.948	-1.546
	(0.218)	(0.750)	(0.779)	(1.151)	(1.381)	(1.272)	(4.601)	(5.483)	(4.970)
Growth rate	0.666	1.073	1.199	0.114	0.581	-1.676	-0.855	0.669	-8.164
	(1.876)	(1.355)	(1.371)	(2.402)	(2.252)	(2.292)	(9.601)	(8.943)	(8.958)
Severity of event		13.814 ***	12.093 **		22.895 ***	12.752		97.439 ***	32.915
		(3.318)	(4.906)		(6.513)	(8.854)		(25.865)	(34.603)
Inventory slack		0.304	0.343		-2.107 **	-1.760 *		-8.292 **	-7.111 *
		(0.596)	(0.687)		(1.006)	(0.994)		(3.997)	(3.884)
Supply chain slack		-0.083	-0.202 **		0.112	0.372		0.751	1.795
		(0.060)	(0.085)		(0.145)	(0.321)		(0.575)	(1.436)
Capacity slack		-1.105 **	-1.261 **		-0.656	-0.566		-0.873	-0.763
		(0.551)	(0.557)		(1.007)	(0.927)		(4.000)	(3.624)
Business scope		0.467	0.404		-2.073	-2.656 *		-8.341	-9.611 *
		(0.929)	(0.931)		(1.552)	(1.424)		(6.162)	(5.566)
Geographic scope		0.359	0.334		-4.170 **	-4.186 ***		-13.386 *	-13.481 **
		(1.085)	(1.105)		(1.796)	(1.660)		(7.131)	(6.489)
Severity of event ×			0.057			-48.935 *			-207.688 ***
Inventory slack			(9.605)			(21.062)			(82.313)
Severity of event ×			-3.517 *			17.280			70.074
Supply chain slack			(1.823)			(12.708)			(82.337)
Severity of event ×			-4.847			-25.705 *			-79.769
Capacity slack			(6.667)			(13.298)			(51.970)
Severity of event ×			-27.756 **			-49.888 **			-157.431 *
Business scope			(11.697)			(24.411)			(94.718)
Severity of event ×			4.637			28.301			18.236
Geographic scope			(13.275)			(36.632)			(143.163)
Model F statistic	5.640 ***	3.032 ***	2.645 ***	10.294 ***	6.484 ***	7.355 ***	8.267 ***	6.000 ***	7.399 ***
N	149	136	136	125	116	116	125	116	116
R^2	0.135	0.195	0.284	0.255	0.382	0.525	0.216	0.364	0.526
Adjusted R^2	0.111	0.131	0.154	0.231	0.323	0.453	0.190	0.303	0.455
ΔR^2		0.060	0.089		0.127	0.143		0.148	0.162

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

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 Figure 3.5. We apply a t-test to evaluate the simple slopes of the low severity and high severity lines (Aiken, West, & Reno, 1991), and we highlight lines with a slope significantly different from zero in red (p-values ≤ 0.05).

Figures 5a and 5b show that supply chain slack and business scope significantly decrease the initial loss when the disruption severity is high, whereas business scope may have a positive effect on initial loss when severity is low. Figures 5a and 5b thus confirm our hypotheses that supply chain slack (H1a) and business scope (H2a) have greater negative effects on initial loss when severity is high.

Figures 3.5c, 3.5d, and 3.5e further support the hypotheses that the effects of operational slack (H1b) and business scope (H2b) on reducing the maximum loss of performance are greater when severity is higher. They do this by showing that operational slack (expressed as inventory slack and capacity slack) and business scope are each negatively associated with maximum loss when severity is high, whereas neither of them has a significant effect on maximum loss when severity is low. Furthermore, Figures 3.5f and 3.5g 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 have no significant effect on total loss over time when severity is low (supporting H1c and H2c).

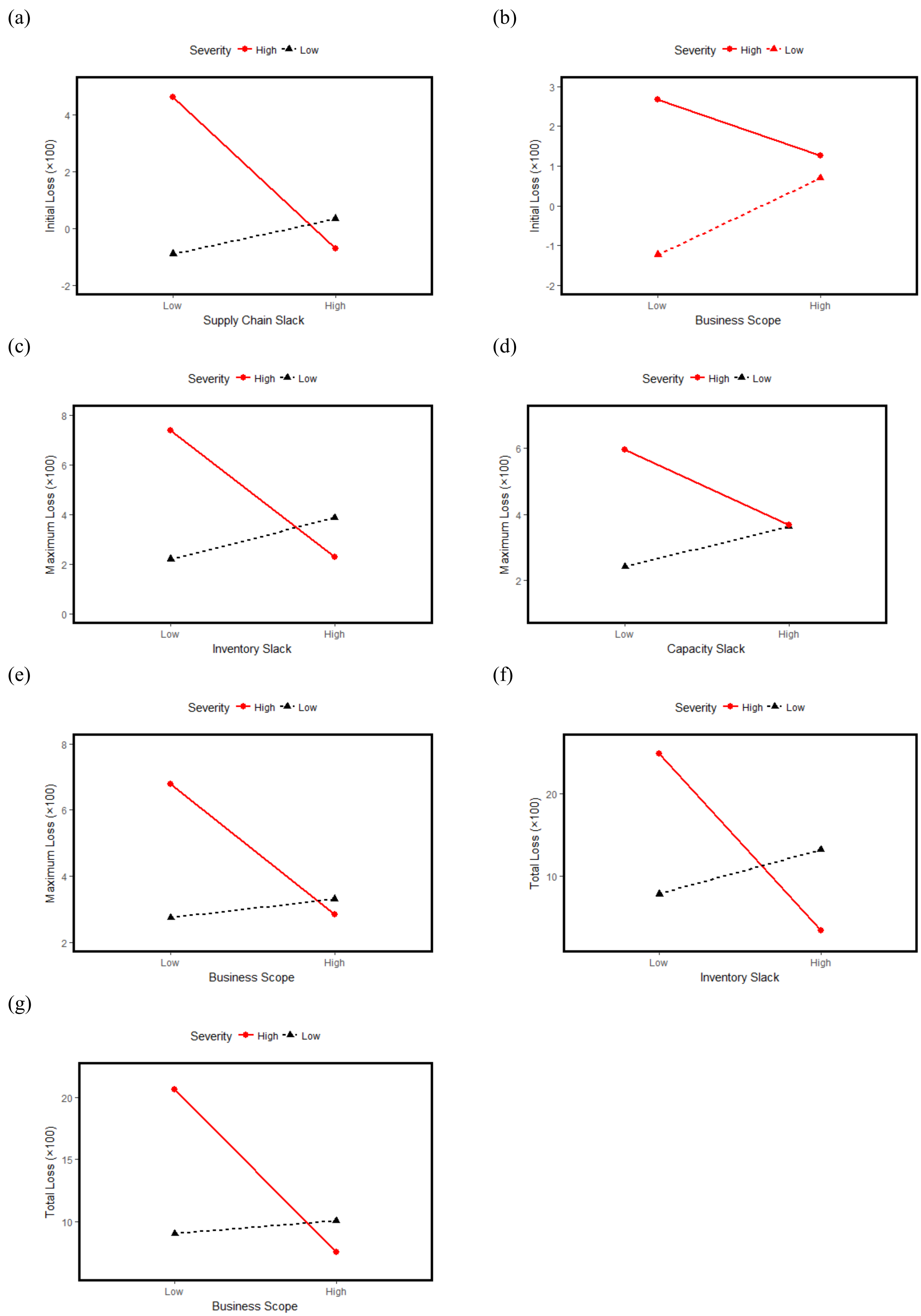

Figure 3.5. Interaction plots

3.6. Robustness check

We run three additional regression analyses for robustness checks. First, we implement two other matching methods used in Hendricks and Singhal (2008) to match each sample firm with control firms: the performance-industry-size-matched method and the performance-size-matched method. These matching methods are described in Appendix A. The results of regression analyses using the performance-industry-size-matched method and the performance-size-matched method are reported in Table 3.4 and 3.5, respectively. Overall, the new results support our initial findings with one exception: the moderating role of supply chain slack is not supported by the results from the performance-industry-size-matched method (Table 3.4).

In order to calculate the dependent variables in the previous sections, we used ROA as a measure of performance. In order to further check the robustness of the results, we also consider operating income and sales over assets (SOA) as other measures of performance from the literature. Tables 3.6 and 3.7 provides the results of regression analyses using operating income and SOA, with the performance-industry-matched method. Overall, these results are consistent with our findings about the moderating effects of operational slack and business scope on the relationship between severity and the negative impacts of disruptions on firms' performance. Similar to our initial results, the new results also show that geographic scope is directly and negatively associated with maximum loss and with total loss over time.

Table 3.4. Results of regression analyses using performance-industry-size-matched method.

	Initial Loss (×100)			Maximum Loss (×100)			Total Loss (×100)		
	Model 1	Model 2	Model 3	Model 1	Model 2		Model 1	Model 2	
Intercept	6.823 ***	2.678 *	3.182 **	14.466 ***	9.711 ***	6.985 ***	41.621 ***	26.546 ***	18.868 ***
	(1.505)	(1.417)	(1.422)	(1.661	(1.862	(1.905)	(5.526)	(6.196)	(5.937)
Firm size	-0.682 ***	-0.223	-0.275	-1.017 ***	-0.451 *	-0.052	-2.937 ***	-1.287	0.125
	(0.224)	(0.206)	(0.205)	(0.246	(0.272	(0.268)	(0.821)	(0.908)	(0.847)
Firm age	-0.018	-0.012	-0.010	-0.030	-0.020	-0.030	-0.103	-0.050	-0.112 *
	(0.024)	(0.018)	(0.018)	(0.025	(0.023	(0.021)	(0.084)	(0.078)	(0.068)
Book to market	-0.056	-0.428	-0.241	-2.949 ***	-1.603	-0.998	-9.146 ***	-3.917	-1.595
	(0.228)	(0.841)	(0.850)	(1.023	(1.198	(1.111)	(3.419)	(3.990)	(3.523)
Growth rate	0.706	1.128	1.121	-1.348	-0.188	-2.226	-2.898	-0.487	-5.766
	(1.987)	(1.460)	(1.470)	(2.148	(1.973	(2.028)	(7.178)	(6.564)	(6.391)
Severity of event		16.709 ***	13.865 ***		22.681 ***	15.303 *		72.924 ***	3.382
		(3.918)	(5.205)		(5.665	(7.889)		(19.124)	(27.664)
Inventory slack		0.318	0.439		-2.128 **	-1.820 **		-8.249 ***	-7.088 ***
		(0.641)	(0.726)		(0.898	(0.894)		(3.007)	(2.828)
Supply chain slack		-0.062	-0.113		0.121	0.304		0.523	1.373
		(0.066)	(0.104)		(0.126	(0.371)		(0.421)	(1.056)
Capacity slack		-1.094 *	-1.330 **		-0.827	-0.904		-0.572	-0.284
		(0.596)	(0.609)		(0.893	(0.831)		(2.939)	(2.602)
Business scope		0.233	0.248		-1.363	-1.917		-5.585	-8.003 **
		(0.996)	(1.001)		(1.372	(1.270)		(4.614)	(4.065)
Geographic scope		0.316	0.170		-3.359 **	-3.080 **		-11.211 **	-12.548 ***
		(1.178)	(1.208)		(1.602	(1.500)		(5.281)	(4.691)
Severity of event × Inventory slack			-0.142			-43.729 **			-130.318 **
			(10.398)			(18.948)			(58.561)
Severity of event × Supply chain slack			-1.685			13.390			56.636
			(2.572)			(8.613)			(36.618)
Severity of event × Capacity slack			-8.888			-23.634 **			-59.012
			(8.020)			(11.847)			(37.310)
Severity of event × Business scope			-29.820 **			-51.762 **			-158.390 **
			(12.341)			(21.457)			(72.634)
Severity of event × Geographic scope			-3.890			37.911			-61.199
			(15.758)			(33.153)			(105.671)
Model F statistic	4.197 ***	2.779 ***	2.466 ***	11.742 ***	7.534 ***	7.939 ***	9.496 ***	7.229 ***	9.166 ***
N	146	133	133	122	113	113	122	113	113
R^2	0.106	0.186	0.240	0.286	0.425	0.551	0.245	0.415	0.586
Adjusted R^2	0.081	0.119	0.143	0.262	0.368	0.482	0.219	0.357	0.522
ΔR^2		0.080	0.054		0.139	0.126		0.170	0.171

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

Table 3.5. Results of regression analyses using performance-size-matched method.

