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The Roles of Prior Experience and the Location on the Severity of Supply Chain Disruptions

Abstract

This study examines relationships between the location of supply chain disruptions (SCDs) within the supply chain, a firm's experience with SCDs, and the disruption severity. Using organizational learning theory, we propose that an organization's prior experience with SCDs will reduce the negative influence of future disruptions. However, the location of disruption occurrence (internal to the firm vs. external to the firm) also plays a vital role in the severity of future disruptions. We consider two measures of SCD severity to quantify the extent of negative influence on firms: (1) the initial loss of return on assets (ROA) and (2) the total loss of ROA over time. We empirically evaluate the performance of 262 publicly traded U.S. firms that experienced an SCD. Our study shows that the influence of internal and external SCDs on firms can be different when firms do and do not have experience with similar events. More specifically, the results show that when firms have not experienced a similar event in the past, internal SCDs are associated with a higher disruption severity than are external SCDs. The results also show that prior experience significantly decreases the disruption severity suffered by firms after internal SCDs.

***Keywords*:** Supply chain disruptions (SCDs); Firm resilience; Organizational learning and knowledge acquisition; Archival research; Regression analysis

1. Introduction

Supply chain disruptions (SCDs) are unexpected events that disrupt the normal flow of materials and goods within a firm's supply chains (Craighead et al., 2007). Firms often face SCDs that are caused by events such as natural disasters or firm-level supply chain failures. Recent events have shown how fragile global supply chains are to several types of disruption; as a result of the COVID-19 pandemic in 2020 more than 90% of the Fortune 1000 companies have experienced SCDs (Sherman, 2020). For example, Hyundai stopped its production in Korea because of shortages of parts from China (Jack et al., 2020). Similarly, an unprecedented winter storm in Texas and jammed ports in the U.S. during the COVID-19 pandemic triggered a global plastic shortage and disrupted Samsung's production in North America, and as a result, many companies that are dependent on semiconductor chips, such as Toyota and Honda (Matthews et al., 2021, McLain, 2021).

SCDs can cause significant financial losses to firms and even an entire industry in both the short and long run (Hendricks and Singhal, 2005a, Zsidisin et al., 2016). For example, production halt at Samsung's chip fabrication plant in Texas, the world's second-largest foundry, reduced semiconductor supply to Qualcomm and Apple, among others, and it is estimated that it will reduce global smartphone production by 5% in the second quarter of 2021 (Hosokawa, 2021). The dangers of SCDs and their cascading negative effects have prompted key research efforts in this area. Many of these studies have focused on understanding supply chain vulnerabilities and how firms can build capabilities with which to address these vulnerabilities (e.g., Kim et al., 2015). This is why designing supply chains and mitigating their risks, especially SCDs, are pivotal.

Generally, the literature has focused on why SCDs occur, which vulnerabilities lead to them, how they influence firm performance, and how to manage and prevent supply chain risks (Bode et al., 2011, Dolgui et al., 2018, Hosseini et al., 2019, Ivanov et al., 2017, Polyviou et al., 2018). Our review of SCD research reveals the following themes: (1) SCD severity (Hendricks and Singhal, 2005b, Hendricks et al., 2009, Craighead et al., 2007, Polyviou et al., 2018); (2) structural supply chain factors that can cause SCDs (e.g., Bode and Wagner, 2015, Kim et al., 2015, Scheibe and Blackhurst, 2018); and (3) designing supply chains that are resilient to SCDs (Ambulkar et al., 2015, Bode and Macdonald, 2017, Ivanov, 2020, Ivanov and Dolgui, 2020a and 2020b, Ivanov et al., 2014, Li et al., 2021, Namdar et al., 2018, Wang et al., 2014). Our thematization of the SCD literature is consistent with recent observations in the literature (Dolgui et al., 2018, Hosseini et al., 2019, Ivanov et al., 2017, Polyviou et al., 2018), and it calls attention to continued investigations on a better understanding of the effect of SCDs.

We contribute to this research stream by proposing that a key understanding of the effects of SCDs can be gained through the lens of organizational learning. Whether SCDs are within a firm's control or not, they represent failures that are highly relevant in organizational learning. In fact, experiencing undesirable events forces firms to search for better ways to manage such events in the future (Madsen and Desai, 2010). Firms that have faced prior SCDs can benefit from the learning gained by encountering those disruptions and possibly develop mechanisms to mitigate the effects of future disruptions.

As an illustration, ASOS plc, a British online fashion and cosmetic retailer, experienced a major fire in one of its warehouses in 2005. The retailer was not fully functional for a month after the incident. In 2014, the retailer experienced another major fire in its global distribution center that held 70% of ASOS' stock. However, because they learned and adapted from the prior incident, they only needed two days to resume operations from the second fire, despite its destruction of 20% of their inventory (Ivanov, 2018). Similarly, Toyota improved its supply chain visibility to deal with SCDs based on lessons learned in the aftermath of the 2011 Tsunami in Japan:

> "The tsunami revealed tier two and three suppliers that we didn't know we needed to manage. That crisis led us, during any crisis we have had since, to recognise how global the supply chain is and the things we need to confirm during the disruption. You definitely have to follow up with more than just your tier one suppliers" Doug Adams, general manager, Toyota Motor North America (Williams, 2021).

Firms can also leverage previous SCDs to learn how to engage in multisourcing and provisions of emergency purchase or invest in and work more closely with their suppliers (Tang et al., 2014), or prepare to be more responsive to future SCDs (Bode and Macdonald, 2017). The learning effect of prior failures, such as SCDs, is cogently described by Maslach (2016):

> When firms succeed, they persist with current actions. When firms encounter failure, they try to rule out the actions that might have caused those failures … Failure also motivates firms to change, take risks, and recombine existing alternatives … Thus, failure might help a firm see that a previous action was incorrect and provide clues about future actions. (p. 715)

Although the organizational learning theory research suggests that organizations learn from both success and failure (Chuang and Baum, 2003; Kim et al., 2009), learning from SCDs has received little attention in the past (Chen et al., 2021; Manhart et al., 2020). In a seminal paper, Bode et al. (2011) studied the moderating impact of prior SCD experience (defined as the number of SCDs in the past 12 months) on the relationship between the impact of the SCD and the pursuit of buffering and bridging strategies. Surveying a large number of firms, they showed that active and passive firms may draw completely different learning experiences and strategies from SCDs. Anderson and Lewis (2014) used system dynamic models to study the effects of disruptive events on learning and productivity and showed that disruptions to individual learning can be benefit firms in the long run, but similar benefits are not observed with collective learning. Azadegan et al. (2019) studied learning from near-miss events and observed that exposure to near-miss events significantly affects organizational response strategies to SCDs. They showed that firms with near-miss events focus more on procedural response strategies and less on flexible response strategies. However, Azadegan et al. (2020) did not find a significant relationship between experience with SCDs and the operational damage of disruption (p. 59).

