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Effects of supply chain disruptions due to COVID-19 on shareholder value

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Abstract

Purpose – The purpose of this research work is to examine the financial effect of supply chain disruptions (SCDs) caused by coronavirus disease 2019 (COVID-19) and how the magnitude of such effects depends on event time and space that may moderate the signaling environment for shareholder behaviors during the pandemic.

Design/methodology/approach – This study analyses a sample of 206 SCD events attributed to COVID-19 made by 145 publicly traded firms headquartered in 21 countries for a period between 2020 and 2021. Change in shareholder value is estimated by employing a multi-country event study, followed by estimating the differential effect of SCDs due to the pandemic by event time and space.

Findings – On average, SCDs due to pandemic decrease shareholder value by −2.16%, which is similar to that of pre-pandemic SCDs (88 events for 2018–2019). This negative market reaction remains unchanged regardless of whether stringency measures of the firm's country become more severe. Supply-side disruptions like shutdowns result in a more negative stock market reaction than demand-side disruptions like price hikes. To shareholder value, firm's upstream or downstream position does not matter, but supply chain complexity serves as a positive signal.

Originality/value – This study provides the first empirical evidence on the financial impact of SCDs induced by COVID-19. Combining with signaling theory and event system theory, this study provides a new boundary condition that explains the impact mechanism of SCDs caused by the pandemic.

Keywords COVID-19, Supply chain disruption, Signaling theory, Event system theory, Stock market reaction

Paper type Research paper

1. Introduction

In December 2019, a novel virus SARS-CoV-2 emerged in Wuhan, a city known for being a manufacturing hub in China. It soon spread to other countries causing a contagious respiratory disease called COVID-19, leading to a pandemic. The COVID-19 pandemic made people refrain from close physical contact, disrupting normal day-to-day activities. It also indirectly orchestrated an environment where private firms and governments had to face disruptions to keep people alive. At the time of writing, the World Health Organization (WHO) reported more than 3 million deaths, making it one of the deadliest pandemics in history. Apart from causing the high mortality, the COVID-19 pandemic also brought severe supply chain disruptions (SCDs) to the world. Firms that had developed an efficient supply chain

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over years faced numerous SCDs. Industries across the globe got affected alarmingly. In the words of Taleb (2010), the pandemic can be called a "black swan" as it is characterized by impact severity, improbable occurrence, and suddenness.

However, COVID-19 differs from the normal challenges caused by SCDs in scope and depth. For instance, the Great East Japan Earthquake (GEJE), considered another black swan event, was primarily a shock to a narrow geography affecting only a limited number of firms and industries (Carvalho *et al.*, 2021; Hendricks *et al.*, 2020). Earlier infectious diseases like Tuberculosis, Severe Acute Respiratory Syndrome and Ebola have been witnessed, but their effect on the supply chain was tangential. By contrast, the COVID-19 pandemic, unlike previous black swan events, remarkably exploited the modern densely connected supply chain networks at a global scale for several years. It disrupts supply or demand, or both, along certainty, stability, availability, visibility and permanence dimensions of a supply chain at the same time (Sodhi and Tang, 2021). Clearly, COVID-19 is an "extreme" black swan event that lies beyond regular supply chain risk management (SCRM) knowledge.

Not surprisingly, the COVID-19 impact is deemed to be devastating for global supply chains. A recent report suggests a loss of €112.7 billion to gross domestic product (GDP) across the Eurozone due to the pandemic-induced disruptions in 2021 (Ollagnier *et al.*, 2022). However, the literature remains unclear to what extend the SCDs caused by the pandemic damage firms in the supply chain. This study intends to fill this gap by estimating the financial impact of SCDs caused due to COVID-19, through changes in the shareholder value. SCD studies have found significant prominence and attention in the recent decade, developing as a subset of the overall SCRM literature (Ho *et al.*, 2015; Xu *et al.*, 2020). Many of the studies have recorded the loss in shareholders wealth due to SCDs (cf. Table 1). However, except for Srinivasan *et al.* (2022), they all address normal challenges (e.g. glitches) caused by