	Initial Loss (×100)			Maximum Loss (×100)			Total Loss (×100)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	2.552	0.173	0.430	17.219 ***	7.749 ***	6.398 ***	46.958 ***	21.750 ***	15.299 ***
	(1.755)	(1.269)	(1.276)	(2.217)	(1.809)	(1.823)	(6.741)	(6.109)	(5.769)
Firm size	-0.139	0.010	-0.040	-1.132 ***	-0.154	0.027	-2.909 ***	-0.551	0.311
	(0.259)	(0.186)	(0.184)	(0.327)	(0.262)	(0.255)	(0.995)	(0.884)	(0.807)
Firm age	-0.030	-0.015	-0.012	-0.039	-0.031	-0.035	-0.145	-0.100	-0.124 *
	(0.027)	(0.016)	(0.016)	(0.034)	(0.023)	(0.021)	(0.102)	(0.077)	(0.068)
Book to market	0.300	0.033	0.141	-7.325 ***	-1.281	-0.730	-20.901 ***	-3.708	-1.011
	(0.254)	(0.706)	(0.728)	(1.392)	(1.184)	(1.136)	(4.233)	(3.997)	(3.595)
Growth rate	-0.244	1.315	1.486	1.895	0.333	-1.070	5.127	1.002	-4.373
	(2.317)	(1.326)	(1.337)	(2.972)	(1.958)	(2.002)	(9.035)	(6.613)	(6.335)
Severity of event		14.322 ***	9.317 ***		17.240 ***	9.150		69.818 ***	41.171 *
		(3.099)	(4.669)		(5.521)	(7.900)		(18.643)	(24.998)
Inventory slack		-0.279	-0.391		-2.568 ***	-2.625 ***		-8.291 ***	-7.717 ***
		(0.569)	(0.642)		(0.840)	(0.869)		(2.836)	(2.751)
Supply chain slack		0.044	-0.030		0.042	0.244		0.220	1.366
		(0.078)	(0.092)		(0.085)	(0.211)		(0.287)	(1.096)
Capacity slack		-0.722	-1.107 *		-0.162	-0.855		0.767	-1.631
		(0.620)	(0.636)		(0.783)	(0.760)		(2.643)	(2.405)
Business scope		0.212	0.220		-1.733	-2.033		-5.559	-6.927 *
		(0.882)	(0.875)		(1.318)	(1.263)		(4.450)	(3.997)
Geographic scope		0.465	0.798		-4.408 ***	-4.002 ***		-12.159 **	-10.424 **
		(1.060)	(1.067)		(1.497)	(1.446)		(5.054)	(4.574)
Severity of event ×			-3.674			-34.030 **			-130.765 **
Inventory slack			(9.007)			(17.430)			(55.152)
Severity of event ×			-3.342 *			8.171			46.608
Supply chain slack			(1.769)			(6.511)			(31.209)
Severity of event ×			0.224			-19.739 *			-43.834
Capacity slack			(6.485)			(11.551)			(36.549)
Severity of event ×			-26.372 ***			-45.597 **			-152.810 **
Business scope			(10.844)			(21.456)			(67.890)
Severity of event ×			-5.948			11.201			25.037
Geographic scope			(12.363)			(30.852)			(97.624)
Model F statistic	1.105	3.129 ***	2.929 ***	15.175 ***	7.107 ***	6.701 ***	13.009 ***	6.712 ***	8.225 ***
N	142	130	130	126	117	117	126	117	117
R^2	0.031	0.208	0.278	0.334	0.401	0.499	0.301	0.388	0.550
Adjusted R^2	0.003	0.142	0.183	0.312	0.345	0.424	0.278	0.330	0.483
ΔR^2		0.177	0.070		0.067	0.098		0.087	0.162

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

Table 3.6. Results of regression analyses using operating income.

	Initial Loss	Maximum Loss	Total Loss
Intercept	2.287	-3.700	-13.952
	(2.193)	(5.317)	(17.502)
Firm size	-0.216	1.569 **	4.483 *
	(0.317)	(0.720)	(2.414)
Firm age	-0.003	0.083	0.199
	(0.028)	(0.061)	(0.208)
Book to market	0.223	-9.785 ***	-7.611
	(1.395)	(3.602)	(10.156)
Growth rate	1.243	5.033	8.074
	(2.729)	(5.807)	(20.030)
Severity of event	6.541	42.669 *	72.146
	(10.045)	(24.385)	(83.550)
Inventory slack	-2.082	-2.415	-9.894
	(1.216)	(2.530)	(8.654)
Supply chain slack	-0.405 ***	-0.498	-1.100
	(0.148)	(0.344)	(1.177)
Capacity slack	-3.019 ***	-6.601 ***	-22.224 ***
	(0.921)	(2.338)	(7.925)
Business scope	-1.273	-1.097	-14.575
	(1.668)	(3.703)	(12.580)
Geographic scope	0.975	-7.648 *	-16.701 **
	(1.879)	(4.659)	(10.102)
Severity of event ×	-15.059	-15.568 **	-63.412 ***
Inventory slack	(20.281)	(5.633)	(12.563)
Severity of event ×	-10.864 ***	-17.601	-53.921
Supply chain slack	(3.416)	(18.878)	(42.011)
Severity of event ×	-52.770 ***	-72.445 **	-222.556 *
Capacity slack	(15.428)	(33.956)	(117.034)
Severity of event ×	-59.524 **	-168.786 **	-402.558 *
Business scope	(30.739)	(73.001)	(237.483)
Severity of event ×	39.904	178.605	490.744
Geographic scope	(27.038)	(117.531)	(364.740)
Model F statistic	1.796 **	2.524 ***	1.906 **
R^2	0.200	0.313	0.249
Adjusted R^2	0.088	0.189	0.119

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

3.7. Discussion

It is well recognized that supply chain disruptions are very common in the current business environment (Business Continuity Institute, 2015) and that they have significant negative impacts on disrupted firms' operating performance and stock returns (Hendricks & Singhal, 2003, 2005a, 2005b). Understanding that it is impossible to avoid all possible disruptive events (Ivanov, Pavlov, Dolgui, Pavlov, & Sokolov, 2016), different strategies have been recommended to mitigate the negative impacts of supply chain disruptions and to improve recovery process after disruptions happen (Tomlin, 2006). The current study seeks to investigate how and when two recommended types of strategies (i.e. maintaining operational slack and broadening operational scope) reduce the negative impacts of supply chain disruptions on firms' performance. In the following sections, we first summarize our theoretical contributions and managerial implications, and then provide the limitations of this study and possible future directions.

Table 3.7. Results of regression analyses using SOA.

	Initial Loss (×100)	Maximum Loss (×100)	Total Loss (×100)
Intercept	6.917	16.106 ***	55.433 ***
	8.910	5.677	(12.068)
Firm size	-1.137	-0.033	-2.085
	1.298	0.813	(1.726)
Firm age	-0.021	-0.075	-0.101
	0.112	0.067	(0.141)
Book to market	-2.603	0.563	7.864
	5.604	3.436	(7.362)
Growth rate	5.282	0.468	-13.645
	9.250	6.272	(13.317)
Severity of event	44.383	57.354 **	53.837
	34.895	25.393	(52.963)
Inventory slack	0.003	-3.029	-3.542
	4.274	2.692	(5.689)
Supply chain slack	-2.016 ***	-0.096	-0.562
	0.522	0.400	(0.873)
Capacity slack	-2.603	2.955	8.753
	3.838	2.543	(5.426)
Business scope	7.889	-6.394	-9.377
	6.397	3.922	(8.225)
Geographic scope	3.460	-5.996	-25.109 ***
	7.439	1.772 ***	(9.573)
Severity of event × Inventory slack	-65.855	-175.026 **	-279.350 *
	71.692	76.388	(160.648)
Severity of event × Supply chain slack	-63.768 ***	-15.423	81.287
	17.300	14.231	(152.257)
Severity of event × Capacity slack	22.353	-45.383	-186.307 *
	69.868	50.579	(106.938)
Severity of event × Business scope	-145.365	-142.182 *	-75.174 **
	87.055 *	74.204	(30.438)
Severity of event × Geographic scope	141.902	230.129	328.066
	133.919	203.674	(217.030)
Model F statistic	1.54 *	2.599 ***	3.964 ***
R^2	0.167	0.300	0.385
Adjusted R^2	0.059	0.185	0.288

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

3.7.1. Theoretical contributions

Our contributions to the literature are threefold:

First of all, this study investigates the roles of operational slack (inventory slack, supply chain slack, and capacity slack) and operational scope (business scope and geographic scope) in reducing the impacts of supply chain disruptions on firms' financial performance (measured by return on assets and operating income). Although Hendricks et al. (2009) evaluate the impacts of these same strategies on the stock market reaction after a supply chain disruption, our work is the first to study the strategies with respect to the firms' financial performance after such disruptions have occurred. Our study demonstrates that the potential benefits of operational slack in terms of inventory slack and operational scope for reducing impacts on firms' ROA, differ from those associated with observing the short-term stock market reactions.

Hendricks et al. (2009) find that inventory slack has no significant effect on the stock market reaction after disruptions. Our results show that operational slack negatively moderates the relationship between the severity of a supply chain disruption and the maximum loss and the total loss. In addition, Hendricks et al. (2009, p. 233) report that "the extent of business diversification has no significant effect on the stock market reaction", however our study shows that business scope does have a significant negative effect on initial loss, maximum loss, and total loss when the severity of a disruption is high. This aligns well with the contingent resource-based view of the firm in the case of both maximum loss and total loss, because the impact of business scope for a less severe disruption was insignificant for both of these measures. The results for the initial loss measure, however, show that business scope actually leads to a significant increase in loss for less severe disruptions. This indicates that it may be the added complexity associated with more business diversity that leads to negative impacts on performance at the very beginning of a disruption.

Hendricks et al. (2009) also report that firms with higher geographic scope experience a more negative stock market reaction. However, our results show that firms with higher geographic scope experience less maximum loss and less total loss after supply chain disruptions than do firms with less geographic scope to their operations. In this case, the behavior is not conditional on the severity of the disruption, demonstrating that there is value in having broader geographic scope regardless of the disruption's severity. Because geographic scope also has no significant effect on the initial loss, this implies that it may take time for the benefits of geographic scope to be operationalized after the initial impacts of a disruption are felt.