Recently, using the agent-based modeling, Chen et al. (2021) showed that different types of suppliers' learning (i.e., learning-to-prevent and learning-to-recover) may improve supply chain performance differently in future disruptions. Although the current studies in the supply chain literature suggest that prior experience has a key role in firms' responses, little is known about how the initial experience of disruption influences the performance of firms in response to future disruptions (Chen et al., 2021; Manhart et al., 2020). Consequently, our study aims to improve understanding of prior experiences and location of SCDs on firm's operational performance using a new source of data, i.e., archival data and real events. The major premise of our is that a firm's experience with SCDs and location of SCDs matter in effectively mitigating negative effects of future SCDs. Traditionally, when firms experience SCDs, they operate in a damage-control control in which they try to minimize the negative effects. However, our study proposes and empirically demonstrates that organizations should also be proactive to find learning opportunities from the SCDs such that future SCDs are prevented, or if not, their effect minimized.

In this study, we focus on a key dependent variable, *SCD severity*, a construct that captures the negative effects of SCDs (Bode and Macdonald, 2017). Our premise is that the actual effects of SCDs on a firm are influenced by the firm's prior experience with the same SCDs, as well as by the *SCD location*—namely, whether the event is internal or external to the firm. We posit that prior experience with an SCD helps reduce the current SCD's severity and that this effect is also contingent on SCD location (internal or external). Formally, the research question that drives our study is as follows:

> RQ. Do a firm's prior SCD experience and the location of the SCD within the supply chain influence how the firm faces new disruptions especially in terms of limiting the current disruption's severity?

The paper proceeds as follows. First, we review the two primary SCD locations within the supply chain and discuss our theoretical perspective of organizational learning. Next, we develop and present our hypotheses—which link prior experience, location, and impact. We then present our empirical study and discuss the results of the hypothesis testing. We conclude by presenting the contributions and implications of this study.

2. Background Literature and Theoretical Foundations

2.1. Internal vs. External SCDs

Many SCDs are not caused by the firm itself but instead occur within a firm's supply-chain network (Kim et al., 2015). For example, SCDs can arise due to halting or slowing down of flow or delivery of goods and materials (due to problems with the supply chain partners, or even natural disasters), or because of internal problems such as a union strike (Habermann et al., 2015). The type of disruption in a supply chain could thus be either internal or external to a firm (Bode et al., 2013; Schmidt & Raman, 2012; Wagner et al., 2012). 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, or even natural disasters directly affecting the firm (Habermann et al., 2015). An example was when the GM facility in Oklahoma was hit by a tornado in 2003 (ibid).

Conversely, an *external disruption* refers to a disruptive event that happens outside the firm's boundaries, such as a supplier failure (Habermann et al., 2015). Habermann et al. (2015) provide an example of the steel shortage in 2004, caused by the increasing demand of steel from China, which led to the shutdown of four Japanese Nissan plants.

Of prime importance to our study is the cost of SCDs, whether internal or external. The cost of SCDs can be measured in terms of their disruption severity (Bode & Macdonald, 2017; Craighead et al., 2007), which is our key dependent variable. Existing supply chain research has linked antecedents of interest to the final bottom line, which is firm financial performance (e.g., Wagner et al., 2012). Similarly, we investigate the impacts of varying SCDs and firm experience with those on our dependent variable of disruption impact. This financial bottom line captures the severity of (negative) impacts of SCDs. Our operationalization of the variable (disruption impact) is discussed in the methodological section.

2.2. Organizational Learning Theory and Learning from Prior Events/Experience

Organizational learning is "the process of acquiring, translating, and enacting new knowledge through organizational routines" (Aranda et al., 2017, p. 1193). The organizational learning literature assumes that firms gradually improve (such as by becoming more efficient) as they build on prior experience using a particular process and reflect on their experiences, draw inferences, and engage in future action based on such understanding (Argote and Ophir, 2002). This learning process leads to beneficial outcomes such as better survival rates, reduced costs, efficiencies in managing processes, and better times to completion (Stan & Vermeulen, 2013). Organizational learning is key to achieving competitive advantage and continued survival (Hoang & Rothaermel, 2010; March, 1991). Previous research identified knowledge acquisition as one of the main steps associated with organizational learning (Huber, 1991). Knowledge acquisition is the process used by organizations to obtain knowledge (Huber, 1991), and it can occur through primarily two mechanisms: experiential knowledge acquisition and vicarious knowledge acquisition (Argote & Hora, 2017; Mena & Chabowski, 2015).

In *experiential knowledge acquisition*, 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; Mena & Chabowski, 2015). In *vicarious knowledge acquisition,* firms attempt to learn from other organizations or other external sources; this is also referred to as ‘second-hand’ learning (Huber, 1991). These two forms of organizational learning play a key role in our theory development.

Regardless of the type of learning, a common conception of organizational learning is that an organization changes as it gains experience, where this prior experience becomes part of the organization’s knowledge that helps it pursue more positive experiences in the future. The importance of organizational learning derives from the fact that firms can improve following prior disruptive experiences by leveraging unique knowledge that only comes from those experiences (Madsen & Desai, 2010), and the future performance, in terms of empirically measurable outcomes, is caused by prior organizational learning (Vera & Crossan, 2004).

Organizational learning theory research has shown that firms learn from their own failures (Chuang and Baum, 2003, Kim et al., 2009). In particular, Raspin (2011) counterintuitively found that firms can learn more effectively from failures than from successes. In the SCD context, the theory of organizational learning through experiential or vicarious knowledge acquisition suggests that firms that experienced an SCD will have more knowledge about that event. They are thus more likely to have documented rules and routines for dealing with similar events (Bode et al., 2011, Elliott et al., 2000).

By contrast, firms without such experience lack relevant knowledge and can face difficulties responding to SCDs (Bode et al., 2011). These firms may suffer from "it couldn't happen here" syndrome (Elliott et al., 2000, p. 17), which consequently prevents them from using the opportunity to learn from near-miss events and SCDs that happen to other firms (Dillon and Tinsley, 2008, Elliott et al., 2000). Ironically, their success in avoiding SCDs leads to risky blind spots, explaining why firms often learn much more from failures than from successes (Madsen and Desai, 2010).

3. Hypothesis Development

3.1. SCD Experience and Future Severity

An organization's supply chain plays a key role in the learning of an organization (Hora and Klassen, 2013, Bellamy et al., 2014). Specifically, knowledge is transferred between organizational units (or between organizations within a supply chain), and if this transfer takes place successfully, an organization will learn from prior experience. From a learning perspective, prior experience with SCDs reinforces the firm's SCD orientation, which strengthens the firm's capacity to respond to SCDs in the future (Bode et al., 2011). It often does so by proactively configuring and managing resources based on prior experience (ibid). The resource-based view of the firm also posits that a firm that learns from unusual events—including SCDs—can develop capabilities with which to anticipate and predict similar events in the future (Hitt et al., 2000). Although such learned capabilities may not make a firm completely resilient to future SCDs, these capabilities can reduce a disruption's negative impact.

In fact, if a firm has faced SCDs, whether external or internal, it is motivated to be proactive and develop capabilities that can improve effectiveness in responding to SCDs in the future (Ramaswami et al., 2009). That is, "firms strive to learn from their past SCD experiences and proactively build capabilities that allow firms to effectively respond to SCDs" (Ambulkar et al., 2015, p. 113). An example of how firms respond positively to disruptive events can be found in the case of the Baltimore and Ohio Railroad Museum Roundhouse (Christianson et al., 2009). The collapse of a roof, a major SCD, allowed the organization to reflect on its existing practices and routines and ultimately to develop skills that made it a far more effective organization.

