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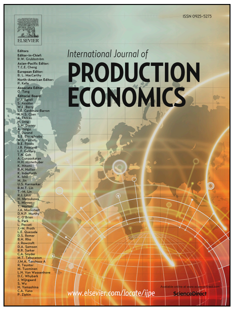


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**Assessing the extended impacts of supply chain disruptions on firms: an empirical study**

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# Assessing the extended impacts of supply chain disruptions on firms: an empirical study


## Abstract

This paper empirically examines the effects of supply chain disruptions on firms' performance by applying a new quantitative measure of a disruption's impact that was adapted from the systems resilience literature. This new measure captures the total amount of loss suffered by a firm, and it supports comparing the relative performance of disrupted firms over time. To illustrate the value of the approach, both the operating performance and the stock market reaction are analyzed for more than 300 firms that suffered a supply chain disruption between 2005 and 2014. After validating the results against the reported behaviors from previous analyses, the new impact measure is explicitly used to show that different sized firms and different industry sectors exhibit varying amounts of loss, not just in the short term, following the announcement of the disruption, but also over an extended period of time after the disruption occurs.


***Keywords***: Supply chain disruptions; Firm performance; System resilience; Empirical study



## 1. Introduction

Within the current global business environment, every organization faces different types of risk that can disrupt the flow of material and information and thus disrupt that organization's supply chain. Although the effects of some disruptions may be relatively easy to manage, others may have a much more significant impact on supply chains' long-term performance. For example, among its other impacts, the Tohoku earthquake and tsunami in 2011 delayed delivery of Apple's iPad2 (Revilla & Sáenz, 2014) and disrupted the automotive sector and retail supply chains on a global scale (Todo et al., 2015; Torabi et al., 2015). Such extended disruptions can also be the result of human actions, as in the case of the West Coast port lockout in 2002 lasted 10 days, cost several billion dollars, and took months for full recovery (Werling, 2014). Examples such as these clearly illustrate that the negative consequences of a supply chain disruption may often extend beyond just short-term financial loss, and that they may continue to impact the supply chain for months or even for years.

Hendricks and Singhal (2005a, 2005b, 2003) studied more than 500 firms that experienced a supply chain disruption during the 1990s. They empirically showed that such disruptions significantly affect firms' short-term operating and stock market performance, and that these effects may still be felt if they are measured again as much as two years later. Their original work was followed by a number of other research studies that continued this focus on trying to better understand the nature of the impacts of supply chain disruptions on firm performance (Ambulkar et al., 2015; Kim et al., 2015; Knemeyer et al., 2009; Shekarian et al., 2020; Wagner & Bode, 2006). Although most of these studies focus on the supply chain response immediately after a disruption, they sometimes also examine the longer-term effects of the disruption by considering the response at later points in time to see if it still exhibits the same types of behavior.

While considering the performance of firms at later points in time provides some limited information about the long-term effects of supply chain disruptions, it does not capture the overall impact of those disruptions over time. The first goal of this paper is thus to expand on the previous efforts in the literature by introducing and analyzing a new resilience-based approach that better supports empirical assessment of the extended effects (i.e. both the short-term effects and the long-term effects) of supply chain disruptions. The new approach, which is derived from the systems resilience literature, is based on quantitatively measuring the disaster resilience of a system that has been directly impacted by a disaster event. It provides the means for measuring either the instantaneous loss or the total loss suffered due to a supply chain disruption, and it is flexible enough to be applied in the context of both financial measures and operational measures of supply chain performance. With this in mind, the second goal of this study is to use the proposed measure to compare the resiliency of firms to supply chain disruptions of different sizes and in different industries.