In order to better evaluate the impacts of supply chain disruptions on firms' performance, our second contribution to the literature is to consider three new metrics drawn from the disruption profile introduced by Sheffi and Rice (2005) and the system resilience literature (Bruneau et al. 2003; Zobel 2011; Zobel and Khansa 2012, 2014; Melnyk et al. 2014). These metrics include the initial loss, the maximum loss, and the total loss over time. The first two metrics, initial loss and maximum loss, capture different aspects of the loss of performance due to a supply chain disruption, whereas the measure of total loss over time encompasses the overall impact of the supply chain disruption on the firm's performance. 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 firms by reducing the negative impacts of disruptions in different ways. Our results show, for example, that although inventory slack and geographic scope reduce the maximum loss and the total loss over time, they may not also have such a negative effect on the initial loss. To the best of our knowledge, this is the first time that such a combination of metrics has been employed to empirically study the impact of supply chain disruptions on firms' performance.

Third, our study contributes more generally to the supply chain disruption management literature by providing insights about the conditions that influence the potential benefits of operational slack and operational scope. Using the contingent RBV, this study shows that although operational slack and operational scope may reduce the impacts of supply chain disruptions, some of these effects are contingent upon the severity of those disruptions. More specifically, our results indicate that the severity of a disruption has a great effect on the potential benefits of inventory slack, supply chain slack, capacity slack, and business scope.

3.7.2. Managerial implications

This study also 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 have differing effects on firms' different abilities to face supply chain disruptions. In particular, we find no significant relationship between inventory slack and initial loss of performance. This surprising result can be related to Hendricks and Singhal's (2005b) observation that supply chain disruptions are positively associated with firms' level of inventory at the first quarter of disruption and therefore excess inventory slack may not be beneficial in this case. The inventory slack, however, does have a negative effect on maximum loss and total loss over time when the severity of the disruption is high. In contrast to inventory slack, supply chain slack has a significant negative effect on the initial loss, but only when the severity of the disruption is high, and it has no effect on the maximum loss or the total loss. Capacity slack, on the other hand, has a significant negative impact on the initial loss regardless of the severity of the disruption, and it has a significant negative impact on maximum loss, but only for more severe disruptions. It also has no effect on the total loss experienced by the firm. Taken together, these results imply that in order to decrease the impacts of a supply chain disruption on a firm's performance, managers should invest in supply chain slack and capacity slack if they wish to reduce their initial loss, they should invest in inventory slack and capacity slack if they wish to lessen their maximum loss, and they should invest in inventory slack if they wish to reduce their total loss over time. Decisions about such investments obviously need to take factors such as their relative cost and their impacts on operational efficiency into account before they are implemented.

As discussed above, the results of the study also show that broadening business scope can be a good strategy to allow a manager to reduce initial loss, maximum loss, and total loss over time, in the case of high severity disruptions. Furthermore, although geographic scope has no significant effect on the initial loss experienced by firms after disruptions, it directly decreases the maximum loss and the total loss of firms after such a disruption occurs. This implies that even though geographic scope may not have benefits in the short term, managers should consider increasing geographic scope as a strategy that can improve firms' overall resiliency to supply chain disruptions.

3.7.3. Limitations and further research

This paper has several limitations that it is important to acknowledge. First of all, it only considers U.S. publicly traded manufacturing firms in the process of collecting data. Because supply chain disruptions and resilience strategies may have different effects on firms' performance after supply chain disruptions that impact other industry sectors and other countries, we are not able to generalize our inferences about the effectiveness of strategies against supply chain disruptions to firms outside of this specific scope. Next, supply chain disruption announcements are collected through searching articles from PR Newswire and Business Wire. These are different news agencies than the Wall Street Journal and Dow Jones News Service, which were previously used by Hendricks and Singhal (2003 and 2005b). There are two reasons why we used different sources of news in this study. First of all, the Wall Street Journal is a tertiary source of news and publishes only important news from their perspective (Schmidt & Raman, 2012; Zsidisin, Petkova, & Dam, 2016). Secondly, the Dow Jones News Service merged into the Dow Jones Institutional News in 2013. After searching for the same terms used in our study in the Dow Jones News Service and the Dow Jones Institutional News, we found fewer relevant news articles than what we found from our chosen news sources. In addition, the relevant articles were scanned manually, which restricted our ability to broaden the scope of the data collection. If data mining techniques were used to find disruption announcements by firms within a much larger number of news agencies, this would potentially save time and provide a higher number of disruption announcements.

This study calculates the quarter of the supply chain disruption based on the public announcement date of the disruption at the firm level. Although, based on Section 409 of the Sarbanes-Oxley Act (SOX), our sample firms are required to disclose any significant unplanned event that may change their financial condition or their operations on an urgent basis (SOX, 2002), we cannot be certain that announced disruptions always take place exactly in the quarter of the announcement. The time frame of our analyses is also a potential limitation. We only consider the performance of firms over the first two years after the supply chain disruptions occurred; however, it may take more than two years for a firm to recover from a disruption, or the firm simply may not recover at all. Although the total loss over time is a meaningful measure even if the firm doesn't recover, being able to assess the actual recovery time for each firm could provide additional valuable information for analysis.

Finally, this study only evaluates the interaction between the different operational strategies and the severity of the disruptive events; however, these strategies may also exhibit significant interactions between them. An important avenue for future research would therefore be to extend the findings of this study by examining the possible interactions between the different resilience strategies. Other recommended strategies could also be evaluated with respect to their ability to decrease the impacts of supply chain disruptions on firms, as reflected in the three metrics developed in this paper. For example, implementing principles of business continuity management is another recommended strategy from the literature that it would be interesting to study in this context. Future research may also consider evaluating the impacts of disruptions on firm performance of firms by using the new metrics in other disruption contexts, such as in the case of product recalls, or perhaps even adapting them to the context of positive disruptions due to product innovations.

Chapter 4: Impacts of Supply Chain Disruptions on Firms' Performance: Role of Disruptions' Origin and Past Experience

4.1. Introduction

Supply chain disruptions, which are unplanned and unexpected events that disrupt the normal flow of materials and goods within a firm's supply chains (Craighead et al., 2007), can cause significant financial losses to firms in both the short-run and the long-run (Hendricks & Singhal, 2003, 2005a, 2005b, 2009). Stories of supply chain disruption events and their negative effects on firms frequently become headlines of business news. For example, in a recent event, Chipotle Mexican Grill Inc., known for its organic and locally sourced ingredients, reported a 44% decline in its 2015 fourth quarter profits after a disruption in its supply chain (Dulaney, 2016). As reported in the media, "*Growing concerns about* ***the company's supply chain*** (emphasis added) ... *dealt a blow to Chipotle's stock price, which dipped to $558.16* ... [on 14 Dec. 2015] *from a 52-week high of $758.61*" (Nordrum, 2015).

Over the past several years, scholars have studied different characteristics of firms, supply chains, and disruptive events in order to gain more and better insights into the relationship between supply chain disruptions and their negative impacts on firms' performance. For example, Hendricks et al. (2009) find that more geographically diversified firms experience a greater negative stock market reaction after supply chain disruptions, even though the extent of the firms' business diversification does not also have a significant impact on the stock market reaction. More recently, Bode and Wagner (2015) show that supply chain complexity drivers - horizontal, vertical, and spatial complexity - are positively associated with the frequency of supply chain disruptions.

In this study, following calls to work with secondary and archival data (Calantone & Vickery, 2010; Roth, 2007), we aim to provide insights about the effects of two other important factors that have received a little attention in previous studies on firms' performance after supply chain disruptions: the origin of the disruptions and the experience of firms with similar disruptive events in the past. The origin of a supply chain disruption event can be either inside or outside of a firm (Bode, Kemmerling, & Wagner, 2013; Schmidt & Raman, 2012; Wagner & Bode, 2008). An internal disruption refers to a disruptive event that happens inside the firm's boundaries, such as a strike by the firm's workers or a machine breakdown. On the contrary, an external disruption refers to a disruptive event that happens outside the firm's boundaries, such as a supplier failure. Since firms have more control over events inside their boundaries, they may respond differently to internal disruptions than they do to external disruptions. At the same time, whether an event is internal or external, we might expect that firms that have experienced a similar disruptive event in the past may be better prepared to face such a disruption again.

To clarify the different ways in which both the disruptions' origins and the firms' experience may impact the firms' performance, we explicitly consider four different output measures to characterize the supply chains' response to the disruptions: the initial performance loss due to the disruption, the maximum amount of loss due to the disruption, the subsequent amount of time needed to recover to an appropriate level of performance, and the overall amount of loss that is suffered over time. Using these four measures as the basis for comparison, we then evaluate the performance of 262 firms that experienced a supply chain disruption between 2005 and 2014. The results of our analyses indicate that both the origin of the supply chain disruptions and the firms' past experience play a significant role in the extent of supply chain disruptions' negative impacts. More specifically, we find that when firms have no experience with a similar event in the past, internal disruptions lead to a higher level of initial loss, a higher level of maximum loss, and more total loss over time than do external disruptions. We also show that past experience is associated with lower recovery time in the case of both internal disruptions. Firms with past experience also encounter less initial loss and total loss over time when disruptions are internal to firms, but past experience may not decrease initial loss and total loss over time in the case of external disruptions. Finally, similar to the results of previous studies about the impacts of supply chain disruptions, we find that larger firms experience fewer negative impacts overall from supply chain disruptions than do smaller firms.

The rest of this paper is organized as follows. Section 2 reviews related research about the impacts of supply chain disruptions on firms' performance, and it introduces the formal hypotheses about the effects of the origin of disruption events and the past experience of firms on post-disruption firm performance. Section 3 outlines the data collection procedures, Section 4 describes the methodology used to conduct the results, and Section 5 provides the results. Further analyses are provided in Section 6. Finally, Section 7 discusses the findings and provides future research directions.

4.2. Literature review and hypotheses

4.2.1. Negative impacts of supply chain disruptions on firm's performance

Supply chain disruptions are significantly associated with an abnormal decrease in shareholder value both in the short-run (Hendricks & Singhal, 2003; Schmidt & Raman, 2012; Zsidisin et al., 2016) and in the long-run (Hendricks & Singhal, 2005a). Hendricks and Singhal (2005a), however, also show that disruptions are associated with a significant decrease in profitability measures (operating income, return on sales, and return on assets) and net sales, as well as with negative assets and inventory performance, and with an increase in costs. They further observe that disrupted firms may not recover to their previous operating performance level even two years after a disruption.

Sheffi and Rice (2005) discuss the concept of a "disruption profile" to broadly describe and quantify a disruption's varying effects on firm performance over time. The disruption profile characterizes not only the impact of a disruption, in terms of decreased performance, but also the time needed for the firm to recover its pre-disruption performance levels. Because some risk management activities, such as maintaining safety stock, can help to address immediate shortages in supply, whereas others, such as contracting with alternative suppliers, can help to speed up recovery, it can be important to be able to understand the extent to which each aspect of a disruption is likely to affect a supply chain. With this in mind, one of the contributions of our study will be to assess performance not only with respect to the impact of a disruption but also with respect to the firm's recovery time, and thus to provide a broader view of the resulting system's behavior. In particular, this study adopts a set of four related metrics identified by Sheffi and Rice (2005) and Melnyk et al. (2014) for profiling the impacts of a disruption on firms' performance. These metrics include the initial amount of performance loss due to the disruption (initial loss), the maximum amount of loss due to the disruption (maximum loss), the length of time that it takes the supply chain to recover its pre-disruption performance level (recovery time), and the total amount of loss suffered by the supply chain over time (total loss over time).