Whether a firm is embedded in a supply chain (some argue that all firms are embedded), the effects of organizational learning can be viewed as the "decrease in the likelihood that an organization will experience a disaster in the future" (Madsen, 2009, p. 862). Given that SCDs are major events, organizations often view them as highly salient and are increasingly motivated to learn from them (Lampel et al., 2009). The importance of organizational learning from prior negative events, which are often atypical, is aptly captured by Garud et al. (2010):

> Organizational learning from unusual experiences implies an ability not only to make sense of and respond to such experiences in real time, but also to assimilate and use what has been learned from these experiences on an ongoing basis. For instance, organizations ought to learn from actual or near disasters in ways that help them reduce the possibility of future disasters or deal with them more effectively should they reoccur. (p. 587)

In fact, SCDs often challenge the status quo of an organization, creating a sense of urgency and reflection and prompting a search for proactive business models—leading to the development of new ideas, knowledge, and the ability to correct problems (Madsen and Desai, 2010). In a supply chain, this reflection and the subsequent development of new ideas often motivate the firm to seek information about its partners—especially if the SCD originated with a partner—and to design a much more effective supply chain (Dekker and Van den Abbeele, 2010). When the SCD originates within the organization, it likewise forces the organization to change its business model, routines, and processes to ensure quick recoverability after a future SCD (Macdonald and Corsi, 2013). The challenges of prior SCDs stimulate exploration and experimentation in an effort to build organizational mechanisms with which to counter such challenges. In fact, prior SCDs or failures can motivate organizations to seek remedial mechanisms on a continual basis. It is thus natural to infer that prior experience with SCDs leads organizations to develop mechanisms that can be used to limit the severity of future SCDs.

We thus expect firms with relevant prior experience to have a greater ability to control the effects of similar SCDs and to recover more quickly. That is, we expect them to experience less severity over time as a result of the SCDs. Therefore, we hypothesize:

H1. Firms that have experienced a given SCD will suffer less severity during a similar future SCD than will firms without such experience.

3.2. SCD Location and Severity

Our discussion revealed two kinds of SCD location: internal and external. *Internal SCDs* are caused by challenges and failures in processes or resources within the boundaries of a company, such as strikes, technological malfunctions, or even natural disasters directly affecting the firm (Park et al., 2016). Conversely, *external SCDs* are caused primarily by disturbances in the flow of goods and services from suppliers (Park et al., 2016); these could include supplier problems due to natural disasters or resource/operational failings (Xiao and Yu, 2006).

Although both internal and external events can negatively influence a firm's performance (Bode et al., 2013), internal SCDs tend to be more momentous than external SCDs, especially in terms of financial impact (DuHadway et al., 2019, Schmidt and Raman, 2012). To explain the higher severity of internal SCDs, Schmidt and Raman (2012) posited that internal SCDs signal to the market that something is wrong with the internal control mechanism of the disrupted firm and thus that the systematic risk of the firm is higher. Further, DuHadway et al. (2019) asserted that internal SCDs are more likely to be isolated to the firm and not experienced by the firm's competitors, whereas an external SCD may also impact competitors that share supply chain elements. They also posited that internal SCDs send a strong negative signal to key stakeholders, such as suppliers and customers, leading to less negotiation power and a lower level of demand.

By contrast, firms are more likely to find an alternative option for external SCDs. As an example, when a supplier of PSA Group located in Hubei stopped its production because of Covid-19 disruption in 2020, PSA Group was able to use its prototype machines to produce the parts with a slower pace until its supplier in China became operational (Patel and Thomas, 2020). External events like the collapse of a supply chain partner firm will certainly have a negative influence. However, the severity will be much higher for the firm itself if it is revealed that the SCD is internal to the firm. Thus, we posit:

H2. Internal SCDs cause higher severity for a firm compared to external SCDs.

3.3. Interaction of SCD Experience and Location on Future Severity

Past firm experience with an SCD provides relevant knowledge about the event and the available options to restore stability (Bode et al., 2011, Elliott et al., 2000). We have proposed that SCD experience decreases a current SCD's severity, but we propose that the negative effects are differentially affected when the SCD is *internal* as opposed to *external*. This is the case because there are differences between organizational learning in response to external SCDs and organizational learning in response to internal SCDs. The former is an example of *vicarious learning*, whereas the latter is a form of *experiential learning*. Vicarious learning occurs when an organization learns from the experiences of other organizations, whereas experiential learning occurs when a firm learns from its own experiences (Madsen and Desai, 2018, Tuschke et al., 2014, Argote and Hora, 2017).

Notably, it is not always possible for firms to learn vicariously from other firms' experiences (Tuschke et al., 2014). One of the primary reasons is aptly summarized by Denrell (2003):

> Learning from others involves drawing inferences from noisy data. As noted by several scholars, the social and individual complications involved in such inferences often lead to systematic biases … a fundamental learning bias with implications for organizational behavior is the biased samples available to managers and other observers of the organization. (p. 227)

Given that external SCDs are inherently stimulants of vicarious learning whereas internal SCDs are primarily stimulants of experiential learning, we propose that experience with external SCDs is less efficacious than experience with internal SCDs. Nonetheless, as posited in H1, both can allow an organization to learn and thus reduce the severity of future SCDs. However, in response to prior internal SCDs, the organization has a better opportunity to learn and adjust than it does in response to a vicarious experience of external SCDs. Although prior experience with both internal and external SCDs provides relevant knowledge about the events and will be valuable in the event of similar SCDs, one would expect a firm to have more authority to respond to events that are internal to the firm and therefore to have a higher capability for executing the knowledge obtained from those experiences.

We thus expect prior experience to be more effective when the events are internal (experiential learning) as compared to external (vicarious learning). Experiential learning is more potent and "internalizable" (Argote and Hora, 2017); thus, it should play a role in the relationship between experience and the current severity of SCDs. Namely, past SCDs reduce future SCD severity; but the SCD location also matters, because a first-person experience is more influential than a vicarious experience. That is, the SCD location (internal or external) should moderate the influence of prior experience on current SCD severity, as follows:

> *H3. The effect of a firm's experience on reducing an SCD's severity will be higher for internal SCDs than for external SCDs.*

4. Methodology

4.1. Sample Frame and Data Collection

The PR Newswire and Business Wire include the vast majority of press releases from publicly traded U.S. firms (Schmidt and Raman, 2012), and they have been used by other researchers to obtain a representative sample of press releases for analysis (e.g., Liu et al., 2014, Mitra and Singhal, 2008). Accordingly, we searched PR Newswire and Business Wire in the Factiva database to find SCD announcements of firms. The search was limited to North American companies and restricted to the time period from the beginning of 2005 to the end of 2014. The keywords used to search the headlines or lead paragraphs of news articles were as follows: *delay*, *disruption*, *interruption*, *shortage*, or *problem*, paired with *component*, *delivery*, *parts*, *shipment*, *manufacturing*, *production*, or *operations*. Similar keywords have been used previously in the literature to find SCD announcements (Schmidt et al., 2020, Hendricks and Singhal, 2005b).

Around 12,000 news items were collected, and the full text of each item was reviewed to extract SCD announcements. A number of news items were not included because they were related to delays in filing annual financial reports or delays in meeting with investors, which are not SCDs. We also deleted SCD announcements that were not related to publicly traded U.S. firms. Because this study evaluates the performance of disrupted firms from the quarter of the SCD announcement to eight quarters after the quarter of the announcement, we further deleted announcements associated with the same firms within the first two years of another SCD, which is the approach taken by Hendricks and Singhal (2005a). We also collected firms' quarterly performance through the COMPUSTAT database available from WRDS (Wharton Research Data Services, University of Pennsylvania). Our final sample consists of 262 publicly traded U.S. firms that experienced an SCD between 2005 and 2014.