Article	Event (*n*)	Context	Time	Mean abnormal returns
Hendricks and Singhal (2003)	Supply chain glitches (519)	USA	1989–2000	−10.28% on event period [−1, 0]
Papadakis (2006)	Taiwan earthquake (4[a])	USA	Sep 20, 1999	−9.30% (only for two firms) on event period [1, 3]
Schmidt and Raman (2012)	Supply chain disruptions (517)	USA	1998–2011	−7.50% prior to, −2.90% after Section 409 of SOX on event period [0, 1]
Kumar *et al.* (2015)	Supply chain disruptions (301)	India	2003–2012	−2.88% on [−5, 5]
Filbeck *et al.* (2016)	Supply chain disruptions (408)	USA, Japan	1990–2010	−0.99% on event period [−5, 5]
Zsidisin *et al.* (2016)	Supply chain glitches (116)	USA	2001–2012	−1.94% on the event day [0]
Liu *et al.* (2018)	Supply chain disruptions (216)	Japan	2000–2013	−0.61% on event period [−5, 5]
Hendricks *et al.* (2020)	Japan earthquake (470[a])	Multiple	Mar 11, 2011	−4.33% on event period [0, 2]
Schmidt *et al.* (2020)	Supply chain glitches (213)	USA	2013–2017	−3.55% on event period [−1, 1]
Baghersad and Zobel (2021)	Supply chain disruptions (397)	USA	2005–2014	−1.64% on the event day [0]
Bai *et al.* (2021)	Operational risks (762)	China	2010–2017	−1.06% on event period [−1, 1]
Srinivasan *et al.* (2022)	Lockdown (467[a])	USA	Mar 19, 2020	−1.08% on event period [−7, 1]

Note(s): [a]Firm-level samples

Table 1. Prior event studies on SCDs during normal times

SCDs. To our knowledge, no studies have contemplated on an extreme black swan event that threatens supply chain operations in most countries in the world simultaneously. The COVID-19 offers a unique setting where we observe extreme conditions facing firms due to pandemic-induced SCDs with a global impact (Micheli *et al.*, 2021).

This study roots its conceptual framework on signaling theory (Spence, 1978), together with event system theory (EST) (Morgeson *et al.*, 2015). The basic idea of signaling theory in this study is that SCDs are unintended negative signals that shareholders (receivers) seek out from independent business outlets about firms (signalers), thus reducing the information asymmetry between the parties. However, shareholders will not be able to interpret the signal accurately if the market is abundant with noises created in the signaling environment (Connelly *et al.*, 2011). In such circumstances, receivers like shareholders may seek out different signals depending on the environment, other than conventional ones to reduce information asymmetry. EST suggests that salient events like COVID-19 are likely to shape firm behaviors, compared to normal happenings. Importantly, those behaviors triggered by the event are moderated by event time and space, such as changing stringency measures, sources of disruptions, firm position in supply chain, and supply chain complexity. Anchoring on this framework, we explore the signaling influence of pandemic-induced SCDs on market value of the firms, and how those signals are changed by the event time and space.

To this end, we collect a sample of 206 pandemic-induced SCD events involving 145 firms across 21 countries from January 2020 till November 2021. By employing a multi-country event study, we find that SCDs caused due to COVID-19 are associated with a decrease in shareholder value of -2.16%. This magnitude is similar to that of SCDs in the pre-pandemic years of 2018 and 2019 (88 events). The magnitude of the pandemic-induced SCDs remains unchanged regardless of whether stringency measures of the firm's countries become more severe. Moreover, the negative market reaction is indifferent to firm's position in the supply chain network. However, the stock market reacts more negatively to supply-side disruptions (e.g. shutdowns) compared to demand-side disruptions (e.g. price hike). Also, consistent with expectations, we find that firms with a high level of supply chain complexity experience a less negative market reaction. The difference is prominent between firms with low and high number of customers.

This study contributes to research and practice as follows. First, we provide the first empirical evidence on the financial impact of SCDs due to the pandemic. SCDs have been studied by numerous SCRM scholars in the literature (Xu *et al.*, 2020). However, examining the financial impact of SCDs caused by extreme events like the COVID-19 pandemic has yet to emerge. Our observation on SCDs due to COVID-19 provides a valuable contribution to the literature by representing a new context to investigate the vulnerability of an extreme event that attracts growing attention in recent supply chain research (Flynn *et al.*, 2021). Second, this study is anchored on the framework of signaling theory and EST, where it explores the role of event time and space for shareholder behaviors toward the pandemic-induced SCDs (i.e. signaling environment). This study reveals how the magnitude of the financial effect of COVID-19 changes by the different signals, helping to expand our understanding of SCRM. Lastly, relatedly, managers can exploit our empirical results to strategically deploy resources and take mitigation strategies to minimize the loss of shareholder's value associated with SCDs due to extreme conditions in the context of supply chains.

2. Literature review

2.1 COVID-19 as extreme SCDs

SCDs have become a frequent ordeal in global business operations. Infectious diseases are one of the main sources. A review of 72 major epidemics and pandemics spanning 2,500 years

(Cirillo and Taleb, 2020) show that pandemics in history are fat-tailed phenomenon with a high tail risk and potentially destructive consequences. Disruptions due to pandemics are seen in the form of drug shortage (Paul and Venkateswaran, 2017), shortage of wards, beds as well as Intensive Care Units (Long *et al.*, 2018; Sun *et al.*, 2014). Subsequently, demand for medical supplies and medical staffs also rise (Anparasan and Lejeune, 2019). In some places, scarcity of food and food distribution challenges are also confronted during a pandemic (Ekici *et al.*, 2014). Apart from these, vaccine development and distribution also face severe challenges and disruptions are likely during the process (Duijzer *et al.*, 2018). Indeed, infectious diseases disrupt supply chain and business operations distinctively. They can spread unpredictably from one region to other, aggravating the SCDs.