4.2.2. Supply chain disruption events' origin

Although both internal and external events can be significant in terms of their impacts on firms' performance (Bode et al., 2013), internal disruptions are shown to have more of a negative impact on the stock market than do external disruptions (DuHadway, Carnovale, & Hazen, 2017; Schmidt & Raman, 2012). To explain the higher impact of internal disruptions, Schmidt and Raman (2012) argue that internal disruptions signal to the market that something is wrong with the internal control mechanism of the disrupted firm, and therefore that the systematic risk of the firm is higher. DuHadway et al. (2017) further argue that internal disruptions are more likely to be isolated to the firm and not experienced by the firm's competitors, whereas an external disruption may also impact those competitors that share elements of their supply chains. They also argue that internal disruptions will send a strong negative signal to key stakeholders such as suppliers and customers, leading to less negotiation power and a lower level of demand. We thus expect, based on these assertions, that internal disruptions will have a higher negative impact on firms' performance and that they will result in longer recovery times than external disruptions. This argument is summarized in the following hypotheses:

H1a. *Internal disruptions are associated with a higher initial loss than external disruptions.*

H1b. *Internal disruptions are associated with a higher maximum loss than external disruptions.*

H1c. *Internal disruptions are associated with a longer recovery time than external disruptions.*

H1d. *Internal disruptions are associated with a higher total loss over time than external disruptions.*

4.2.3. Past experience

Organizational learning, or the continuous process of improving operations through better knowledge and understanding (Fiol & Lyles, 1985), is key to achieving competitive advantage and continued survival (Agrawal & Muthulingam, 2015; Hoang & Rothaermel, 2010; March, 1991; Pucik, 1988; Sinkula, Baker, & Noordewier, 1997; Tippins & Sohi, 2003). Previous research identified knowledge acquisition as one of the main steps associated with organizational learning (Huber, 1991; Hult, Ketchen, & Slater, 2004; Pentland, 1995). Knowledge acquisition is the process used by organizations to obtain knowledge (Huber, 1991) and it can occur through three different mechanisms: experiential knowledge acquisition, vicarious knowledge acquisition, and contact knowledge acquisition (Mena & Chabowski, 2015). In experiential knowledge acquisition, which is the focus of this research effort, organizations obtain information or knowledge through their own experience, whether intentionally or unintentionally, such as by going through the process of developing a new product or recalling an existing product (Huber, 1991; Levinthal & March, 1993; Mena & Chabowski, 2015).

Research on organizational learning theory shows that firms learn from their own past failures (Chuang & Baum, 2003; J.-Y. Kim, Kim, & Miner, 2009). In particular, Raspin (2011) finds that firms learn more effectively from failures than they do from successes. In the context of supply chain disruptions, the theory of organizational learning through experiential knowledge acquisition suggests that firms that experienced a disruption event will have more knowledge about that event. They are thus more likely to have documented rules and routines to deal with similar events, given their past experiences (C. Bode, Wagner, Petersen, & Ellram, 2011; Elliott, Smith, & McGuinnes, 2000; Green & Welsh, 1988).

On the other hand, firms with no prior related experience lack relevant knowledge and can face difficulties in response to the disruption events (Bode et al. 2011). These firms may suffer from "it couldn't happen here" syndrome (Elliott et al., 2000), which consequently prevents them from using the opportunity to learn from near-miss events and disruptions that happen to other firms (Dillon & Tinsley, 2008; Elliott et al., 2000). We would therefore expect firms with relevant past experience to have a greater ability to absorb the negative impacts of similar disruption events and to recover more quickly after such disruptions. In other words, we would expect them to suffer fewer negative impacts over time as a result of the disruptions. The second set of hypotheses formalizes this expectation about the effect of past experience on the impact that disruptions have on firms' performance:

H2a. *Firms with past experience with a given type of supply chain disruption will experience less initial loss due to a similar event than will firms without such past experience.*

H2b. *Firms with past experience with a given type of supply chain disruption will experience less maximum loss due to a similar event than will firms without such past experience.*

H2c. *Firms with past experience with a given type of supply chain disruption will experience a shorter recovery time due to a similar event than will firms without such past experience.*

H2d. *Firms with past experience with a given type of supply chain disruption will experience less total loss over time due to a similar event than will firms without such past experience.*

4.2.4. Interaction of past experience and origin of events

Past experience of a firm with a supply chain disruption event provides relevant knowledge about the event and the available options to restore stability (Bode et al., 2011; Elliott et al., 2000). However, the new knowledge needs to be integrated into firms' capabilities that allow execution of the new knowledge (Hoang & Rothaermel, 2010). Although past experience with both internal and external disruptions provides relevant knowledge about the events and will be valuable in case of similar types of disruption, one would expect a firm to have more authority to respond to events which are internal to the firm, and therefore to have higher capability for executing the knowledge obtained from those past experiences. We thus would expect past experience to be more effective when the events are internal. This expectation is formalized in the third set of hypotheses:

H3a. *The effect of past experience on reducing the initial loss due to supply chain disruptions will be higher for internal disruptions than for external disruptions.*

H3b. *The effect of past experience on reducing the maximum loss due to supply chain disruptions will be higher for internal disruptions than for external disruptions.*

H3c. *The effect of past experience on reducing the recovery time after supply chain disruptions will be higher for internal disruptions than for external disruptions.*

H3d. *The effect of past experience on reducing the total loss over time due to supply chain disruptions will be higher for internal disruptions than for external disruptions.*

Given these three sets of hypotheses, Figure 4.1 presents the relationships of interest in this study.

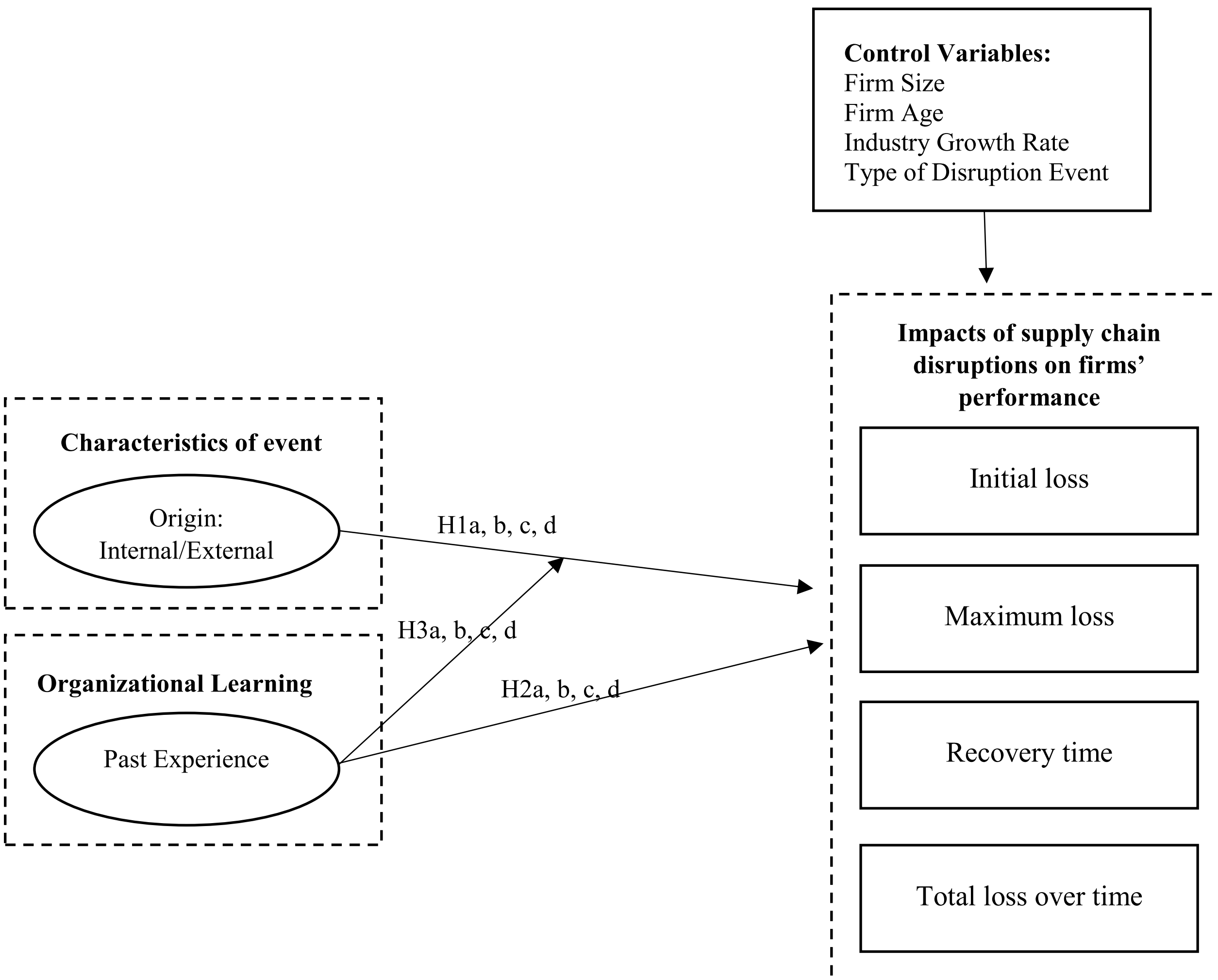

Figure 4.1. Research model

4.3. Data collection and sample description

In this study, we used our dataset developed in Chapter 2 (please see Section 2.3 for more information). We were not able to find the source of disruption for a number of the announcements. This reduces the number of our sample firms to 262. Table 4.1 presents the distribution of sample firms across industry sectors, where the industry sector groups are determined according to the firms' Standard Industrial Classification (SIC) codes. Table 4.1 shows that the sample firms include all types of industry sectors, except the public administration sector. The manufacturing sector, with 47% of the total number of firms, the transportation and utilities (transportation, communications, electric, gas and sanitary service) sector with 19%, and the mining sector with 15% of the firms are the most common industry sectors between the sample firms.