Table 1 provides 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 1 shows that the sample firms include all industry sectors except public administration. The manufacturing sector, with 47% of the total number of firms; the transportation and utilities sector (transportation, communications, electric, gas, and sanitary service), with 19%; and the mining sector, with 15%, are the most common industry sectors among the sample firms. Regarding the type of SCDs in the sample data, 30% of disruptions are caused by natural disasters. Most common natural disasters include floods, hurricanes, tornados, and cyclones. Twenty-six percent of disruptions are caused by accidents, such as explosion and fire, equipment breakdown, environmental deviation in manufacturing, power failure, and electrical surge, and 44% of disruptions were intentional, primarily because of labor strikes due to not reaching an agreement on a new labor contract. Figure 1 presents the distribution of the collected SCD announcements. Notably, the number of SCDs announced in 2005 and 2008 is higher than in other years, which aligns with the high likelihood that Hurricane Katrina (in 2005) and the global financial crisis (in 2008) had widespread negative effects on supply chain operations.

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4.2. Measures and Operationalized Model

4.2.1. Dependent Variable: SCD Severity

Of prime importance to this study is the cost of SCDs, whether they are internal or external. *SCD costs* can be measured in terms of an SCD's *severity* (Craighead et al., 2007, Bode and Macdonald, 2017). Problematically, assessing SCD costs can often be uncertain and inaccurate. In fact, a key to understanding the efficacy of a supply chain is unearthing the downstream effects that the supply chain produces (Jüttner et al., 2003). Extant supply chain research has thus always linked antecedents of interest to the final bottom line, which is firm financial performance (Rai et al., 2006, Cao and Zhang, 2011, Salvador et al., 2014, Wagner et al., 2012). For example, Hendricks and Singhal (2005a) and Schmidt et al. (2020) used operational performance and stock market reactions to evaluate the impacts of SCDs on firms.

Similarly, we investigate the effects of varying SCDs and firm experience with the same on the associated financial outcomes. This financial bottom-line captures SCD severity. Like previous studies, ours uses ROA as a proxy to calculate SCD severity. Sheffi and Rice Jr. (2005) discussed the concept of a "disruption profile" to broadly describe and quantify an SCD's varying effects on a firm over time. The disruption profile characterizes both SCD severity (i.e., decreased performance) and the time needed for the firm to recover its pre-disruption performance levels. It is crucial to consider disruption severity over time because some risk management activities, such as maintaining safety stock, can help to address immediate supply shortages, whereas others, such as contracting with alternative suppliers, can help to speed up recovery and reduce severity over time.

In particular, our study adopts a set of two related metrics identified by Sheffi and Rice Jr. (2005) and Melnyk et al. (2014) for profiling the effect of an SCD on firms' performance. These metrics include the initial amount of performance loss due to the SCD (i.e., initial loss of ROA) and the total amount of loss suffered by the supply chain over time (i.e., total loss of ROA over time). Our use of these two metrics is further inspired by extant literature, as follows.

Initial loss. The literature explains that some SCDs have an immediate influence that is expressed in terms of "initial loss." An example of an internal SCD that had an immediate financial impact was the shutting down of the Union Carbide Corporation's chemical plant immediately following the Bhopal Gas Disaster in India in 1984 (Sheffi and Rice Jr., 2005). The initial loss thus measures the immediate impact of a supply chain disaster.

Total loss of ROA over time. Total loss measures the cumulative effects of the losses in each time period following the SCD. For example, when a fire at one of Toyota's brake suppliers resulted in direct damages of about $195 million, the total estimated loss was about $325 million (Zhang et al., 2018). Total loss over time measures not only the immediate financial impact of the SCD but also the financial impact in the long term, including that caused by long-term damage to reputation (Aqlan and Lam, 2015). For example, when a large earthquake hit Kobe, Japan, in 1995, a local network of small-scale shoe factories lost 90% of its business over time, because most buyers shifted to other manufacturers permanently (Sheffi and Rice Jr., 2005).

To calculate the initial and total loss of ROA over time—and to account for exogenous factors, such as year and industry, which may have an impact on firm performance—we first matched each sample firm to a set of control firms using three matching methods developed by Hendricks and Singhal (2008): matched by performance and industry, matched by performance, industry, and size, and matched by performance size. The matching set of nondisrupted firms are similar to the sample firm considering different characteristics. Therefore, by comparing the sample firm's performance with the set of matched firms, we account for the exogenous factors, such as year and industry, that may influence the firms' performance. After finding the set of control firms, using the approach by Hendricks and Singhal (2008), we calculated the abnormal ROA of each sample firm at quarter t (ΔROA_t) using the difference between its actual ROA and the expected ROA in that quarter:

$$\Delta ROA_t = \textit{Actual ROA of sample firm at quarter } t - \textit{expected ROA of sample firm at quarter } t \tag{1}$$

Note that the calendar quarters of all firms are measured relative to their SCD. Thus quarters -4, 0, and 4 represent 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' 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 ΔROA_t indicates that the sample firm's ROA was less than its expected ROA and thus that it experienced a relative loss at quarter *t*. Using formula (1), the abnormal ROA of each sample firm is calculated from quarter zero (the quarter of the SCD announcement) to quarter eight (eight quarters after the quarter of SCD announcement).

Because ROA is a ratio measurement, it allows us to compare SCD severity across firms with different sizes. For example, consider a firm with total assets of $1,000 and a net income of $500 and a second firm with total assets of $1 million and a net income of $500,000. Now, assume that an SCD decreases the net income of the first firm by $250 and that of 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 SCD's severity on the performance of the first firm is much higher than on the second firm (the SCD has almost no severity on the second firm). Considering ROA as the performance unit, however, the SCD severity on the firms using formula (1) is –25% and –1%, respectively. Thus, using ROA as our performance unit, we are able to compare SCD severity across firms with different sizes.

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

$$L_0 = -\Delta ROA_0 \quad (2)$$

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 of ROA.

The total loss of ROA over time is then calculated as the sum of the positive loss values over the first two years after an SCD:

$$\mathit{Total\ loss}\text{ of ROA }\mathit{over\ time} = \sum_{t=0}^{8} \max(0, L_t) \quad (3)$$

where $L_t = -\Delta ROA_t$. Because each individual loss value is calculated relative to the performance of a matching set of nondisrupted firms, this cumulative loss value represents the total shortfall suffered by the disrupted firm over the given two-year time interval. However, we also consider net performance of ROA over time as another performance measurement in the robustness check section.

4.2.2. Independent variables: SCD location

While collecting the SCDs, we reviewed the announcements to determine their location of occurrence. When the location was not clearly indicated, we eliminated the announcement from our sample (54 announcements were dropped). The location was then treated as a dummy variable (external SCDs = 0, internal SCDs = 1) in our analyses. Table 2 shows two SCD announcements and their assigned locations.

---------------------------- Insert Table 2 approximately here ----------------------------

4.2.3. Independent variables: Prior Experience

For prior experience, we are interested to find if a firm experienced a similar event in the past.