We begin the discussion by empirically analyzing the performance of a set of firms that were disrupted between the years of 2005 and 2014. We first confirm that this newer empirical data set exhibits similar behavior to that previously reported by Hendricks and Singhal (2003, 2005a, 2005b), and discuss this behavior in the context of the new measure of disruption impact. We then use the measure to validate several additional insights about overall firm performance in the presence of supply chain disruptions. In particular, by analyzing both the short-term and longer-term losses suffered by disrupted firms in recent years, we are able to show that larger firms tend to suffer less loss over time because of supply chain disruptions than do smaller firms. We also demonstrate that firms in some industry sectors generally suffer less overall loss from supply chain disruptions than do firms in other sectors.

The rest of the paper is organized as follows. Section 2 reviews related research about supply chain disruptions and system resilience, and it introduces the formal hypotheses. Section 3 outlines the data collection procedures, Section 4 describes the methodology used to conduct the results, and Section 5 provides the results. Finally, Section 6 discusses the findings and provides future research directions.

## 2. Background and hypotheses development

*2.1. Supply chain disruptions*

The topic of supply chain disruptions has been studied extensively in the literature, with a significant amount of research focused on understanding the types of supply chain risk that can lead to disruptions. Rice & Caniato (2003) provide one of the few research efforts that directly categorizes the different types of disruptions, rather than the risks with which they are associated. Their "failure modes" are specifically associated with disruptions in supply, transportation, internal operations, communication, and human resources. Revilla and Sáenz (2014) offer a similar categorization of disruptions, focusing on disruption types that affect supply, transportation, internal operations, and communications. Ambulkar et al. (2015), in turn, are able to provide real-world context by conducting a survey of supply chain professionals about the disruptions they have actually witnessed. The results of their survey also identify supply disruptions, logistics/delivery disruptions, and in house/plant disruptions as significant, but they further suggest including an additional category of external disruptions related to natural hazards and to regulatory and political issues.

In their seminal work on supply chain resilience, Christopher and Peck (2004) also adopt this broader view of external as well as internal disruptions, but they specifically characterize the categories of disruption *risk*, rather than the types of disruptions. They focus on three types of risk: the internal risks of disruption to the firm, i.e. those that are associated with internal processes and control; the disruption risks that are external to the firm but internal to the supply chain, such as the risk of supply or demand disruptions; and the environmental risks that are external to the supply chain network but can affect supply, demand, and internal operations within that network. This perspective is echoed by Tang (2006) and Ho et al. (2015) who focus on differentiating between operational risks, or micro-risks (due to uncertainties in standard operational procedures) and disruption risks, or macro-risks (due to large-scale events such as natural disasters or economic crises). Kleindorfer and Saad (2005) also discuss external disruption risks arising from such events as natural hazards, terrorism and political instability, in addition to the risks that originate from within the supply chain.

With these results in mind, our focus in this paper is on the larger-scale disruptions to firms and/or their supply chains that are typically caused by environmental disruption risks, as characterized by Christopher and Peck (2004) (and more recently Parast and Shekarian, (2019)), rather than on the more frequent and predictable operational risks that result from uncertainties in standard supply chain activities. As in Christopher and Peck (2004), the actual impact of such disruptions may be felt on either the supply, or the demand, or the internal operations of the particular supply chain being considered.

*2.2. Effects of supply chain disruptions*

It is important to recognize that 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 (Ding et al., 2018). 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 are associated with an abnormal decrease in shareholder 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 firms with higher growth prospects experience a more negative stock market reaction. However, Hendricks and Singhal (2003) also found that the abnormal returns were not significant over a longer 60-day time period (equivalent to a single quarter in calendar time) 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 stock market reaction and that more geographically diversified firms experience a more negative stock market reaction. 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. Yang et al. (2014), in turn, showed that public announcements about operational management can have either a positive or a negative effect on stock market value.

Investigating the long-run effects of supply chain disruptions is more difficult than the short-run effects, because of the 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 between 1989 and 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, and with an increase in total assets and in total inventory, and 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).