Table 4.1. Distribution of the sample firms per industry

Industry sector	Range of SIC code	Number of firms	Percentage
Agriculture, Forestry and Fishing	0100-0999	2	0.76
Mining	1000-1499	39	14.89
Construction	1500-1799	2	0.76
Manufacturing	2000-3999	124	47.33
Transportation, Communications, Electric, Gas and Sanitary service	4000-4999	49	18.70
Wholesale Trade	5000-5199	8	3.05
Retail Trade	5200-5999	10	3.82
Finance, Insurance and Real Estate	6000-6799	3	1.15
Services	7000-8999	25	9.54
Public Administration	9100-9729	0	0.00
Total		262	100.00

4.4. Measures and descriptive statistics

4.4.1. Dependent variables: impact of supply chain disruptions on firms' performance

As in previous empirical studies (Gligor, Esmark, & Holcomb, 2015; Kovach et al., 2015; Wagner, Grosse-Ruyken, & Erhun, 2012), we choose return on assets (ROA) as a proxy for firm performance. To measure the impact of supply chain disruptions on the sample firms' performance, we matched each sample firm to a set of control firms using three different matching methods developed by Hendricks and Singhal (2008): the performance-industry-matched method, the performance-industry-size-matched method, and the performance-size-matched method. After finding the set of control firms, using Hendricks and Singhal's (2008) approach, we calculated the abnormal performance of each sample firm at quarter t (Δ_t) by using the difference between its actual ROA and the expected ROA in that quarter:

$$\Delta_t = \textit{Actual ROA of sample firm at quarter t - expected ROA of sample firm at quarter t} \qquad (4\text{-}1)$$

Note that the calendar quarters of all firms are measured relative to their disruption event. Thus quarters -4, 0, and 4 present four quarters before the announcement quarter, the quarter of the announcement, and four quarters after the announcement quarter, accordingly.

The expected ROA of the sample firm at quarter *t*, where $0 \leq t < 4$, is estimated from the firms's 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*. Similarly, the expected ROA of the sample firm at quarter *t*, where $4 \leq t \leq 8$, 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 performance was less than its expected performance, and thus that it experienced a relative loss at quarter *t*. Using formula (1), the abnormal performance of each sample firm is calculated from quarter zero (the quarter of the supply chain disruption announcement) to quarter eight (eight quarters after the quarter of supply chain disruption announcement). Since ROA is a ratio measurement, it allows us to compare the degree of disruptions' impacts across firms with different sizes. For example, consider a firm with total assets of $1,000 and net income of $500 and a second firm with total assets of 1 million dollars and net income of $500,000. Now, assume that a supply chain disruption decreases net income of the first firm by $250, and the second firm by $1,000. Although, the amount of net decrease in income for the first firm is less than that for the second firm, we know that the degree of the disruption's impact on the performance of the first firm is much higher than on the second firm (the disruption has almost no impact on the second firm). Considering ROA as the performance unit, however, the impact of the disruption on the firms using formula (1) is -25% and -1%, respectively. Therefore, using ROA as our performance unit, we are able to compare the impact on disruptions across firms with different sizes.

As mentioned before, in order to broadly characterize and quantify the different types of impacts that a disruption can have on a firm's performance, we adopt a set of four related metrics identified by Sheffi and Rice (2005) and Melnyk et al. (2014) in profiling the impacts of a disruption on firms' performance. These metrics include the initial loss, the maximum loss, the recovery time, and the total loss over time.

The initial loss is measured as the amount of loss at the quarter of the disruption announcement:

$$L_0 = -\Delta_0 \tag{4-2}$$

Considering that Δ_0 will be negative if the actual ROA is less than expected at quarter zero, a larger positive value of L_0 indicates more initial loss. Maximum loss is the maximum amount of loss between the quarter of the announcement of a disruption and eight quarters (our time frame in this paper) after that announcement:

$$L_{max} = \max_{t=0\ to\ 8}\{-\Delta_t\} = \max_{t=0\ to\ 8}\{L_t\} \tag{4-3}$$

The total loss over time is then calculated as the sum of the positive loss values over the first two years after a supply chain disruption:

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

where $L_t = -\Delta_t$. Because each individual loss value is calculated relative to the performance of a matching set of non-disrupted firms, this cumulative loss value represents the total shortfall by the disrupted firm over the given two year time interval.

The time to recovery is more difficult to measure than other metrics, since a disrupted firm may not return exactly to its previous performance level (or it may not recover at all). In our study, recovery time is calculated by finding the last quarter (within the two year time window) in which the sample firm has an L_t value greater than some small $\varepsilon > 0$ (i.e. the last quarter in which the amount loss is not close to zero). We then take the next quarter after that to represent the time of recovery and calculate the recovery time (in quarters) accordingly. In our analyses below, we use $\varepsilon = 0.01$ for this calculation. Finally, all sample firms with a recovery time of nine are removed from the analysis, since this indicates that the firm did not recover during the two year post-disruption period.

4.4.2. Independent variables

4.4.2.1. Origin of disruption

While collecting the supply chain disruptions, we reviewed the announcements to find the origin of each disruption event. When the origin was not clearly indicated we eliminated the disruption announcement from our sample. The disruption origin was then treated as a dummy variable (external disruptions=0, internal disruptions=1) in our analyses.

4.4.2.2. Past experience

For each sample firm in our dataset, we carefully searched the entire Factiva database, including firms' quarterly and annual reports, to find news related to the firm's similar past experience. For example, if a firm was disrupted by Hurricane Katrina, we searched the Factiva database to find related news for the firm and similar events with keywords such as: hurricane, tornado, typhoon, storm, and flood. We limited our search from the date of the supply chain disruption announcement back to five years before the announcement. Any similar experiences older than five years are potentially subject to loss of organizational memory. The dummy variable for past experience was then set to 1 if a given sample had a similar past experience, and 0 otherwise.

4.4.2.3. Control variables

Along with the origin of a supply chain disruption (internal or external), the type of disruption event also may have a significant effect on the impact of a supply chain disruption (Stecke & Kumar, 2009). In an attempt to assess this, we divided the supply chain disruption events into three categories proposed by Stecke and Kumar (2009): natural disaster (such as severe weather, floods, and wild fire), accident (unintentional man-made catastrophes, such as equipment breakdown), and intentional (such as labor strikes, and government regulations). When a sample firms did not explain the type of disruption in the announcement, we searched for related information in the news after the announcement in the Factiva database. Even with this additional effort, we were unable to find the type of disruption for a number of supply chain announcements and these were eliminated from the final sample. We controlled for the impact of the type of disruption by including two dummy binary variables: accidental disruption and intentional disruption, with natural disaster representing the baseline (accidental disruption = 0 and intentional disruption = 0).

It is important to consider that supply chain disruptions may have higher impacts on firms that operate in highly intense industries (Hendricks & Singhal, 2005b). We therefore also controlled for industry intensity by considering industry growth rate, calculated as the average sales growth rate of firms with the same two digit SIC code as the sample firm. We further controlled for two additional factors: age and size of firms. Because older firms may have more general knowledge and experience, this might help them to reduce negative impacts of supply chain disruptions. Age of each firm is calculated as the difference between the year of the disruption announcement and the first year that the firm is listed in COMPUSTAT. Similarly, larger firms probably have more resources to face unplanned events and therefore they likely have a greater ability to absorb the negative impacts of supply chain disruptions and to recover after the disruptions. We thus controlled for the size of firms by considering the natural logarithm of the number of employees one year prior to the year of a disruption announcement.

4.4.3. Descriptive statistics

Zero-order correlations, means, and standard deviations for the dependent, independent, and control variables are reported in Table 4.2. The dependent variables reported in Table 4.2 are calculated using the performance-industry-matched method. The average initial loss of firms, calculated based on the performance-industry-matched method, is 1.18 percent, and is significantly greater than zero ($p\text{-value} \leq 0.01$), which indicates that supply chain disruptions have significant negative impacts on firms' performance. Average initial loss calculated from other two matching methods are also significantly greater than zero ($p\text{-values} \leq 0.05$). Similar to initial loss, recovery time, and total loss calculated from all three matching methods are significantly greater than zero ($p\text{-value} \leq 0.01$).

Table 4.2. Means, standard deviations, and correlations

Variable*		1	2	3	4	5	6	7	8	9	10	11	12
1.	Initial loss (×10^2)	1.00											
2.	Maximum loss (×10^2)	0.47	1.00										
3.	Recovery time	0.04	0.08	1.00									
4.	Total loss over time (×10^2)	0.51	0.89	0.10	1.00								
5.	Origin	0.06	0.03	-0.09	0.00	1.00							
6.	Past experience	-0.11	-0.04	-0.13	-0.11	0.11	1.00						
7.	Disasters (type 1)	-0.08	-0.10	-0.08	-0.11	0.01	0.21	1.00					
8.	Accidental disruption (type 2)	-0.03	-0.08	-0.05	-0.02	0.13	0.08	-0.39	1.00				
9.	Intentional disruption (type 3)	0.10	0.16	0.11	0.12	-0.12	-0.27	-0.58	-0.53	1.00			
10.	Industry growth rate	0.07	-0.07	0.07	-0.03	0.04	-0.01	0.10	-0.09	-0.01	1.00		
11.	Firm age	-0.16	-0.21	-0.11	-0.23	0.18	0.21	-0.06	0.08	-0.01	0.03	1.00	
12.	Firm size	-0.26	-0.35	-0.19	-0.40	0.18	0.28	0.05	-0.03	-0.01	0.05	0.56	1.00
	Sample size	262	227	132	227	262	262	262	262	262	262	262	262
	Mean	1.18	5.08	3.61	13.05	0.82	0.47	0.30	0.26	0.44	0.10	30.16	1.31
	Standard deviation	7.58	11.01	3.36	24.91	0.39	0.50	0.46	0.44	0.50	0.16	19.79	2.17

* The first three variables are calculated using the performance-industry-matched method

4.5. Results

Ordinary Least Squares (OLS) regression is used to test the hypotheses provided in Section 4.2. As mentioned earlier, we measure the impacts of supply chain disruptions on firms using four different dependent variables, and the results of regression models considering four different variables are reported separately in the following sections. In order to reduce the impacts of outliers on the results, Cook's D value is calculated for each observation in each model, and observations with a Cook's D value higher than 4 over the sample size are excluded in the final model (Colbert, Kristof-Brown, Bradley, & Barrick, 2008; Fox, 1991). The variance inflation factor is also calculated for independent variables in all models, and the largest variance inflation factor found was lower than the recommended cut-off threshold in the literature. Therefore, we do not expect multicollinearity issues in our analyses.

4.5.1. Initial loss

In Table 4.3, we present the regression results of initial loss calculated using the three matching methods. The F-values of the three models are all greater than 4.00 and each of them is statistically significant at the 1% level with a R^2 value of as high as 0.15. Results of all three models indicate that intentional disruptions have a higher initial impact on firms than do accidental and disaster disruptions (p-values ≤ 0.10). Based on the results from the first two matching methods, firms that operate in industries with higher growth rates experience higher initial loss than firms that operate in other industries. Table 4.3 also shows that firm size is negatively associated with initial loss (p-values ≤ 0.01), indicating that larger firms, in general, experience less initial loss than smaller firms. However, the results also show that firm age has no effect on the initial loss value (p-values > 0.10).

Table 4.3 further reveals that when the past experience variable is zero, the disruptions' origin is positively associated with initial loss (p-values ≤ 0.10), indicating that in case of no past experience, internal disruptions result in more initial loss than external disruptions. The interaction term is also statistically significant at the 10% level considering the results from all three methods.