However, COVID-19 is unique and novel in that this epidemic causes extreme conditions for global supply chain management. For instance, in order to contain the outbreak, most countries closed their borders, shut down factories and workplaces, and restricted movement, thereby affecting supply of products and services. Likewise, demand of essential products spiked uncharacteristically, leading to hoarding and panic-buying. Perhaps, an eccentric element of COVID-19 is its damage propagation across the world, triggering multiple simultaneous SCD events. Unlike flood, hurricanes, earthquakes, financial crises or terrorist attacks, it does not act as a single one-time SCD event. The epidemic of COVID-19 disrupts supply chains along supply- and demand-side for 1–2 years and even beyond. Therefore, the context of COVID-19 demands a separate examination.

This study suggests that COVID-19 is different from normal SCDs in its scope and depth. In terms of scope, unlike normal SCDs that are all limited to a specific region or an industry (Craighead *et al.*, 2020), COVID-19 has caused disruptions that occur across virtually every sector of the world economy. What is worse, COVID-19 disrupts every aspect of supply chain such as supply, demand, and channel infrastructure simultaneously (cf. Kilpatrick and Barter, 2020). This simultaneous nature of COVID-19, which propagates damage across densely connected global supply chains, makes the consequence worse (i.e. depth). For example, COVID-19 causes a sharp increase in demand like panic-buying (Sodhi and Tang, 2021). Such dramatic changes in demand were not common for SCDs during normal times. Moreover, SCDs due to COVID-19 are not temporary. It is prolonged, continuing for several years. This may put firms at risk of being disrupted constantly. Consequently, SCDs due to COVID-19 are considered extreme black swan events.

Numerous SCRM studies have developed a typology that categorizes SCDs. Based on the classification, COVID-19 is said to be an environmental risk that is exogenous to the supply chain, which can be considered "extremely" catastrophic (Jüttner *et al.*, 2003; Sodhi and Tang, 2021; Wagner and Bode, 2008). However, although the literature does provide guidance to classify various SCDs, most of them are so closely intertwined that it is often difficult to separate them. For example, black swan events like GEJE affect supply chain internally by disrupting supply and demand. The epidemic of COVID-19 is particularly the case in that subsequent SCDs occur under extreme conditions that disrupt multiple aspects (demand, supply, etc.) of a supply chain simultaneously.

2.2 Financial impact of SCDs

Several studies have computed the financial impact of SCDs that are mostly internal to the supply chain (see Table 1). Examples of such SCDs include parts shortages, manufacturing malfunction, quality problems or plant/store shutdown. A notable example is Hendricks and Singhal (2003) who recorded that supply chain glitches decrease shareholder value by 10.28%. Their study was conducted over the period 1997–2000, followed by Zsidisin *et al.* (2016) covering the period 2001–2012 and then by Schmidt *et al.* (2020) covering the period 2013–2017. Except for the early study, the two follow-up studies indicate a near identical negative market reaction of around 2% associated with SCDs. As summarized in Table 1, several other studies have also been conducted in a different setting (e.g. country) to examine the financial impact of the SCD events that are internal to supply chain.

SCDs external to supply chain are also of great concerns. For example, earthquake and tsunami in the Tohoku region of Japan in 2011 is known to disrupt supply chains in Japan and elsewhere (Carvalho *et al.*, 2021; Son *et al.*, 2021). In the same year, automotive and electronics supply chain was disrupted by flood in Thailand (Haraguchi and Lall, 2015). In 2017, the US pharmaceutical supply chain faced similar disruption due to Hurricane Maria (Lawrence *et al.*, 2020). On September 11, 2001, terrorists attacked the US, causing severe SCDs besides other casualties (Lee and Hancock, 2005). The global financial crisis in 2008, caused by the bursting of US housing bubble, also had a devastating impact on the supply chain of multinational firms (Schotter and Thi My, 2013). In the infectious disease category, Avian flu pandemic affected supply chain of US firms (Kumar and Chandra, 2010), and so did Ebola in Liberia (Sumo, 2019).

These prior external SCD studies indicate financial damages resulting from numerous black swan events. However, they are all included within normal challenges caused by SCDs that affect only a limited number of firms and specific industries for a short period. What has not been addressed in the literature is an empirical examination of the financial effect of SCDs caused by extreme conditions like COVID-19. There are few studies examining the financial consequence of COVID-19; but they are all limited to a specific sector like shipping industry (Gavalas *et al.*, 2022), or to a market-level analysis such as US (Harjoto *et al.*, 2021) and China (Ding *et al.*, 2022). More importantly, except for Srinivasan *et al.* (2022) that is still limited in scope to the US market only, no prior studies examine the financial impact of pandemic-induced SCDs in the context of supply chains. In this study, we fill this gap by estimating the market valuation effect of SCDs due to COVID-19 and how its magnitude changes by event time and space factors.