Several recent publications have extended these previous efforts by considering specific disruption contexts, such as toy industry product recalls (Ni et al., 2016; Wood et al., 2017), or the impacts of specific technologies, such as social media, on shareholder reactions to disruptions (Schmidt et al., 2020). There have also been a number of studies that have looked at the effects of supply chain disruptions in countries other than the United States, like Japan (Hendricks et al., 2019; Liu et al., 2018), India (Sanjay et al., 2015), and China (Zhao et al., 2013).

### *2.2.1. Short-term impacts of supply chain disruptions*

We begin our look at the new resilience-based measure developed below by substantiating the previously reported short-term effects of supply chain disruptions. Our analysis is based on firms' performance during the period from 2005 to 2014, and we consider the disruptions' effects not only on stock market performance but also on operating performance. Our initial hypothesis is thus as follows:

**H1.** *Supply chain disruptions are associated with negative changes in operating performance and stock market performance in the short-term.*

Similar to Schmidt et al. (2020), we present this hypothesis as a means of confirming the previous results in the context of our new data set, and thus as a foundation for supporting further analysis. In addition, however, we also use it to validate the new resilience-based measure, specifically in this context of assessing the disruptions' short-term impacts. The second hypothesis, introduced below, will be used to examine the new measure's ability to actually capture the longer term impacts of such disruptions, and the third hypothesis will examine both the short term and the long-term impacts.

*2.2.2. Long-term 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 long-term 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.

On the other hand, although smaller firms have limited resources to face supply chain disruptions, these resource constraints force the smaller firms to expand their capability to reconfigure the available resources to deal with daily challenges (Parker & Ameen, 2018). The regular practice of resource reconfiguration helps smaller firms to be more flexible, agile, and proactive in facing irregular events. Previous studies show that flexibility, in particular, is an important element of being resilient to supply chain disruptions (Tang & Tomlin, 2008). Parker and Ameen (2018) also argue that larger firms, because of resource rigidity, are more dependent to external resources. This resource rigidity and resource dependency may prevent larger firms from reconfiguring resources as quickly as smaller firms (Parker & Ameen, 2018). Therefore, from this point of view, we can also argue that smaller are better prepared and more resilient to supply chain disruptions than larger firms.

Based on the above discussions, Hypotheses 2a and 2b formalize our arguments about the resilience of firms of different sizes.

**H2a (H2b).** *Larger firms are more (less) resilient to supply chain disruptions than smaller firms.*

*2.2.3. Short- and long-term impacts of supply chain disruptions on different industry sectors*

Finally, one might also expect different industry sectors to be prepared differently against supply chain disruptions. Industry sectors are highly interdependent. Leontief's model, also known as input-output model, explains the relationship between industry sectors through a simple linear system of equations (Miller & Blair, 2009; Okuyama, 2007). The input-output data shows that some industry sectors provide higher amount of inputs to other sectors and are vital for economy security and daily life of communities. These industry sectors that provide essential services to other industries and communities and form the backbone of a nation are known as critical infrastructure sectors (Chopra & Khanna, 2015). The US Department of Homeland Security has identified 16 sectors as critical infrastructure sectors, including the energy, water and wastewater, and transportation sectors (The US Department of Homeland Security, 2013).

Disruption of firms or systems in the critical infrastructure sectors may result in regional or national consequences because of high dependency of other firms and sectors on the services provided by these firms (He et al., 2017; Min et al., 2007). For example, the power outage of 2003 caused significant disruptions in other sectors, such as the transportation sector, by shutting down traffic lights, subways and trains, health care providers, banks, and sporting activities (Min et al., 2007). Since the disruption of firms in critical infrastructure sectors results in significant losses and attracts a lot of public attention and criticism, these firms are usually well prepared for disruptions and have learned over time both to resist disruptions and to recover more quickly. As an example, Florida Power & Light (FPL), a major power utility company in the US, has a comprehensive storm plan which focuses on readiness, restoration, and recovery (Wilson & Biichle, 2008). This leads us to our third hypothesis, regarding the relative effect of different industry sectors on firm resilience:

**H3.** *Firms associated with essential industry sectors experience lower levels of loss in both the short-term and the long-term.*

## 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 10-year time period from 2005 to the end of 2014. The beginning of this period comes immediately after Section 409 of the Sarbanes Oxley Act was implemented in 2004 (p.35: Tarantino, 2006). This action updated the requirement for public companies to publicly disclose information that may impact their financial condition or operations, and it therefore increased the likelihood of an announcement by public companies after a supply chain disruption.