Table 4.3. Results of regression of initial loss ($\times 10^2$)

	Performance-industry-matched		Performance-industry-size-matched		Performance-size-matched	
	B	t-value	β	t-value	β	t-value
Intercept	0.12	0.21	0.01	0.03	0.20	0.37
Control variables						
Accidental disruption (type2)	0.02	0.04	0.01	0.02	-0.25	-0.55
Intentional disruption (type 3)	0.75	1.77[d]	0.90	2.14[c]	1.10	2.65[a]
Industry growth rate	1.82	1.71[d]	1.84	1.73[d]	0.81	0.78
Firm age	0.00	-0.34	-0.01	-0.63	0.00	-0.32
Firm size	-0.34	-3.49[a]	-0.30	-3.1[a]	-0.41	-4.28[a]
Direct effects						
Origin	0.94	2.04[c]	1.15	2.53[a]	0.76	1.68[d]
Past experience	0.01	0.02	-0.06	-0.17	0.33	0.91
Interactions						
Origin × past experience	-1.60	-1.74[d]	-2.00	-2.19[c]	-1.49	-1.65[d]
F	4.03[a]		4.64[a]		5.18[a]	
df	254		250		251	
R^2	0.12		0.13		0.15	

Note: All tests are two-tailed. p-values: [a] $p \leq 0.01$, [b] $p \leq 0.025$, [c] $p \leq 0.05$ and [d] $p \leq 0.10$

To facilitate interpretation of the disruptions' origin and past experience's effects on the initial loss of firms, Figure 4.2 plots average initial loss values for external and internal disruptions both with and without past experience. Figure 4.2 indicates that external disruptions are statistically associated with more initial loss when firms do not have similar past experience. Figure 4.2 also shows that past experience decreases the initial loss of firms when disruptions are internal to firms, but that past experience does not decrease the initial loss in the case of external disruptions. Figure 4.2 further reveals that the initial loss from external disruptions are close to zero, which, together with results from the maximum loss and the total loss, suggests that external disruptions may have a delayed negative impact on firms' performance.

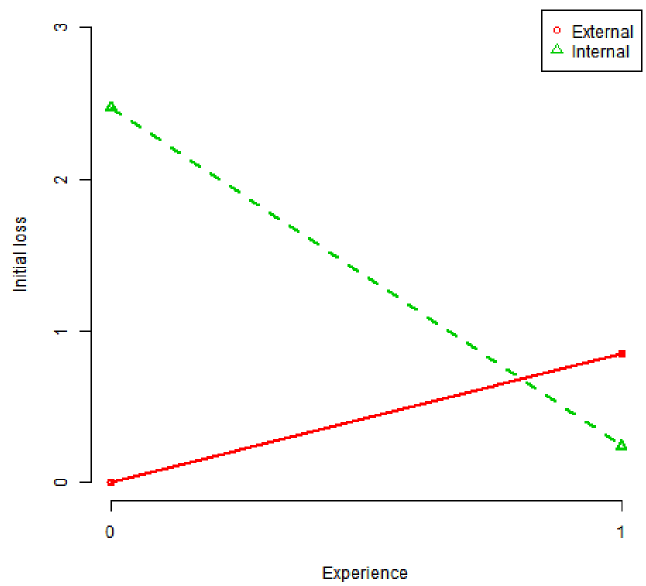

Figure 4.2. Average initial loss ($\times 10^2$) based on origin of disruptions and past experience of firms.

Note: all values are calculated based on the performance-industry-matched method.

4.5.2. Maximum loss

Table 4.4 provides the results of regression models using maximum loss as the dependent variable. All three models are statistically significant with F-values higher than or equal to 10.23 (p-values ≤ 0.01). The largest R^2 of the three models is 0.34, which is higher or comparable in value to similar cross-sectional regression analyses in the literature. Between control variables, only firm size is significantly associated with maximum loss after supply chain disruptions (p-values ≤ 0.01). Similar to initial loss, when the past experience variable is zero, the disruptions' origin is positively associated with initial loss (p-values ≤ 0.10), indicating that in the case of no past experience, internal disruptions result in more maximum loss than do external disruptions. In contrast to initial loss, however, the interaction between disruption's origin and past experience has no significant effect on the maximum loss (p-values > 0.10). Figure 4.3 shows average maximum loss values calculated from the performance-industry-matched method for external and internal disruptions, both with and without past experience. Once again differing from initial loss, maximum loss for both internal and external disruptions is significantly greater than zero.

Table 4.4. Results of regression of maximum loss (×10^2)

	Performance-industry-matched		Performance-industry-size-matched		Performance-size-matched	
	β	t-value	β	t-value	β	t-value
Intercept	4.68	4.96[a]	5.51	5.52[a]	5.45	4.81[a]
Control variables						
Accidental disruption (type2)	-0.41	-0.54	-1.10	-1.37	-0.72	-0.81
Intentional disruption (type 3)	1.28	1.83[d]	0.72	0.98	0.92	1.1
Industry growth rate	-0.80	-0.45	-2.50	-1.34	-4.00	-1.61
Firm age	-0.02	-1.32	-0.02	-0.96	-0.03	-1.29
Firm size	-1.36	-7.81[a]	-1.53	-8.3[a]	-1.44	-6.91[a]
Direct effects						
Origin	1.65	2.03[c]	1.73	2.02[c]	1.61	1.66[d]
Past experience	0.83	1.35	0.93	1.44	1.01	1.37
Interactions						
Origin × past experience	-2.28	-1.41	-1.38	-0.8	-2.73	-1.4
F	12.72[a]		13.26[a]		10.23[a]	
df	218		215		211	
R^2	0.33		0.34		0.29	

Note: All tests are two-tailed. p-values: [a] *p ≤ 0.01,* [b] *p ≤ 0.025,* [c] *p ≤ 0.05 and* [d] *p ≤ 0.10*

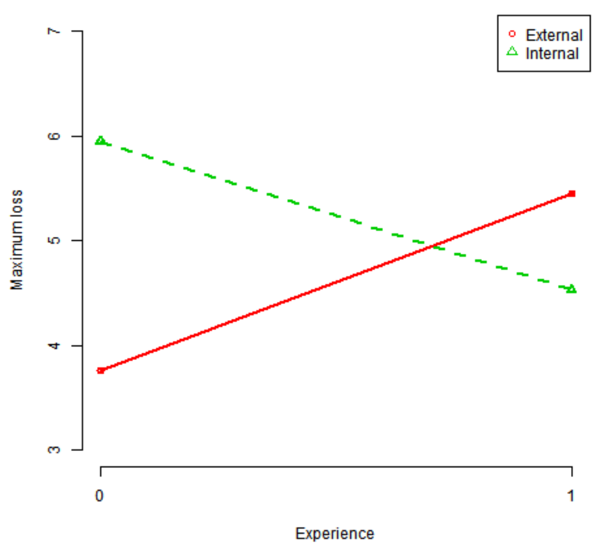

Figure 4.3. Average maximum loss (×10^2) based on origin of disruptions and past experience of firms.

Note: all values are calculated based on the performance-industry-matched method.

4.5.3. Recovery time

The results of the regression models for recovery time are reported in Table 4.5. All three regression models are significant (p-value ≤ 0.05) with an R^2 value greater than or equal to 0.14. Similar to the results for initial loss and maximum loss, Table 4.5 also shows that larger firms experience a smaller recovery time after supply chain disruptions (p-values ≤ 0.025). The results from the performance-industry-size-matched and performance-size-matched models further indicate that past experience is negatively associated with recovery time (p-values ≤ 0.10), however, the coefficients of the disruption origin variable and the interaction term are not statistically significant in these two models.

Figure 4.4 illustrates the average value of the recovery times based on the origin of the disruptions and the past experience of firms. According to Figure 4.5 and the results from two last models, we can infer that past experience decreases the recovery time when disruptions are internal to firms, but that past experience may not decrease the recovery time in the case of external disruptions.

Table 4.5. Results of regression of recovery time

	Performance-industry-matched		Performance-industry-size-matched		Performance-size-matched	
	β	t-value	β	t-value	β	t-value
Intercept	3.84	3.74[a]	5.90	6.96[a]	4.20	5.44[a]
Control variables						
Accidental disruption (type2)	0.16	0.2	-0.23	-0.41	-0.02	-0.03
Intentional disruption (type 3)	0.97	1.37	-0.23	-0.45	-0.18	-0.35
Industry growth rate	1.89	0.8	-0.77	-0.47	-0.15	-0.08
Firm age	0.02	1.11	-0.02	-1.52	-0.01	-0.4
Firm size	-0.39	-2.29[b]	-0.58	-4.3[a]	-0.44	-3.45[a]
Direct effects						
Origin	-0.94	-1.07	-0.06	-0.07	0.14	0.2
Past experience	-0.47	-0.69	-1.05	-2.21[c]	-0.81	-1.69[d]
Interactions						
Origin × past experience	-3.86	-2.33[b]	-1.70	-0.98	-1.26	-0.91
F	2.24[c]		7.33[a]		3.78[a]	
df	123		162		175	
R^2	0.14		0.28		0.15	

Note: All tests are two-tailed. p-values: [a] *p ≤ 0.01,* [b] *p ≤ 0.025,* [c] *p ≤ 0.05 and* [d] *p ≤ 0.10*

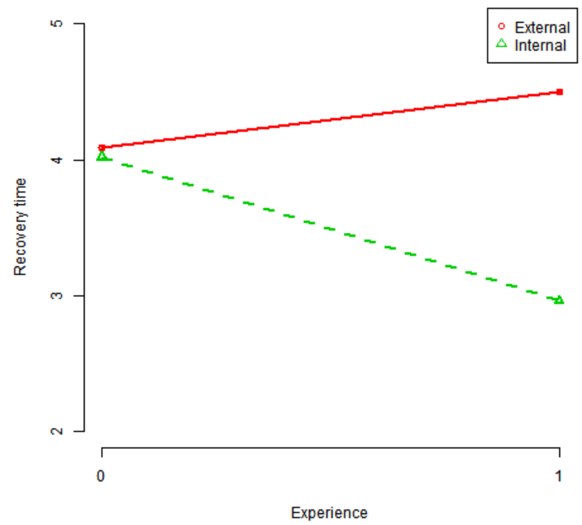

Figure 4.4. Average recovery time based on origin of disruptions and past experience of firms.

Note: all values are calculated based on the performance-industry-matched method.

4.5.4. Total loss over time

The results of the regression models for total loss over time against the independent variables are provided in Table 4.6. The regression models are all statistically significant with an F-value greater than or equal to 6.18 (p-values ≤ 0.01). The lowest R^2 of the three models is equal to 0.19, which is comparable to similar studies in the literature such as Hendricks et al. (2009). Table 4.6 shows that firm size is negatively associated with total loss over time (p-values ≤ 0.01), which is in line with our previous findings in earlier sections. None of the other control variables have a significant relationship with total loss over time (p-values > 0.10), except for industry growth rate in the second regression model (p-value ≤ 0.05). The interaction term between the disruptions' origins and the past experience of firms is significant in all three regression models (p-values ≤ 0.05).