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 prior experience. For example, if Hurricane Katrina disrupted a firm, we searched the Factiva database to find related news for the firm and similar events using keywords such as *hurricane*, *tornado*, *typhoon*, *storm*, and *flood*. As another example, for a workers' strike, we searched *strike* and *work stoppages* and identified the related events, if any. We limited our search from the date of the SCD 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 experience was then set to "1" if a given sample had a similar experience and "0" otherwise.

4.2.4. Control variables

Along with SCD location (i.e., internal or external), SCD *type* may also significantly affect severity (Stecke and Kumar, 2009). To address this possibility, we categorized the SCDs into three categories proposed by Stecke and Kumar (2009): (1) *natural disaster* (i.e., disruptions originating in nature, such as severe weather, floods, and wildfire); (2) *accident* (i.e., unintentional, manmade disruptions not originating in nature, such as equipment breakdown, software bugs, data-entry mistakes, roof collapse in a warehouse, and loss of goods from a truck rollover); and (3) *intentional* (i.e., intentional manmade disruptions, such as labor strikes, government regulations, war, theft, and cyberattacks). When a sample firm did not explain the SCD type 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 SCD type for a few supply chain announcements, and these were thus eliminated from the final sample. We controlled for SCD type by including two dummy binary variables: accidental and intentional; natural disaster represented the baseline (accidental and intentional are both zero in the baseline).

Crucially, the location where any of these types of SCDs (i.e., natural disaster, accident, or intentional) impacts a supply chain can be either internal or external—resulting in six combinations of these two control variables in our dataset. For example, an "internal" natural disaster is one that caused an SCD that occurred at the firm itself (e.g., floods damage its warehouse for goods ready to ship); an "external" natural disaster is one in which a firm's supply chain partner suffers an SCD that then, in turn, affects the firm (e.g., typhoons knock out power in Southern China, causing the manufacturing at a key partner to come to a halt). Table 3 shows the distribution of these six different combinations of SCDs (i.e., location x type) across our dataset.

--------------------------- Insert Table 3 approximately here ---------------------------

It is important to consider that SCDs may have higher negative effects on firms that operate in highly competitive industries (Hendricks and Singhal, 2005a). We thus also controlled for industry competitiveness 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. The age of each firm is calculated as the difference between the year of the SCD announcement and the first year that the firm is listed in COMPUSTAT. We controlled for the size of firms by considering the natural logarithm of the number of employees one year prior to the year of an SCD announcement.

4.3. Descriptive Statistics

Zero-order correlations, means, and standard deviations for the dependent, independent, and control variables are reported in Table 4. The reported dependent variables (*initial loss* and *total loss over time*) are calculated using the first matching method. The average total loss of ROA over time is 13.05 percent and is significantly greater than zero (p-value ≤ 0.01), which indicates that SCDs have significant severity on firms. The other two values for the average total loss of ROA over time, based on the alternative matching methods, are also significantly greater than zero (p-values ≤ 0.05).

--------------------------- Insert Table 4 approximately here ---------------------------

5. Analysis and Results

We used ordinary least squares (OLS) regression to test the hypotheses. To reduce the influence of outliers on the results, we calculated Cook's D value for each observation in each model, and we excluded observations with a Cook's D value higher than 4 over the sample size from the final model (Colbert et al., 2008, Fox, 1991). We calculated the variance inflation factor (VIF) for the independent variables in all models, and the largest VIF was lower than the threshold recommended in the literature (i.e., 5.0, Johnston et al., 2018). Thus, it was unlikely that multicollinearity was an issue in our analyses.

However, before conducting OLS, we tested its statistical assumptions. First, we used the Durbin-Watson test to detect the presence of autocorrelation in the residuals of our regression models. All p-values were greater than 0.05, and we concluded that the residuals in the regression models were not autocorrelated. We used the Breusch–Pagan test to test for heteroskedasticity in our models. All p-values were greater than 0.05, and thus we failed to reject the null hypotheses. Therefore, the variance of errors from the models were not dependent on the values of independent variables. To test the normality of the residuals, we used the Shapiro-Wilk normality test. All p-values were greater than 0.05, and thus we failed to reject the null hypotheses that the residuals are normally distributed. Finally, we calculated the mean of residuals from the models, and all of them were approximately zero.

Although it is almost impossible to eliminated endogeneity from empirical analysis (Guide & Ketokivi, 2015), we minimize the impact of endogeneity in the model theoretically and methodologically. In the regression analysis, the endogeneity issue arises when an independent variable is correlated with the error term (Lu et al., 2018). Theoretically, the endogeneity can be a problem if the exogenous variables can be construed as endogenous variables. In our model, the exogenous variables are SCD prior experience and location. Given how we constructed our dataset and the analysis, the exogenous variables can be regarded as "largely, approximately, or plausibly exogenous" (Conley et al., 2012; Roberts and Whited, 2013).

Additionally, the other endogeneity issue can arise if the dependent variable is not really an outcome of SCD experience and location. As mentioned in sections 2 and 3, the supply chain management literature, in line with the organization learning theory, suggests that both SCD prior experience and location greatly influence a firm's post-disruption performance (Azadegan et al., 2019; Chen et al., 2021; DuHadway et al., 2019; Schmidt and Raman, 2012). Making sense of causal connection requires theoretical anchoring, and the causal hypotheses in our study follow the literature and theory. Reverse causality can also cause the endogeneity issue. However, the reverse causality is not a concern in our model because the prior experience is captured in previous quarters, and the severity of an SCD cannot theoretically impact the location of SCD. Methodologically, we included several control variables (type of SCD, industry, firm age, and firm size) to minimize the potential impact of omitted variables. We also added several robustness tests using different matching methods and performance measures (Net Performance of ROA, and ROS).

5.1. Initial Loss

In Table 5, we present the regression results of initial loss calculated using the three matching methods. All the *F*-values of the three models are greater than 4.00, and each of them is statistically significant at the 1% level, with an R^2 value as high as 0.15. The results of all three models indicate that intentional SCDs have a higher initial severity on firms than do accidental and disaster SCDs (*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 5 also shows that firm size is negatively associated with initial loss (*p*-values ≤ 0.01), indicating that in general, larger firms 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).

---------------------------- Insert Table 5 approximately here ----------------------------

Table 5 further reveals that when the prior experience variable is zero, the SCD location is positively associated with initial loss (*p*-values ≤ 0.10), indicating that in the case of no experience, internal SCDs result in more initial loss than external SCDs. The interaction term is also statistically significant at the 10% level considering the results from all three methods.
To facilitate interpretation of the effects of SCD location and firm SCD experience on the initial loss of firms, Figure 1 plots average initial loss values for external and internal SCDs both with and without experience.

To test the hypothesis that a slope differs from zero, we ran a *t*-test as described by (Aiken et al., 1991). Lines with a slope significantly different from zero are highlighted with green color (p-value ≤ 0.05). Figure 1 indicates that internal SCDs are statistically significantly associated with more initial loss when firms do not have similar prior experience. Figure 1 also shows that experience decreases the initial loss of firms when SCDs are internal to firms, but that experience does not decrease the initial loss in the case of external SCDs. Figure 1 further reveals that the initial loss from external SCDs is close to zero, which together with results from the maximum loss and the total loss, suggests that external SCDs may have a delayed severity on firms' performance.