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: component, delivery, parts, shipment, manufacturing, production, 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 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).

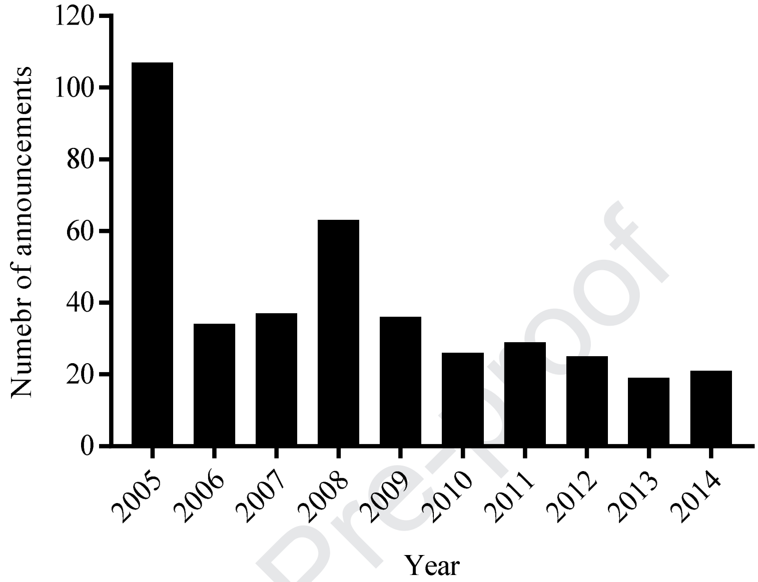


Figure 1. Distribution of the disruption announcements per year.

Table 1. Descriptive statistics of sample firms (*N*=397)

| | Four quarters before the announcement quarter | | | Quarter before the announcement quarter | | | Four quarters after the announcement quarter | | |
|---|---|---|---|---|---|---|---|---|---|
| Measure | 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 |

Descriptive statistics of the sample firms for different quarters around the disruption announcements quarter are presented in Table 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 3 then 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. Table 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)

Table 2. 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 3. 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 |

sector with 17%, and the mining sector with 15% are the most common industry sectors between the sample firms.

## 4. Methodology

Sections 4.1 and 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.

### *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 control firm must have same amount of data available as the sample firm.
- The control firm must have same quarter-ending month as the sample firm.
- The control firm has at least same three-digit SIC code as the sample firm.
- The sales and total assets of 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 or no more matches can be found.

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 1:

$$d_t = \frac{Sales_t^s - Sales_{t-4}^s}{|Sales_{t-4}^s|} - \frac{Sales_t^c - Sales_{t-4}^c}{|Sales_{t-4}^c|} \qquad (1)$$

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.

*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*.

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

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*.

### *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 measuring different characteristics of this response curve (Li et al., 2020) and/or 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; Li & Zobel, 2020; Zobel, 2014; Zobel & Khansa, 2012).

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:

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

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, $Q(t_0)$ can be interpreted as the system's robustness, with higher values of $Q(t_0)$ corresponding to more resistance to initial loss. Resilience is then a function of both robustness and the length of time until recovery, otherwise known as the system's recoverability.