3. Theory and hypothesis development

3.1 Shareholder behaviors under signaling theory

Shareholders are essentially the owners of the company who play an indirect role through the stock market. Fama (1970) notes that firms' activities like investment decisions provide "signals" for shareholders, which will be reflected fully (i.e. efficiently) in the firms' stock price. In this sense, shareholder behaviors are widely explained by signaling theory (Spence, 1978), which posits that information asymmetry between parties in a context can be reduced via signals. In the classic example of labor-market problem, employers often face information asymmetry regarding the quality of candidates. To overcome this, they observe candidates who have undergone certification courses and separate high-quality from low-quality candidates. Similarly, in the absence of complete information, shareholders are uncertain about the firm's future prospects and "may seek out signals that provide information about unobservable attributes and likely outcomes" (Bergh *et al.*, 2014, p. 1335). Related to the context of our study, supply chain events serve as signals offering information about firm's unobservable attributes, as well as the likely outcomes of the events.

Signaling framework consist of five elements: signaler, signal, receiver, feedback and the signaling environment (Connelly *et al.*, 2011). For supply chain events, signalers could be executives, products, processes, or firms who obtain the information unavailable to receivers (e.g. shareholders). Signals are "conducts and observable attributes that alter the beliefs of, or convey information to, other individuals" (Ndofor and Levitas, 2004, p. 688), which could be positive like collaboration (Liu *et al.*, 2020) or negative like corruption (Kim and Wagner, 2021). Unlike positive ones, negative signals are "often an unintended consequence of the insider's action" (Connelly *et al.*, 2011, p. 45). Hence, negative signals may not always be announced by the firms but can be reported by independent media outlets. Shareholders, which are the focus of this study as receivers, take clue from these signals and share their feedback by marking up or discounting the firm's stock price. This process of signaling takes place in an environment, which can moderate the relationship between the signaler, signal, receiver and feedback, and hence the signals interpreted may or may not be accurate (Janney and Folta, 2006). Signaling environment refers to the context in which the signalers, signals, receivers and feedbacks exist in time and space (Connelly *et al.*, 2011). In that sense, the signaling environment in the labor-market example of Spence (1978) lies in the job market. Likewise, for our study, the signaling environment is the context of supply chain events during the COVID-19 pandemic.

The signaling environment plays a vital role in *signal observability*, the receiver's ability to notice the signals (Connelly *et al.*, 2011). Environmental distortion occurs when the medium for propagating signals reduces the signal observability. For supply chain events, medium can be press releases, shareholder meetings, annual reports, newspapers or even social media (Srinivasan *et al.*, 2022). Low signal observability also occurs due to the introduction of noise in the signaling environment, which may further impact the feedback mechanism (Connelly *et al.*, 2011). As such, where signal observability becomes low, monitoring the environment can be particularly important for receivers. Ndofor and Levitas (2004) argue that effective signals are those that create a separating equilibrium, in which an uninformed agent is able to differentiate between high and low qualities. Therefore, in a signaling environment with weak observability of the original signal, receivers may scan for other signals to provide the separating equilibrium. For example, firms having superior products but inconspicuous to investors, other information like credible suppliers, investment bank, etc. could resolve the asymmetry (Thakor, 1982).

The pandemic has created an environment of noisiness due to myriads of signals from firms, policymakers, central bankers, world leaders, etc. Some firms have used tweets as signals to communicate distinguishing positive actions to investors (Srinivasan *et al.*, 2022). While Srinivasan *et al.* (2022) explored how firms may use tweets to distinguish positive actions in a noisy signaling environment, our context is unintended negative signals arising from SCDs caused by the pandemic. With noise in the environment, shareholders (receivers) may have to look for other relevant signals that can differentiate highly affected firms from less affected ones. In the context of rare events like the pandemic, where a large number of firms are affected by SCDs, other signals in the time and space can provide the separating equilibrium (Connelly *et al.*, 2011).

3.2 Stock market reaction to COVID-19-induced SCDs

Firms take years to develop suitable supply chain strategies through technological investments, supplier development and collaboration, which allows them to obtain an efficient supply chain (Lee *et al.*, 2011). Efficiency, reliability and responsiveness of supply chain strategy affect the cash flows and earnings of a firm, as well as its reputation and credibility (Hendricks and Singhal, 2003). Under normal circumstances, SCDs tend to adversely affect a firm's revenue, costs, assets, and intangibles (i.e. reputation or credibility), providing a negative signal to shareholders. This indicates skeptical future growth prospects and therefore, a negative stock market reaction is evident (Hendricks and Singhal, 2003). As observed in Table 1, a study conducted for the pre-pandemic period of 2013–2017 demonstrated a roughly 3.55% negative market reaction to SCDs (Schmidt *et al.*, 2020). Comparing this result with that of other studies (e.g. Baghersad and Zobel, 2021; Hendricks *et al.*, 2020; Zsidisin *et al.*, 2016), the magnitude of a negative market reaction to SCDs is similar in the range of 1–4%, which is expected financial damages due to SCDs in the pre-pandemic period.