--------------------------- Insert Figure 1 approximately here ---------------------------

5.2. Total Loss of ROA over Time

Table 6 provides the results of the regression models for total loss of ROA over time against the independent variables. 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 the results of similar studies (e.g., Azadegan et al., 2020, Hendricks et al., 2009, Schmidt and Raman, 2012). Table 6 shows that firm size is negatively associated with total loss of ROA over time (p-values ≤ 0.01). None of the other control variables have a significant relationship with total loss over time (p-values > 0.10), except for the industry growth rate in the second regression model (p-value ≤ 0.05). The interaction term between SCD location and firm SCD experience is significant in all three models (p-values ≤ 0.05).

--------------------------- Insert Table 6 approximately here ---------------------------

To further analyze these effects, we plot the average total loss of ROA over time for the different levels of the SCD location and firm SCD experience variables, as shown in Figure 2. Lines with a slope significantly different from zero are highlighted with green color (p-value $\leq$ 0.05). Based on Figure 2, internal SCDs are associated with a higher total loss of ROA over time than are external SCDs when firms have no prior experience. Conversely, firms with experience have significantly less total loss of ROA over time in the case of internal SCDs.

--------------------------- Insert Figure 2 approximately here ---------------------------

We also checked the robustness of our results using several other variables. These results are provided in the supplementary materials.

6. Discussion

6.1. Summary of Findings

This study investigates the relationships between SCD origin, firm SCD experience, and SCD severity. We adopted initial loss of ROA and total loss of ROA over time to quantify SCD severity. Evaluating the performance of a set of 262 disrupted firms between 2005 and 2014, we find that internal SCDs are associated with a higher initial loss of ROA and a higher total loss of ROA over time when firms lack experience with a similar event in the past.

To clarify the various ways in which both SCD origin and the firm experience may affect a firm's performance, we explicitly consider two different output measures to characterize a supply chain's response to an SCD: (1) the initial performance loss due to the SCD and (2) the total loss over time. Using these two measures as the basis for comparison, we then evaluate the performance of 262 firms that experienced an SCD between 2005 and 2014. The results of our analyses indicate that both the SCD origin and a firm's experience play a leading role in determining SCD severity. Namely, the results indicate that when firms have no experience with a similar event in the past, internal SCDs lead to a higher level of initial loss and more total loss over time than do external SCDs. By contrast, firms with prior experience suffer less initial loss and total loss over time when SCDs are *internal* to firms; however, this experience may not decrease initial loss and total loss over time in the case of *external* SCDs. Finally, similar to the results of previous SCD studies, we find that larger firms experience less severe disruptions than do smaller firms.

In summary, Hypotheses 1 and 2 are partially supported, and Hypothesis 3 is fully supported considering both initial loss and total loss over time:

- Firms that have experienced a given *internal* SCD will experience less severity due to a similar future event than will firms that lack such experience.
- Internal SCDs cause higher severity than do external SCDs, but only *in the case of no experience.*
- The effect of experience on reducing the severity due to SCDs will be higher for internal SCDs than for external SCDs.

6.2. Contributions to Research, Theory, and Practice

6.2.1. Revelatory Theoretical Insights

We believe our study offers a revelatory perspective and thus makes a strong theoretical contribution. Our study provides novel insights into the positive and negative outcomes of SCDs and also paves the way for researchers to further tease out multiple nuances of how prior experience of and organizational learning based on SCDs can eventually lead to the establishment of a robust supply chain. We discuss our major contributions below.

First, our study contributes to the literature by evaluating the effect of two important factors—that is, SCD origin and firm SCD experience—on financial performance after SCDs. The effect of these two factors on firms' financial performance in this context has received little attention in previous studies. In a study that investigated related behaviors, Schmidt and Raman (2012) found that internal SCDs have more severity on the stock market than do external SCDs. Our study, however, shows for the first time that the severity of internal and external SCDs on firms' performance can be different when firms do not have experience. Furthermore, our results show that experience may not decrease the severity of external SCDs.

Our second theoretical contribution is associated with evaluating the negative effects of SCDs on firm performance using two different but complementary metrics: initial loss and total loss over time. Using these two metrics, we are able to show that SCD origin and firm experience may have different *types* of effects on firms' performance after SCDs. For example, our study shows that an SCD has a significant effect on the amount of initial loss experienced by a firm. When SCDs originate externally, the initial loss suffered by the firm is not significant; however, when SCDs originate within a firm, the initial loss experienced by the firm is significant. This finding is in line with the observation of Ellis et al. (2010) that SCDs may have either immediate or delayed impact on firm performance. Considering the initial loss, we also observe that experience significantly reduces the amount of loss suffered by a firm in the case of internal SCDs.

Conversely, SCD origin and firm experience have different effects with respect to the total loss over time metric. The results show that the total loss over time due to an internal SCD is higher than the total loss over time due to an external SCD when firms do not have similar experience. When such experience does exist, it decreases the total loss over time for internal SCDs but may not have the same effect on the total loss over time for external SCDs.

6.2.2. Practical Usefulness

Practical usefulness is also necessary for a strong theoretical contribution. This paper provides two important insights for practitioners in the field of supply chain risk management. First, although the severity of SCDs on firms' performance can vary significantly, our study shows that compared to external SCDs, internal SCDs generally result in higher initial loss and higher total loss over time 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 SCDs, they may often be able to respond to different types of external SCDs using a single 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 its response to a supplier's on-site strike, if each SCD type ultimately leads to the same amount of shortfall in supply. This implies that when firms do not have experience with an SCD, an internal one can lead to more loss than an external one. This argument is further supported by the fact that although experience with SCDs significantly reduces total loss in the case of internal SCDs, such experience is not associated with a reduction of total loss in the case of external SCDs. In summary, this suggests that firms need, and can benefit from, a higher degree of preparation against internal SCDs than they do against external SCDs.

The second relevant insight for practitioners is that firms without experience suffer a higher initial loss and a higher total loss of ROA after an internal SCD 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 path to knowledge acquisition. Firms can obtain knowledge through two other 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 et al., 2008).

Conversely, in contact knowledge acquisition, firms obtain knowledge from formal relationships with other firms (Mena & Chabowski, 2015; Ordanini et al., 2008). Recently, this knowledge acquisition has been extended theoretically in supply chains to the idea of broadening a firm's knowledge by "absorbing" partners' experiences systematically via its absorptive capacity and collaborative capabilities (Briel et al., 2019). Thus, to better protect themselves from the negative effects of SCDs, supply chain managers should consider these two types of knowledge acquisition—vicarious and contact knowledge acquisition (ideally as strategic knowledge absorption and collaboration with partners)—as important tools to improve organizational resilience against SCDs.

Prior studies have shown that the type of events (success and failure) is closely related to knowledge acquisition in organizations (Ellis et al., 2006) and that organizational learning from failures is usually higher than from successes (Raspin, 2011). Consequently, one would also expect that types of SCDs (natural disaster, accident, and intentional) have impacts on organizational learning. Vicarious and contact knowledge acquisition may also be more effective in the case of natural disasters compared to accident and intentional disruptions. Therefore, future studies might study the relationship between types of SCDs and organizational learning.