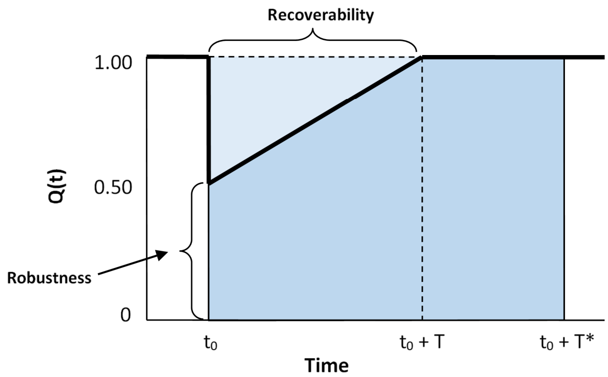


Figure 2. Predicted resilience (adapted from Zobel, 2011)

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 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:

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

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 5, as follows:

$$d_{t_0}^{\pm} = |d_t| \quad \text{if both negative and positive deviations are destructive,}$$
$$d_{t_0}^{\pm} = \begin{cases} 0 & if\ d_t \geq 0 \\ d_t & if\ d_t < 0 \end{cases} \quad \text{if only negative deviation is destructive, and} \tag{5}$$
$$d_{t_0}^{\pm} = \begin{cases} d_t & if\ d_t \geq 0 \\ 0 & if\ d_t < 0 \end{cases} \quad \text{if only positive deviation is destructive.}$$

Robustness, as a measure of the initial impact of the disruption, can then be defined as:

$$Robustness = 1 - \frac{|d_0|}{d_{max}} \tag{6}$$

where $\boldsymbol{d_{max}}$=1 if $\boldsymbol{d_0}$ represents a percentage deviation in the performance measure's value. As illustrated in Figure 2, this is effectively the complement of the deviation at time 0.

## 5. Results

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

*5.1.1. Impacts on operating performance*

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. This allows us to capture the immediate response, or robustness, of the firms to disruptions, but by using an approach that is consistent with the previous work of Hendricks and Singhal (2005b). Table 5 thus 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, 5 percent of all data is trimmed symmetrically from each tail.

Table 4. Control-adjusted change in operating performance measures at quarter 0

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

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

The results show 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 (i.e., the sign rank tests for median and percentage were both negative) 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 -4.82% (-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, instead of quarter 0, 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 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 7.01%, both of which are significantly different from zero (p-values $\leq 0.025$). 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.

Since robustness, as defined in (6), is simply the complement of the absolute percent deviation, we may also use these results to conclude that the corresponding mean and median robustness values (calculated from the results in Table 5 as ($1 - |\bar{d}|$) and ($1 - |\tilde{d}|$) respectively, in each case) are also significantly different from 1, at the reported level of significance for each measure. This is simply an alternative way of describing the extent to which the firms were able to resist the disruptions' impacts on their normal performance, across the variety of performance measures being tested. It is beneficial, in this case, to base our discussion on the deviations from which robustness is calculated because they are also able to indicate the direction (positive or negative) of the disruptions' effect.

To summarize, the results given in Table 5 show that supply chain disruptions are indeed associated with negative changes in operating performance, but it depends on which performance measures are being considered. The first part of Hypothesis 1 is therefore partially supported.

*5.1.2. Impacts on stock prices*

In addition to their demonstrated association with different aspects of operating performance, we may also show that supply chain disruption announcements are associated with a negative abnormal stock market return in the short-run. Figure 3 shows the 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 the abnormal returns of sample firms for the same period of time from three other models and the reaction of the stock market to disruption announcements was almost the same, so the other figures are not also included.