The COVID-19 pandemic seems to induce higher stock market return volatility (see Figure 1). Based on this, together with recent studies (e.g. Flynn *et al.*, 2021; Kilpatrick and Barter, 2020; Micheli *et al.*, 2021), we expect that the magnitude of the consequence of SCDs

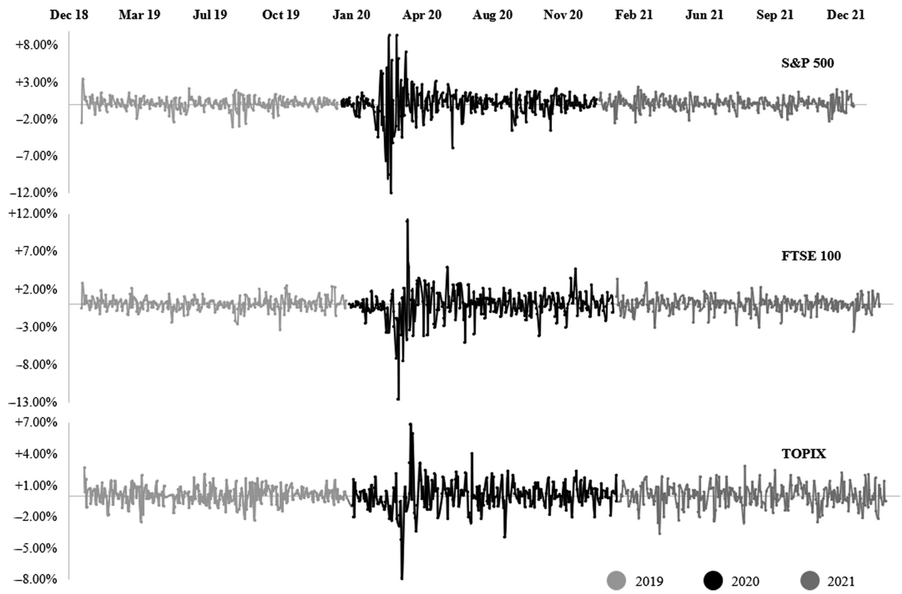

Figure 1.
Stock market return of S&P 500, FTSE 100 and TOPIX of 2019, 2020 and 2021

due to COVID-19 would be more severe. During the COVID-19 pandemic, several events of labor shortage, material shortage, delivery delay, supplier failure, and sudden variation in demand were observed (Sharma *et al.*, 2020). Such SCDs were not simply for particular firms or industries but more for densely connected supply chain networks across the globe extending over time, making conditions more extreme (Sodhi and Tang, 2021). Moreover, movement of goods and people were restricted due to lockdown measures by governments, causing multiple simultaneous disruptions in the entire supply chain. In most cases, recovery from SCDs under such extreme conditions would be more challenging than normal times (Flynn *et al.*, 2021). With this negative signal, shareholders may doubt a firm's growth prospects and discount its stock price more severely. Hence, we posit that:

H1. The stock market reaction to SCDs due to COVID-19 is more negative than that of the pre-pandemic period.

3.3 Roles of event time and space during the pandemic

In the previous section, we discussed how the magnitude of the overall stock market reaction to SCDs due to COVID-19 is different than under normal circumstances. Next, by integrating EST, we attempt to explain the moderating role of event time and space in the market reaction to pandemic-induced SCDs (Morgeson *et al.*, 2015). Event time centers on the nature of events that are bounded in time, while event space focuses on the origin of the event and how its effects spread. Event time can be reflected by the severity of COVID-19 that presents how the strength of the COVID-19 pandemic changes over time. Source of disruptions indicate where pandemic-induced SCDs originate (i.e. origin of the event), while both firm position in supply chain and supply chain complexity reflect how effects of the SCDs spread across the densely connected supply chain. Therefore, the difference in such event time and space factors could influence the direction and magnitude of the overall stock market reaction to pandemic-induced SCDs, which we investigate next.