Table 4.6. Results of regression of total loss over time (×10^2)

	Performance-industry-matched		Performance-industry-size-matched		Performance-size-matched	
	β	t-value	β	t-value	β	t-value
Intercept	13.86	5.79[a]	13.91	7.48[a]	12.64	6.12[a]
Control variables						
Accidental disruption (type2)	0.17	0.09	-0.99	-0.66	0.39	0.23
Intentional disruption (type 3)	1.28	0.72	0.77	0.56	1.68	1.09
Industry growth rate	-2.11	-0.47	-6.90	-1.97[c]	-6.22	-1.59
Firm age	-0.04	-1	-0.01	-0.27	-0.04	-1.11
Firm size	-2.22	-5.02[a]	-2.56	-7.46[a]	-2.16	-5.78[a]
Direct effects						
Origin	0.09	0.04	-0.70	-0.45	-0.71	-0.41
Past experience	0.52	0.33	1.30	1.08	1.77	1.31
Interactions						
Origin × past experience	-8.63	-2.14[c]	-7.44	-2.37[b]	-8.89	-2.57[a]
F	6.18[a]		11.44[a]		8.30[a]	
df	218		215		215	
R^2	0.19		0.31		0.24	

Note: All tests are two-tailed. p-values: [a] *p ≤ 0.01,* [b] *p ≤ 0.025,* [c] *p ≤ 0.05 and* [d] *p ≤ 0.10*

To further analyze these effects, we plot the average total loss over time for the different levels of the disruption origin and past experience variables in Figure 4.5. Based on Figure 4.5, internal disruptions are associated with a higher total loss over time than are external disruptions when firms have no past experience. On the other hand, firms with past experience have significantly less total loss over time in the case of internal disruptions.

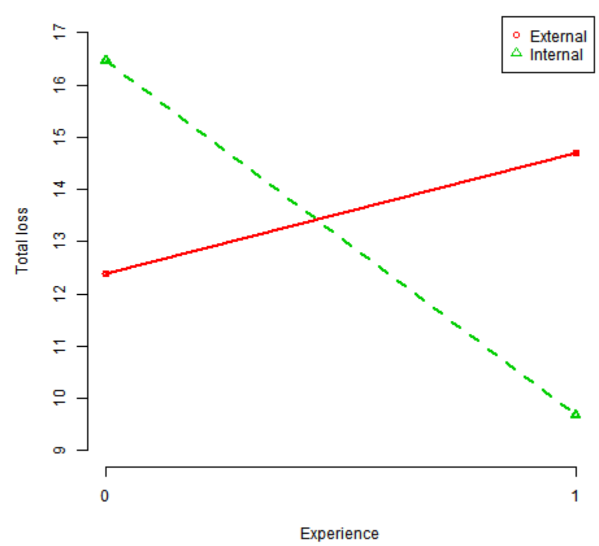

Figure 4.5. Average Total Loss over Time (×10^2) based on Origin of Disruptions and Past Experience of Firms.

Note: all values are calculated based on the performance-industry-matched method.

4.6. Further analyses

4.6.1. Net performance

As mentioned earlier, the main aim of this study is to evaluate the effects of disruptions' origins and firms' past experience on the negative impacts that supply chain disruptions have on firms' performance. Therefore, in calculating total loss, we only considered the loss experienced by firms during the first two years after supply chain disruptions and ignored the positive gains made by firms during this time.

In order to extend our initial analysis to assess the combined impact of both losses and gains, we subsequently calculated the net performance over time using the following formula, where Δ_t is allowed to take on both positive and negative values:

$$net\ performance = \sum_{t=0}^{8} \Delta_t \tag{4-5}$$

Table 4.7. Results of regression of net performance ($\times 10^2$)

	Performance-industry-matched		Performance-industry-size-matched		Performance-size-matched	
	β	t-value	β	t-value	β	t-value
Intercept	-0.01	-0.19	-0.04	-1.23	0.03	1.02
Control variables						
Accidental disruption (type2)	-0.01	-0.24	-0.02	-0.84	-0.04	-1.82
Intentional disruption (type 3)	-0.02	-0.86	-0.03	-1.28	-0.05	-2.39[b]
Industry growth rate	-0.07	-1.21	0.01	0.19	-0.06	-1.07
Firm age	0.00	-0.4	0.00	0.00	0.00	0.77
Firm size	0.01	2.71[a]	0.02	3.11[a]	0.01	1.77[d]
Direct effects						
Origin	-0.03	-1.22	0.00	-0.18	-0.04	-1.58
Past experience	0.02	0.93	-0.02	-1.1	-0.01	-0.62
Interactions						
Origin × past experience	0.09	1.77[d]	0.11	2.00[c]	0.10	1.92[d]
F	2.40[a]		2.29[b]		2.44[b]	
df	213		212		211	
R^2	0.09		0.08		0.09	

Note: All tests are two-tailed. p-values: [a] *p ≤ 0.01,* [b] *p ≤ 0.025,* [c] *p ≤ 0.05 and* [d] *p ≤ 0.10*

The results of regression models using all three matching methods are significant using this measure of net performance as the dependent variable. These results are reported in Table 4.7. With respect to the main independent variables, we find a significant relationship between the interaction term and net performance, indicating that firms with past experience have significantly better performance over time in the case of internal disruptions, which is in line with our findings using the total loss as the dependent variable.

4.6.2. Robustness checks

In the analysis above, we considered ROA as the unit of firms' performance, and then calculated the dependent variables based on the impacts of supply chain disruptions on the ROA of our sample firms. To check the robustness of the results, we recalculated all four dependent variables using return on sales (ROS), another common measure of firms' performance (Kovach et al., 2015; Tsikriktsis, 2007), instead of ROA. The performance-industry-matched method is used to match each sample firm to a set of control firms based on ROS performance, and then the four dependent variables are calculated as described in Section 4.4.

Table 4.8 provides the results of regressing initial loss, maximum loss, recovery time, and total loss over time with ROS as the performance measure. All four models are statistically significant (p-values ≤ 0.10) with R^2 values ranging from 0.06 to 0.17. Overall, results related to the main independent variables (origin and past experience) with ROS as the performance measure are in line with our previous findings in Section 4.5.

Table 4.8. Results of regression of initial loss (×10^2), maximum loss (×10^2), recovery time, and total loss over time(×10^2) calculated based on ROS

	Initial loss		Maximum loss		Recovery time		Total loss	
	β	t-value	β	t-value	β	t-value	β	t-value
Intercept	-0.30	-0.15	5.17	2.98[a]	3.94	3.81[a]	30.34	3.78[a]
Control variables								
Accidental disruption (type2)	2.50	1.49	-0.35	-0.25	0.23	0.29	4.62	0.7
Intentional disruption (type 3)	2.27	1.48	1.57	1.25	0.89	1.24	5.44	0.9
Industry growth rate	4.92	1.29	13.97	3.77[a]	1.82	0.76	37.82	2.18[c]
Firm age	-0.05	-1.3	0.00	-0.02	0.01	0.67	-0.04	-0.28
Firm size	0.23	0.64	-0.87	-2.92[a]	-0.35	-2.03[c]	-3.49	-2.54[a]
Direct effects								
Origin	2.75	1.67[d]	2.83	1.86[d]	-0.82	-0.92	-0.53	-0.08
Past experience	-2.03	-1.52	-1.74	-1.54	-0.27	-0.39	-5.40	-1.02
Interactions								
Origin × past experience	-5.43	-1.66[d]	-1.65	-0.53	-3.57	-2.13[c]	-23.60	-1.78[d]
F	2.04[c]		5.27[a]		1.83[d]		2.96[a]	
df	254		219		125		228	
R^2	0.06		0.17		0.11		0.10	

Note: All tests are two-tailed. p-values: [a] $p \leq 0.01$, [b] $p \leq 0.025$, [c] $p \leq 0.05$ and [d] $p \leq 0.10$

4.7. Discussion and conclusion.

4.7.1. Summary of findings

This study investigates the relationships between the origin of supply chain disruptions, the past experience of firms, and the impacts of supply chain disruptions on firms' performance. We consider four metrics to quantify the impacts of supply chain disruptions on firms' performance: initial loss, maximum loss, recovery time, and total loss over time. Evaluating the performance of a set of 262 disrupted firms between 2005 and 2014, we find that internal disruptions are associated with a higher initial loss, a higher maximum loss, and a higher total loss over time when firms lack experience with a similar event in the past.

The results also show that the impact of supply chain disruptions is less for larger firms with respect to the amount of initial loss, maximum loss, recovery time, and the total loss suffered over time. Interestingly, we find that past experience decreases the initial loss, the recovery time, and the total loss over time when disruptions are internal to firms, but past experience may not decrease the initial loss, the recovery time, and the total loss over time in the case of external disruptions. Furthermore, there is no support for past experience decreasing maximum loss in either internal or external disruptions.

4.7.2. Contribution to theory

This study makes two important contributions to the academic literature. First, our research contributes to the supply chain disruption literature by evaluating the effect of two important factors, i.e. the origin of supply chain disruptions and firms' previous experience, on firms' performance after supply chain disruptions. The effect of these two factors on firms' performance in this context has received little attention in previous studies. One such study that looks at related behaviors is that of Schmidt and Raman (2012), who find that internal disruptions have more negative impact on the stock market than do external disruptions. Our study, however, for the first time, shows that the impact of internal and external supply chain disruptions on firms' performance can be different when firms do not have past experience. Furthermore, our results show that past experience may not decrease the negative impacts of disruptions in the case of external disruptions.

Our second theoretical contribution is associated with evaluating the impacts of supply chain disruptions on firms' performance using four different but complementary metrics: initial loss, maximum loss, recovery time, and total loss over time. Utilizing these four metrics, we are able to show that the origin of disruptions and firms' past experience may have different *types* of effects on firms' performance after supply chain disruptions. For example, the study shows that origin of a disruption has a significant impact on the amount of initial loss experienced by a firm. When disruptions are originated externally, the initial loss experience by the firm is not significant; however, when disruptions are originated within a firm, the initial loss experienced by the firm is significant. This finding is in line with Ellis et al. (2010)'s observations that supply chain disruptions may have either immediate or delayed negative impact on firms' performance. Considering the initial loss, we also observe that past experience significantly reduces the amount of loss experienced by a firm in case of internal disruptions.

On the other hand, the disruptions' origins and the firms' past experience have different effects with respect to the maximum loss and the total loss over time metric. The results show that the maximum loss and total loss over time due to an internal disruption is higher than the maximum loss and the total loss over time due to an external disruption when firms do not have similar past experience. When such past experience does exist, it decreases the total loss over time for internal disruptions but may not have same effect on the total loss over time for external disruptions. We also did not observe the positive impact of past experience on the maximum loss metric in case of both internal and external disruptions.

4.7.3. Contribution to practice

This paper provides two important insights for practitioners in the field of supply chain risk management. First of all, although the impact of supply chain disruptions on firms' performance can vary significantly, our study shows that internal disruptions, in general, result in higher initial loss, maximum loss, and higher total loss over time, compared to external disruptions, when firms did not experience a similar disruptive event in the past. Although a firm may need different procedures and knowledge to respond to different types of internal disruptions, they may often be able to respond to different types of external disruptions using the same approach. For example, a firm needs different types of preparation to respond to an on-site fire than it does to respond to an on-site strike. However, the firm's response to a supplier's on-site fire can be similar to their response to a supplier's on-site strike, if each type of disruption ultimately leads to the same amount of shortfall in supply. This implies that when firms do not have past experience with disruptions, then internal disruptions can potentially lead to more loss than external disruptions. This argument is further supported by the fact that although past experience with supply chain disruptions is shown to significantly reduce total loss in the case of internal disruptions, such past experience is not associated with a reduction of total loss in the case of external disruptions. In summary, this suggests that firms need (and can benefit from) a higher degree of preparation against internal disruptions than they do against external disruptions.