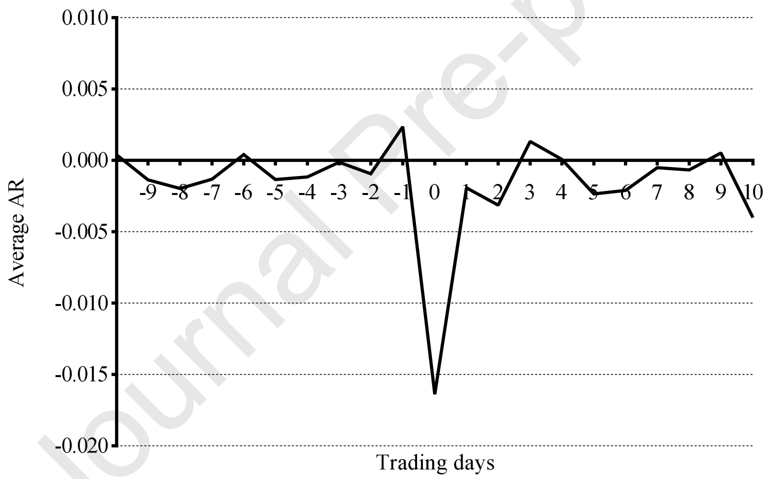


Figure 2. Average abnormal returns from the market model from day -10 to day +10

Table 6 provides the 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. As above, these results can also be interpreted in terms of the significance of the firms' robustness to disruptions, with a perfectly robust system being represented by an insignificant amount of deviation from normal stock price fluctuations. In summary, because a significant amount of deviation was measured in each case, the second part of Hypothesis 1 is supported.

Table 5. 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. $*$ $p \leq 0.05$, $**$ $p \leq 0.025$, and $***$ $p \leq 0.01$ for two-tailed tests.

*5.2. Relation between size of firms and resilience*

The next part of the analysis focuses on examining the use of the resilience metric to capture the longer-term effect of disruption impacts. Just as a larger value for the robustness measure indicates less deviation from normal behavior at the time of the disruption, a larger value for the resilience metric indicates less total deviation over time. To illustrate 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 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

Table 6. 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) N. | Mean | S.D. | Group 2 (larger firms) N. | Mean | S.D. | Two-sample t-test value for difference between group 1 and 2 |
|---|---|---|---|---|---|---|---|
| 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. * $p \leq 0.05$, ** $p \leq 0.025$, and *** $p \leq 0.01$ for two-tailed tests.

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). Hypothesis 2a is therefore supported, and Hypothesis 2b is not supported.

In this study, we calculate the total resilience using loss experienced by firms over time. Therefore, our results indicate that larger firms are more resilient than smaller firms considering this particular resilience measure. This analysis does not provide insights about the recovery behavior of firms of different sizes, however. To offer deeper insight into the long-term response behavior of smaller and larger firms, therefore, we also compare the control-adjusted change in operating performance of the smaller and the larger firms in quarter 1. The results are reported in Table 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.

In summary, these results indicate that smaller firms initially experience a higher amount of loss than larger firms, however their losses after only a few quarters are no longer significantly higher than those of larger firms. This observation suggests that smaller firms might be more nimble than larger firms and thus able to recover more quickly after supply chain disruptions (even though they initially experience higher loss). Although our current analysis does not focus more specifically on the details of firms' actual recovery behaviors, these results imply that there may be good opportunity for future studies to look at this more closely.

Table 7. Control-adjusted change in operating performance measures of the smaller and the larger sample firms at quarter 1.

| | Group 1 (smaller firms) | | | Group 2 (larger firms) | | | Two-sample t-test value for difference between group 1 and 2 |
|---|---|---|---|---|---|---|---|
| Unit of initial loss | 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.

*5.3. Comparing industry sectors*

To estimate the difference between the total resilience and the initial loss (i.e., robustness) of firms facing supply chain disruptions from different industry sectors, we ran a series of ANOVA tests considering the 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 9 presents the ANOVA and Tukey's studentized range test results for the impact of industry sectors on the initial loss 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 subsequently 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 hypothesis 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. Hypothesis 3 is thus also partially supported.

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 8. Impact of industry sectors on the initial loss and the total resilience 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 ≤ 0.05, ∗∗ p ≤ 0.025, and ∗∗∗ p ≤ 0.01 for two-tailed tests.

### *5.4. Additional results*

#### *5.4.1. 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 10 presents descriptive statistics of the total resilience of sample firms during the two time periods. The last column of Table 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

Table 9. 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.

is not enough evidence that the total resilience of firms has improved from 2005-2009 to 2010-2014 (p-values > 0.05).