3.3.1 The severity of COVID-19. The fast spread of the virus from China to other countries took many by surprise. Rising infections and mortality news dominated headlines. Several stringent measures were taken by government authorities that created a distressing environment for human lives, which further created turbulence in the work environment. Borders were closed to prevent the spread of infections, and unexpected social distancing protocols were ordered. Workplaces were shut down and people were ordered to stay at home. In many parts of the world, public transportation was halted, and internal movements were restricted. Thus, these preventive measures create a changing environment of high uncertainty. For firms facing severe stringency, the uncertainty regarding future course of actions remains high. In this case, multiple related and unrelated events offer diverse signals creating a noisy signaling environment. Such distortions in the environment reduce the observability of the signals (Connelly *et al.*, 2011). In high-noise environment, firms cannot process signals in isolation (Steigenberger and Wilhelm, 2018) and the impact of the signal may weaken. Following this, we expect that severe stringency measures adopted to prevent rise in infection growth creates a noisy signaling environment between firms (signalers) and shareholders (receivers). The unintended negative signals in the form of SCDs may fail to grab appropriate attention from shareholders in such a dynamic environment. Therefore, the feedback from shareholders in response to SCDs faced by firms at a time of severe stringency measures would be less negative than those that are relatively non-severe. Given the discussion, we posit that:

H2. The negative stock market reaction is smaller for pandemic-induced SCDs at a time of severe stringency than non-severe stringency.

3.3.2 Sources of disruption. High transmission rate and global connectivity facilitated the outbreak to expand to almost all corners of the world and started disrupting different parts of supply chain. Most of the SCDs were triggered by the direct or indirect effects of the preventive measures taken by governments and firms to contain the outbreak (Baker *et al.*, 2020). China, a major manufacturing hub for the world, had to restrict mobility inside and disconnect from the world. In several countries, factories were shutdown, transportation restricted, and cities came under lockdown (Hille *et al.*, 2020) and component shortages rose up. As the uncertainty loomed over, several buyers canceled orders from suppliers, while end consumers started to panic-buy and hoard day-to-day products. Demand of almost all categories of products flipped, sending shocks from the demand-side. Retailers faced inventory shortages and rationing was practiced to balance demand and supply (Mitchell, 2020). Clearly, all these highlight supply-side and demand-side disruptions during the pandemic.

Disruptions in the supply-side disrupt the supply of products, raw materials or the services, while those in the demand-side disrupt the demand of the same irrespective of the position in the supply chain network. Supply-side disruptions signal high costs, as firms take years of heavy investments to create an environment of efficient sourcing, transportation, and delivery of physical goods. Events like production shutdowns or delayed product deliveries could also be worse for firms' investment in consumer channels. However, such demand-side disruptions send mixed signals. On one hand, a sudden drop in demand can lead to bigger survival crisis, like aircraft manufacturers receiving cancellation of orders from airline firms (Tangel, 2020). On the other hand, events like panic-buying of essential items during the pandemic may favor retailer's earnings in the short term, and hence shareholders may receive it as less negative or even positive signals. Another aspect of concern is the recovery from SCDs. Supply-side disruptions often origin from deeper tiers embedded in the supply chain network (Elliott, 2021), making recovery challenging. On the contrary, losses due to demand-side disruptions can be overcome by flexible capacity utilization (Meng *et al.*, 2016). Therefore, shareholders would observe the sources of disruption to differentiate the impact of COVID-induced SCDs on the firms. This means that the market would treat the SCD signals differently coming from these two sources, reacting more negatively to supply-side disruptions. Given the discussion, we hypothesize that:

H3. The negative stock market reaction is greater for firms facing supply-side disruptions caused by the pandemic than demand-side disruptions.

3.3.3 Position in the supply chain. A supply chain network is better understood from a relational perspective rather than physical flow of materials (Carter *et al.*, 2015). The transformation of raw materials into final products and services for ultimate consumption by end-users create firms with different specialization. Some of these firms are highly specialized in the upstream stages of production, while others specialize in the downstream stages. These firms are embedded in a large network tied through buyer–supplier relationships (Borgatti and Li, 2009). In this regard, many prior studies have conceptualized a broader view of upstream and downstream layers, which makes it possible to differentiate a firm's position in the supply chain network. For example, firms with the shortest distance from the end consumers or final demand are to be said downstream (Antràs *et al.*, 2012; Osadchiy *et al.*, 2021). In the same way, firms specializing in equipment manufacturing or are close to raw materials can be considered to be upstream. This network perspective (Carter *et al.*, 2015) is an upgrade to the industry-wide classification of firms, which is widely adopted by supply chain researchers.

Under normal conditions, markets are more crowded with firms in the downstream stages than upstream (Osadchiy *et al.*, 2021). In such a competitive condition, firms differentiate their products or others through quality signals (e.g. branding) that can reduce uncertainty in a signaling environment (Taeuscher, 2019). In this case, unintended negative signals such as pandemic-induced SCDs could be easily observed, because downstream firms are competing with positive intended signals that bear costs already. This improved signal observability may negatively moderate the signal-feedback relationship for SCDs during the pandemic. On the contrary, upstream firms may have little incentives to compete with others on such costlier signals. Thus, in a less competitive condition, where positive signaling is less observed, such SCDs, as unintended negative signals, would not be easily distinguished. As earlier noted, signal observability is of paramount importance in a noisy signaling environment (Connelly *et al.*, 2011). Further, the crowding effect in the downstream stages creates a difference (i.e. improvement) in signal observability from that of upstream. This means that shareholders would react more negatively to downstream firms for SCD signals during the COVID-19 pandemic. We hypothesize that:

H4. The negative stock market reaction is greater for downstream firms facing SCDs caused by the pandemic than upstream firms.