The second relevant insight for practitioners is that firms without past experience encounter a higher initial loss, a longer recovery time, and a higher total loss after an internal disruption than firms that faced similar disruptive events in the past. This finding highlights the importance of knowledge acquisition about disruptive events. Experiencing an event, however, is not the only way of knowledge acquisition. Firms can also obtain knowledge through two other different mechanisms: vicarious knowledge acquisition, and contact knowledge acquisition (Mena &

Chabowski, 2015). In vicarious knowledge acquisition, firms obtain knowledge by observing the behavior of other firms through secondary sources (Huber, 1991; Mena & Chabowski, 2015; Ordanini, Rubera, & DeFillippi, 2008). On the other hand, in contact knowledge acquisition firms obtain knowledge from formal relationships with other firms (Mena & Chabowski, 2015; Ordanini et al., 2008). In order to better protect themselves from the impacts of supply chain disruptions, supply chain managers should consider these two types of knowledge acquisition, i.e. vicarious, and contact knowledge acquisition, as potential mitigation strategies before the disruptions occur.

4.7.4. Limitations and future research

Similar to all research studies, this study has several limitations. The first limitation is that we only considered U.S. publicly traded firms in the process of collecting data. It is important to recognize that supply chain disruptions may have different effects on firms in other countries, and therefore that we are not able to generalize our inferences about the effects of the origin of disruptions and past experience on firms' performance after disruptions to firms in this broader context. The second limitation of the study is related to time frame of our analyses. In this study, we evaluated the performance of firms for a two year period after the occurrence of a supply chain disruption. The actual recovery process, however, may take longer than two years in some cases and thus future studies might consider a longer time period for assessing firm performance after a disruption. Additionally, as mentioned earlier in this study, we calculated initial loss, maximum loss, recovery time, and total loss over time based on firms' ROA and ROS performances. It is important to recognize, however, that one could use other measures such as net sales and operating income to calculate the same four metrics, i.e. initial loss, maximum loss, recovery time, and total loss over time.

Furthermore, this study adopted an encoding of past experience as a binary variable with a value of 1 if the firm has a similar past experience in its past five years, and 0 otherwise. By using this representation, we lose important information about the past experience of firms, such as whether or not firms may have encountered a particular type of disruption event more than once in the past. By considering the *number* of past experiences and the length of time since the most recent experience, for example, one could potentially provide even more insight about the effect of past experience on firms' performance after supply chain disruptions.

Chapter 5: Conclusions

5.1. Summary

The main purpose of this dissertation was establishing new metrics to evaluate firms' resiliency to supply chain disruptions and analyzing relationships between the developed resilience metrics and a number of factors and strategies that may have significant impacts on firms' resiliency. In this dissertation, we first collected operating and stock market performances of over 300 U.S. publicly traded firms that experienced a supply chain disruption during 2005 to the end of 2014. The data is similar to that collected by Hendricks and Singhal (2005b and 2003) but updated to cover a more recent time period. Despite increasing knowledge about supply chain disruptions and recent recommendations from scholars for reducing the effects of disruptions, our analyses show that supply chain disruptions are still associated with a significant decrease in operating income, return on sales, return on assets, sales, and a negative performance in total assets. Supply chain disruptions are also still associated with a significant negative abnormal stock return on the day of the supply chain disruption announcements. Unlike Hendricks and Singhal (2005b), however, we only found a weak association between supply chain disruptions and a negative performance in total cost and inventory.

After showing that supply chain disruptions are still associated with significant negative impacts on firms' performance, we used the systems resilience literature to develop three complementary metrics of a system loss: the initial loss, the maximum loss, and the total loss over time. The initial loss and maximum loss metrics evaluate different characteristics of the magnitude of a disruption's impact on a firm's performance, whereas total loss over time gives a broader measure of the overall effect of that disruption, on that firm, over time.

We used the three developed metrics to evaluate the moderating effects of operational slack (expressed in terms of inventory slack, supply chain slack, and capacity slack) and operational scope (expressed in terms of business scope and geographic scope) on the relationship between the severity of supply chain disruptions and the different impacts of those disruptions on firms' performance. By empirically analyzing the performance of manufacturing firms disrupted between 2005 and 2014, we found that maintaining certain aspects of operational slack and broadening business scope can affect these different measures of loss in different ways, although these effects are contingent on the disruptions' severity. We also showed that although geographic scope of operations has no corresponding significant impact on initial loss, it has a direct negative effect on the maximum loss and on the total loss over time.

In this dissertation, we also provided insights about the effects of two other important factors on firms' performance after supply chain disruptions: the origin of the disruptions and the experience of firms with similar disruptive events in the past. The results of our analyses indicated that both the origin of the supply chain disruptions and the firms' past experience play a significant role in the extent of supply chain disruptions' negative impacts. More specifically, we found that when firms have no experience with a similar event in the past, internal disruptions lead to a higher level of initial loss, a higher level of maximum loss, and more total loss over time than do external disruptions. We also showed that past experience is associated with lower recovery time in the case of both internal disruptions. Firms with past experience also encounter less initial loss and total loss over time when disruptions are internal to firms, but past experience may not decrease initial loss and total loss over time in the case of external disruptions. Finally, similar to the results of previous studies about the impacts of supply chain disruptions, we found that larger firms experience fewer negative impacts overall from supply chain disruptions than do smaller firms.

5.2. Implications

In the following sections, we summarize some of important implications for supply chain risk managers from our research.

- Our first study shows that, in spite of increasing knowledge about supply chain disruptions and recent recommendations from scholars for reducing the effects of disruptions, supply chain disruptions still negatively affect performance of firms in the short-run and the long-run. This finding indicates that firms should consider investing more resources into their robustness and recovery capacities. MacKenzie and Zobel (2016) introduced a framework that can help managers decide how to allocate limited resources between reducing the initial loss and the recovery time. Explicitly considering the tradeoffs between investing in robustness and investing in reducing recovery time can help managers to build more resilient firms in the presence of supply chain disruptions.
- In our second study, we find no significant relationship between inventory slack and initial loss of performance. This surprising result can be related to Hendricks and Singhal's (2005b) observation that supply chain disruptions are positively associated with firms' level of inventory at the first quarter of disruption and therefore excess inventory slack may not be beneficial in this case. The inventory slack, however, does have a negative effect on maximum loss and total loss over time when the severity of the disruption is high. In contrast to inventory slack, supply chain slack has a significant negative effect on the initial loss, but only when the severity of the disruption is high, and it has no effect on the maximum loss or the total loss. Capacity slack, on the other hand, has a significant negative impact on the initial loss regardless of the severity of the disruption, and it has a

significant negative impact on maximum loss, but only for more severe disruptions. It also has no effect on the total loss experienced by the firm.

Taken together, these results imply that in order to decrease the impacts of a supply chain disruption on a firm's performance, managers should invest in supply chain slack and capacity slack if they wish to reduce their initial loss, they should invest in inventory slack and capacity slack if they wish to lessen their maximum loss, and they should invest in inventory slack if they wish to reduce their total loss over time. Decisions about such investments obviously need to take factors such as their relative cost and their impacts on operational efficiency into account before they are implemented.

- Our third study shows that firms without past experience encounter a higher initial loss, a longer recovery time, and a higher total loss after an internal disruption than firms that faced similar disruptive events in the past. This finding highlights the importance of knowledge acquisition about disruptive events. Experiencing an event, however, is not the only way of knowledge acquisition. Firms can also obtain knowledge through two other different mechanisms: vicarious knowledge acquisition, and contact knowledge acquisition (Mena & Chabowski, 2015). In vicarious knowledge acquisition, firms obtain knowledge by observing the behavior of other firms through secondary sources (Huber, 1991; Mena & Chabowski, 2015; Ordanini, Rubera, & DeFillippi, 2008). On the other hand, in contact knowledge acquisition firms obtain knowledge from formal relationships with other firms (Mena & Chabowski, 2015; Ordanini et al., 2008). In order to better protect themselves from the impacts of supply chain disruptions, supply chain managers should consider these two types of knowledge acquisition, i.e. vicarious, and contact knowledge acquisition, as potential mitigation strategies before the disruptions occur.

5.3. Limitations and future research directions

As mentioned before, studies in this dissertation have a number of limitations that it is important to acknowledge. First of all, we only consider U.S. publicly traded firms in the process of collecting data. Because supply chain disruptions may have different effects on firms' performance after supply chain disruptions that impact other countries, we are not able to generalize our inferences to firms outside of this specific scope. Next, supply chain disruption announcements in this dissertation are collected through searching articles from PR Newswire and Business Wire. Public firms should file an 8-k form whenever significant corporate events (such as disruptions) take place that trigger a disclosure. Therefore, 8-k forms submitted by public firms can be used in the future as a more comprehensive source of supply chain disruption announcements.

Next, this study calculates the quarter of the supply chain disruption based on the public announcement date of the disruption at the firm level. Although, based on Section 409 of the Sarbanes-Oxley Act (SOX), our sample firms are required to disclose any significant unplanned event that may change their financial condition or their operations on an urgent basis (SOX, 2002), we cannot be certain that announced disruptions always take place exactly in the quarter of the announcement. The time frame of our analyses is also a potential limitation. We only consider the performance of firms over the first two years after the supply chain disruptions occurred; however, it may take more than two years for a firm to recover from a disruption, or the firm simply may not recover at all. Although the total loss over time is a meaningful measure even if the firm doesn't recover, being able to assess the actual recovery time for each firm could provide additional valuable information for analysis.

In this dissertation, we only evaluated impacts of supply chain disruptions on the focal firms. Recently, researchers have used the Bloomberg Terminal to map firms' supply chain relationships. An important avenue for future research therefore would be mapping disrupted firms' supply chain networks and extend the findings in this dissertation across supply chain networks. Future research may also consider evaluating the impacts of disruptions on firm performance of firms by using the new metrics developed in this dissertation in other disruption contexts, such as in the case of product recalls, or perhaps even adapting them to the context of positive disruptions due to product innovations.

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Appendix A

Matching methods

We matched a set of control groups to sample firms using three matching methods developed by Hendricks and Singhal (2008) - these methods are described as follows. Please note that before starting the matching method, all sample firms were removed from the set of possible control firms, and firms were then matched based on their operating data four quarters before the quarter of the disruption announcement.

First matching method: performance-industry-matched

Step 1. For each sample firm, identify all potential control firms in the COMPUSTAT database with the same two-digit SIC code as the sample firm and with ROA between 0.90 and 1.10 of the sample firm's ROA. Firms that satisfy these criteria are considered as control firms for the sample firm.

Step 2. If no firm is found for the sample firm in step 1, change the first criteria to the one-digit SIC code.

Step 3. If, again, no firm is found for the sample firm in step 2, disregard the first criteria and only consider the ROA criteria.

Step 4. If, again, no firm is found for the sample firm in step 3, select the nearest firm to the sample firm with respect to the ROA.

Second matching method: performance-industry-size-matched

Consider the results of first matching method. For each sample firm, exclude control firms that are not within a factor of 50 of the sample firm's total assets.

Third matching method: performance-size-matched

Step 1. For each sample firm, identify all potential control firms in the COMPUSTAT database with ROA between 0.90 and 1.10 of the sample firm's ROA, and total assets between 0.70 and

1.30 of the sample firm's ROA. Firms that satisfy these criteria are considered as control firms for the sample firm.

Step 2. If no firm is found for the sample firm in step 1, select the firm that meets the total assets criteria and is nearest firm to the sample firm with respect to the ROA.