*5.4.2. Impact of repeated disruptions*

As discussed above, our initial processing of the disruption announcement data removed 47 announcements that happened within the first two years after another recorded disruption to the same supply chain (38 announcements). Although initial loss was not changed by removing these announcements, there is certainly a possibility that the presence of multiple disruptions could have impacted the total resilience measure (TR), as calculated in this paper. In order to confirm that the original results were valid, therefore, we went back and removed the 38 recorded disruption announcements that led to the original deletions. We then reran the test for the difference between the total resilience of the smaller and the larger sample firms (Table 7), excluding all data associated with multiple disruptions within the first two years after an initial disruption.

Table 11 presents the resulting descriptive statistics and the updated test results. It is clear that these new results support the original findings shown in Table 7. For the sake of completeness, we also reran the tests presented in Tables 9 and 10 on the adjusted data set, and the new results were again similar to the original findings.

Table 11. Test results for the difference between the total resilience of the smaller and the larger sample firms, excluding data associated with multiple disruptions

| 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 (%) | 82 | 98.6 | 1.95 | 101 | 99.18 | 1.21 | -2.46** (8538.5***) |
| Return on sales (%) | 66 | 98.7 | 1.72 | 100 | 99.27 | 1.12 | -2.59*** (6434***) |
| Return on assets (%) | 79 | 98.45 | 2.15 | 93 | 99.15 | 1.01 | -2.80*** (6992.5***) |
| Sales (%) | 92 | 97.48 | 2.3 | 136 | 98.11 | 2.05 | -2.17* (10278***) |
| Total assets (%) | 107 | 97.54 | 2.35 | 132 | 98.39 | 2.1 | -2.95*** (13590***) |
| Total costs (%) | 79 | 98.3 | 1.92 | 77 | 98.59 | 1.57 | -1.03 (6411) |
| Total inventory (%) | 59 | 97.41 | 2.47 | 110 | 98.01 | 1.98 | -1.72 (5965) |

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.

## 6. Discussion

### *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 in the short-run by using a new set of supply chain disruptions announced during 2005 to 2014, and it introduces the concept of robustness in this context. 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 different levels of resilience in the long-run. Larger firms are more resilient than smaller firms considering profitability measures, sales, and total assets. 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.

*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 overall resilience 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.

*6.3. Limitations and future directions*

This study has several limitations related to data collection. First, we only considered U.S. publicly traded firms, even though supply chain disruptions may have different effects on firms in other countries. This means that 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. In particular, 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. We also only collected supply chain disruption announcements for a 10-year period beginning in 2005. Future research efforts may want to consider longer or more contemporary time frames.

Another limitation of this study is that we did not consider the impact of learning and experience on firms' ability to be resilient. For this particular research effort, we removed all instances of reported disruptions that occurred within two years of some other initial disruption, in order to avoid biasing the results. There is significant opportunity for future research to consider the effects of repeated exposure to disruptions, particularly in terms of how different aspects of resilience may be affected over time. Related to this is also the opportunity to learn from the *positive* impacts that may be experienced by some firms as a result of a supply chain disruption. For example, construction firms will often experience an increase in business after a natural disaster (Dottore & Zobel, 2014). This implies that there is also opportunity for future research to carefully assess the implications of the long-term resilience associated with such behaviors.

A third potential limitation of this study is the possibility of bias in the results due to the economic impacts of the great recession (2007-2009), which occurred during our study period. Because we followed the approach of Hendricks and Singhal (2005b), however, and compared the operating performance of each firm against the performance of a set of control firms (using several different matching schemes), we were able to base our analysis on the control-adjusted change in performance. By making this choice, we did our best to remove the effects of larger catastrophic events, such as the economic downturn, that would have impacted both the disrupted firm and the set of control firms at the same time.

A fourth limitation of the study 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.

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