Disruptions knowledge, acquired by experiential, vicarious, and contact knowledge acquisition processes, can be used in creating or improving a digital SC twin to manage disruption risks, as proposed in recent studies in the literature (Becue et al., 2020; Ivanov and Dolgui, 2020a; Ivanov et al., 2019). A digital SC twin presents SC network states in real-time and combines optimization, simulation, and data analytics for managing SCD risks (Ivanov and Dolgui, 2020a). Including disruptions knowledge in the digital SC twin improves the disruption risk management systems and avoids organizational forgetting that sometimes happens because of employee turnover and organizational mergers or acquisitions. At the same time, as decision-makers increasingly rely on algorithms and their outcomes for decision-making, knowledge from prior experience may prevent blind flights since the knowledge provides an understanding of SCD events.

Knowledge acquisition and subsequently investment in proactive and reactive resilience strategies can explain the positive effect of prior experience. However, investment in resilience strategies is costly, and supply chain managers should consider the costs and benefits of different resilience actions (Aldrighetti et al., 2021). Because firms with prior experience have more knowledge about details of the disruption event, prior experience may also benefit firms in selecting the most efficient and effective proactive and reactive resilience strategies in response to similar future similar disruptions.

6.3. Limitations and Future Research Implications

Our study is highly contextualized, and thus our design and theoretical choices naturally give rise to limitations, which point to compelling research opportunities. In particular, we believe our study can provide avenues for further testing and operationalization of our theory, thus making it scientifically useful.

One clear area of future investigation could be to test our theory in other contexts. In our study, we considered only publicly traded U.S. firms in the process of collecting data. This has the advantage of providing control through general homogeneity; however, SCDs may have different effects on firms in other countries, and therefore we are unable to generalize our inferences to firms in this broader context. We believe, for example, it would be particularly interesting and relevant to study these effects in China, especially because it is a large market that acts as a key center in global manufacturing supply chains. China is a heavily regulated market with many large state-owned enterprises that is subject to strong cultural influences, such as guanxi (Cai et al., 2010; Lai et al., 2016); compared to Western cultures, China also exhibits empirical differences in uncertainty avoidance and power distance (Lowry et al., 2011). These and other factors could result in different prevention philosophies, responses, and learning approaches to SCDs. Similarly, investigating our theory in the context of other developing economies, such as South America and India, could also reveal important country- and culturespecific differences.

Another possible avenue for future research is to extend our study's time period of analysis. In this study, we evaluated the performance of firms for a two-year period after the occurrence of an SCD. The actual recovery process, however, may take longer than two years in some cases and may be faster in others. Thus, future studies of firm performance after an SCD should consider both shorter and longer time periods.

In this study, we calculated initial loss and total loss over time based on firms' ROA and ROS performances. It is important to recognize, however, that researchers could likely use other performance measures, such as net sales, to calculate the same two metrics of initial loss and total loss over time. Production capacity is another closely related performance measure of the effects of SCDs. However, it is much more difficult, if not impossible, to collect the production capacity data over time after SCDs. Thus, it would be useful for future research to consider and compare such surrogate measures of supply chain performance, to establish which ones are most robust and reliable. Furthermore, firms' response to SCDs is a crucial factor in controlling the impacts of SCDs. However, data on firms' reactions are not available from secondary sources. Future studies may use primary data collection techniques, such as interviews, to collect firms' reactions to SCDs and evaluate their relationship with SCDs.

As mentioned, we searched the Factiva database to find SCD announcements. All the announcements were issued by firms to report significant SCDs in firms' routine operations. Accordingly, all the SCDs considered in this study were severe events that can have significant negative effects on firms' performance. Although each of these SCDs can be categorized as a major event, they nevertheless differ in terms of their size and extensiveness. We thus considered the SCD type to control for some of the unique aspects of each SCD. Future research could focus on developing a better mechanism to control for the size of SCDs. In this research, we also did not consider the strategy of firms, organizational design, and structure. These factors may have significant impacts on firms' response to SCDs. For example, prior studies have shown that the firm strategy, such as cost leadership and differentiation strategies, significantly affects firms' success or failure (Bryan et al., 2013). Future studies may also consider evaluating the impact of these factors on the severity of SCD.

Finally, we adopted an encoding of prior experience as a binary variable with a value of "1" if the firm had a similar experience in its past five years and "0" otherwise. Although this succinct representation is defensible and consistent for parsimony reasons, we call for future research to delve deeper into the experience of firms, such as whether or not firms have encountered a particular SCD type more than once in the past and also over a longer time frame, such as 10 years. Studies might also investigate the role of experience in reducing not just disruption severity but also the likelihood of disruption occurrence in the future. Also worthy of further consideration, but much more difficult to measure, is the number and degree of prior SCDs. In this study, we did not consider the number of prior events, the degree of those events, and the length of time since the most recent experience. By considering these variables researchers could potentially provide even more insights into the effect of experience on firms' performance after SCDs.

7. Conclusion

Drawing on the organizational learning literature, this study investigates the relationships between SCD origin, firm SCD experience, and the resulting severity in terms of the firm's financial performance. We consider two metrics to quantify SCD negative impact: initial loss and total loss over time. Evaluating the performance of a set of 262 disrupted firms between

2005 and 2014, we find that internal SCDs are associated with a higher initial loss and a higher total loss over time when firms lack experience with a similar event in the past. Our findings have important implications for the literature on organizational learning and its pivotal role in addressing SCDs. We expect that our study will encourage researchers to investigate other ways in which organizational learning can be used to manage SCDs.

Acknowledgments

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Table 1: Distribution of the Sample Firms by 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

Table 2: Two SCD Announcements and Their Assigned Locations

Reference and date	Announcement	Location	Value of location variable
Business Wire – Jan. 25, 2005	"Atlantic Tele-Network, Inc. (AMEX: ANK), announced that its Guyana operations were affected by severe flooding over the past week … Work has also begun on repairing the damage caused to GT&T's equipment and infrastructure, although it will likely be some time before that work is complete."	Internal	1
Business Wire – Aug. 31, 2005	"Terra Industries Inc. (NYSE: TRA) announced today that it has ceased ammonia production at its Yazoo City, Miss., nitrogen products manufacturing facility due to its natural gas supplier's declaration of force majeure."	External	0

Table 3: Distribution of the Six Different Combinations of SCDs in the Dataset

SCD Location	**SCD Type**		
	Type 1: Natural disaster	Type 2: Accidental (manmade)	Type 3: Intentional (manmade)
Internal (within the firm)	64	62	88
External (supply chain partner)	14	7	27

Table 4: Means, Standard Deviations, and Correlations

Variable*	1	2	3	4	5	6	7	8	9	10
Initial loss ($\times 10^2$) [1]	1.00									
Total loss over time ($\times 10^2$) [2]	0.51	1.00								
Location [3]	0.06	0.00	1.00							
Prior experience [4]	-0.11	-0.11	0.11	1.00						
Disasters (type 1) [5]	-0.08	-0.11	0.01	0.21	1.00					
Accidental SCD (type 2) [6]	-0.03	-0.02	0.13	0.08	-0.39	1.00				
Intentional SCD (type 3) [7]	0.10	0.12	-0.12	-0.27	-0.58	-0.53	1.00			
Industry growth rate [8]	0.07	-0.03	0.04	-0.01	0.10	-0.09	-0.01	1.00		
Firm age [9]	-0.16	-0.23	0.18	0.21	-0.06	0.08	-0.01	0.03	1.00	
Firm size [10]	-0.26	-0.40	0.18	0.28	0.05	-0.03	-0.01	0.05	0.56	1.00
Sample size	262	227	262	262	262	262	262	262	262	262
Mean	1.18	13.05	0.82	0.47	0.30	0.26	0.44	0.10	30.16	1.31
Standard deviation	7.58	24.91	0.39	0.50	0.46	0.44	0.50	0.16	19.79	2.17

* The first two variables are calculated based on the matched by performance and industry method.