3.3.4 Supply chain complexity. We now take forward the network perspective on supply chain complexity (Choi and Kim, 2008). The complex system perspective is widely used in the context of supply chain for explaining its underlying mechanism (Carter *et al.*, 2015). Choi and Krause (2006) identified a firm's supply chain complexity based on the number of suppliers, their differentiation, and degree of interrelation. It suggests that high number of suppliers of a firm would increase transaction costs, supply risk and reduce responsiveness (Choi and Krause, 2006), rather than providing resilience from disruptions via redundant capacity (Birkie and Trucco, 2020). In the context of disruptions, supply chain complexity would make firms more vulnerable to SCDs (Bode and Wagner, 2015; Craighead *et al.*, 2007). This is because the management of complex supply chain requires a visibility of the entire network from point of origin to its consumption, which is nearly impossible. In general, the literature on supply chain complexity suggests that a great number of connections with suppliers or customers and the inter-relationships between these connections could hinder a firm's resilient response due to disruptions (Basole and Bellamy, 2014; Choi and Krause, 2006; Son *et al.*, 2021).

During the pandemic, however, firms with complex supply chains are better prepared than others to manage the extreme event (Choudhary *et al.*, 2021; Kilpatrick and Barter, 2020).

These firms have diversified their supply chain network, relying on multi-sourced key suppliers that act as a buffer during the pandemic. Moreover, under such extreme events, internal and external collaborations are needed (Sodhi and Tang, 2021), and supply chain complexity could enhance such innovative collaborations by allowing firms to access to ample sources of SCRM knowledge embedded in the diverse network (Ateş *et al.*, 2022). Information regarding supply chains (suppliers and customers) are available in financial regulatory filings (e.g. 10-K reports) and can be accessed by interested parties. Therefore, shareholders may seek out a firm's supply chain complexity as a signal to assess the financial impact of SCDs, responding less negatively to pandemic-induced SCDs facing firms with complex supply chains. Given the discussion, we posit the following hypothesis:

H5. The negative stock market reaction to SCDs caused by the pandemic is smaller for firms with complex supply chains.

4. Research design

4.1 Sample selection

We collected our sample of SCD announcements from ABI/INFORM Collection, a database containing historical news contents around the world. Our major sources of announcements on publicly traded firms' SCDs are from the online version of *The Wall Street Journal, Financial Times, Reuters, The Australian Financial Review, The Economic Times* and *Nikkei Asia* from January 2020 till November 2021. Following prior SCD event studies (e.g. Hendricks and Singhal, 2003), we use the combination of the following two or more keywords: shipment delay, shutdown, failure, order cancellation, disruption, inventory, launch delay, introduction delay, manufacturing delay, shortage, production shortfall, recall, hoarding, price gouging and other related keywords. As a result, our initial search yielded 439 announcements on SCDs. We then removed 112 announcements on firms that are not publicly traded, leaving 327 SCD announcements.

Our focus of study is SCD caused due to the pandemic. To qualify the objective, we read the announcement fully to ensure the following two aspects: the announcement is related to supply chains and the SCD is caused by the pandemic only. To make sure the second criterion, we filtered the pool of announcements with keywords of COVID, coronavirus, and pandemic. Therefore, of the remaining 327 SCD announcements from the initial search, we additionally removed 55 announcements that are not related to supply chains and SCDs that are from other causes of disruption like delay, flood, etc. Further, we removed additional 90 announcements if they are: the SCD faced by the industry as a whole; duplicate or subsequent announcements; SCD announcement on the day close to any other potentially confounding events like mergers, acquisitions, earnings etc.; SCDs affecting the same firm due to separate causes but occurring within a span of 10 trading days.

We followed an iterative process to verify the announcements for each sample firm, leading us to a final sample of 182 announcements. Some examples of SCD due to pandemic-only event announcements are as follows:

- "Coronavirus triggers bad case of 'Hamsterkauf'", *The Australian Financial Review*, March 5, 2020.
- "Boeing orders slip below 5,000 on MAX cancellations", *The Wall Street Journal*, May 12, 2020.
- "Tesla to suspend US car production over coronavirus", *The Wall Street Journal*, March 19, 2020.

Stock market return data are obtained from Refinitiv Eikon (Thomson Reuters). Information on the firms' numbers of suppliers and customers before pandemic-induced SCD events are also obtained from the same database. Refinitiv Eikon has been used widely for recent supply chain network research, which provides a list of suppliers or customers in the supply chain (Choudhary *et al.*, 2021). We obtained the stringency index (SI) to measure the growth of pandemic from www.ourworldindata.org, which is published by Hale *et al.* (2021).