Table 5: Results of Regression of Initial Loss ($\times 10^2$)

	Matched by performance and industry (M1)		Matched by performance, industry, and size (M2)		Matched by performance and size (M3)	
	β	*t*-value (VIF)	β	*t*-value (VIF)	β	*t*-value (VIF)
Intercept	0.12	0.21	0.01	0.03	0.20	0.37
Control variables						
Accidental SCD (type 2)	0.02	0.04 (1.42)	0.01	0.02 (1.42)	-0.25	-0.55 (1.42)
Intentional SCD (type 3)	0.75	1.77^{d} (1.48)	0.90	2.14^{c} (1.47)	1.10	2.65^{a} (1.48)
Industry growth rate	1.82	1.71^{d} (1.01)	1.84	1.73^{d} (1.02)	0.81	0.78 (1.01)
Firm age	0.00	-0.34 (1.55)	-0.01	-0.63 (1.55)	0.00	-0.32 (1.55)
Firm size	-0.34	-3.49^{a} (1.58)	-0.30	-3.1^{a} (1.87)	-0.41	-4.28^{a} (1.58)
Direct effects						
Location	0.94	2.04^{c} (1.12)	1.15	2.53^{a} (1.11)	0.76	1.68^{d} (1.12)
Prior experience	0.01	0.02 (1.20)	-0.06	-0.17 (1.19)	0.33	0.91 (1.20)
Interactions						
Location × Prior experience	-1.60	-1.74^{d} (1.08)	-2.00	-2.19^{c} (1.07)	-1.49	-1.65^{d} (1.08)
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} $p \leq 0.10$

Table 6: Results of Regression of Total Loss of ROA over Time (×10^2)

	Matched by performance and industry (M4)		Matched by performance, industry, and size (M5)		Matched by performance and size (M6)	
	β	*t*-value (VIF)	β	*t*-value (VIF)	β	*t*-value (VIF)
Intercept	13.86	5.79[a]	13.91	7.48[a]	12.64	6.12[a]
Control variables						
Accidental SCD (type2)	0.17	0.09 (1.42)	-0.99	-0.66 (1.42)	0.39	0.23 (1.42)
Intentional SCD (type 3)	1.28	0.72 (1.47)	0.77	0.56 (1.46)	1.68	1.09 (1.44)
Industry growth rate	-2.11	-0.47 (1.01)	-6.90	-1.97[c] (1.01)	-6.22	-1.59 (1.01)
Firm age	-0.04	-1.00 (1.42)	-0.01	-0.27 (1.42)	-0.04	-1.11 (1.44)
Firm size	-2.22	-5.02[a] (1.44)	-2.56	-7.46[a] (1.44)	-2.16	-5.78[a] (1.46)
Direct effects						
Location	0.09	0.04 (1.13)	-0.70	-0.45 (1.12)	-0.71	-0.41 (1.12)
Prior experience	0.52	0.33 (1.21)	1.30	1.08 (1.20)	1.77	1.31 (1.21)
Interactions						
Location × Prior experience	-8.63	-2.14[c] (1.09)	-7.44	-2.37[b] (1.09)	-8.89	-2.57[a] (1.08)
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] $p \leq 0.01$, [b] $p \leq 0.025$, [c] $p \leq 0.05$, *and* [d] $p \leq 0.10$

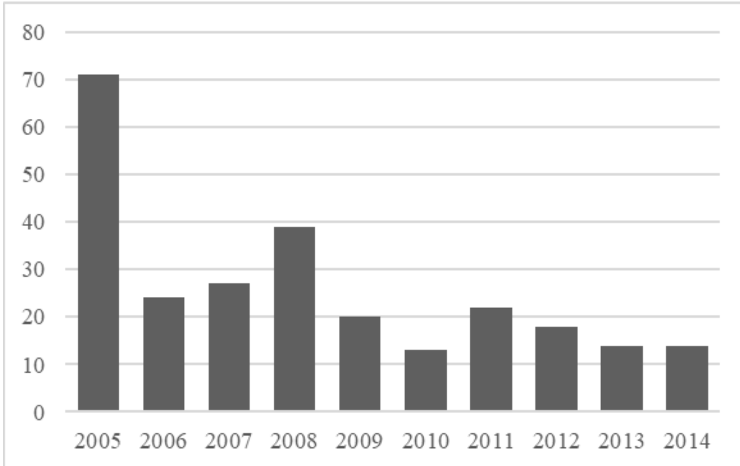

Figure 1. Number of SCD Announcements per Year

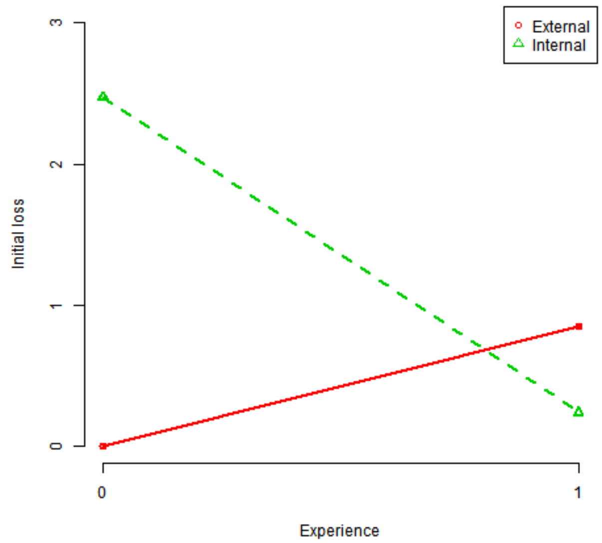

Figure 2: Average Initial Loss ($\times 10^2$) Based on SCD Location and Prior SCD Experience

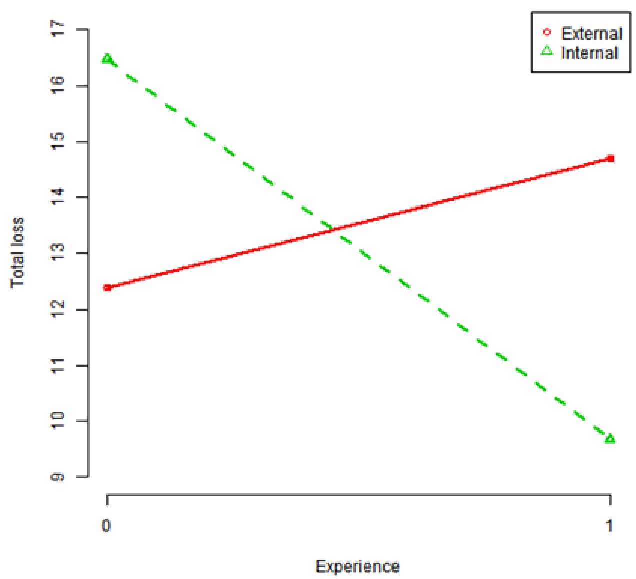

Figure 3: Average Total Loss of ROA over Time ($\times 10^2$) Based on SCD Location and Prior SCD Experience