4.2 Descriptive statistics

The 182 announcements reported 206 unique pandemic-induced SCD events, which involved 145 publicly listed firms headquartered in 21 countries. Several news announcements reported more than single events and several firms faced multiple disruptive events during the pandemic. Panel A of Table 2 lists the distribution of firms based on countries they are headquartered. A significant number of firms in our sample have their headquarters in the US Panel B of Table 2 offers the distribution of the firms' industries on basis of the Global Industry Classification Standard (GICS) industry code. Automobile, consumer durables and other consumer-facing industries had the maximum occurrences. Panel C of Table 2 reveals a summary of the statistical information of the firms in the fiscal year preceding January 2020 (i.e. before the effect of the pandemic was observed). In our sample, the first occurrence of SCD due to pandemic was observed on 29th January 2020.

4.3 Empirical approach

4.3.1 Event study. Using an event study analysis, we estimate the overall effect of SCD due to COVID-19 on market returns, which will be a basis for testing our hypotheses. Event

Table 2.
Descriptive statistics of the sample firms

Panel A. Corporate headquarters' countries of sample firms

Countries	Occurrence	Countries	Occurrence
USA	80 (38.8%)	Australia	8 (3.9%)
Japan	19 (9.2%)	The Netherlands	6 (2.9%)
India	18 (8.7%)	Denmark	5 (2.4%)
UK	18 (8.7%)	France	5 (2.4%)
Germany	14 (6.8%)	Taiwan	5 (2.4%)
Canada	9 (4.4%)	Other countries (including China)	19 (9.2%)

Panel B. Industry distribution of sample firms

GICS industry code	Industry description (position in the supply chain[a])	Occurrence
1010–2030	Energy (*U*), Materials (*U*), Capital goods (*U*), Transportation	53 (25.7%)
2510–3030	Automobiles and components (*D*), Consumer durables and apparel (*D*), Consumer services (*D*), Retailing (*D*), Food and staples retailing (*D*), Food, beverage and tabacco (*D*), Household and personal products (*D*)	119 (57.8%)
3510–3520	Healthcare, Pharmaceuticals, biotechnology and life sciences (*U*)	16 (7.8%)
4510–5510	Information technology, Communication services, Utilities	18 (8.7%)

Panel C. Sample firms' statistics at the end of fiscal year before january 2020

	Mean	Median	SD	Min	Max
Total assets ($ million)	68438.94	30301.86	99675.29	143.95	547128.00
Revenue ($ million)	52016.38	21506.39	87558.35	4.11	523167.42
Market-to-book Equity	1.88	2.25	32.20	−304.48	76.22
Debt-to-equity	0.86	0.27	1.75	0.00	10.92

Note(s): [a]*U* indicates strictly upstream areas, while *D* indicates strictly downstream areas study offers a rigorous approach to estimate the magnitude of abnormal returns as a result of the stock market's reaction to an event (Brown and Warner, 1985). It is based on the efficient market hypothesis, according to which the stock market reflects all available information in the market (Fama, 1970). Albeit regarded as a powerful method, the yield of the event study depends on the unconventional nature of the event, content of the event and the timeous availability of the first occurrence of the event (Hendricks and Singhal, 2003).

We conduct an event study on pandemic-induced SCDs using the market model which is widely used to estimate the abnormal return in the stock market. The market model assumes a linear relationship between the stock return and the market return (Brown and Warner, 1985) and the stock return is estimated as:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}$$

where r_{it} is the return on the firm stock i on day t, r_{mt} is the return of the market index on day t, α_i is the intercept of the relationship, β_i is the systematic risk of the stock i, and ε_{it} is the error term. As our sample firms are traded in different countries, we compute r_{mt} by using the dominant market index (e.g. S&P 500 for American firms, FTSE 100 for British firms or TOPIX for Japanese firms) of the firm i's country. The abnormal return A_{it} of stock i on day t is calculated based on the market model as:

$$A_{it} = r_{it} - (\widehat{\alpha}_i + \widehat{\beta}_i r_{mt})$$

where $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ of the corresponding stocks are estimated by running an ordinary least squares (OLS) regression over a 200-day estimation period with a 10-day offset prior to the event (i.e. from −211th day to −11th day of the event day). The abnormal return for day t can then be aggregated over all N events as:

$$\overline{A}_t = \sum_{i=1}^{N} \frac{A_{it}}{N}$$

where N is the number of all SCD events in our sample. Lastly, the cumulative abnormal return (CAR) for an event period $[t_1, t_2]$ is measured by adding the abnormal returns from day t_1 to day t_2, i.e. from beginning to end of the event period, as follows:

$$CAR[t_1, t_2] = \sum_{t=t_1}^{t_2} \overline{A}_t$$

In our sample, as noted, several firms faced multiple SCD events over the period of the pandemic. This may violate the assumption of event study that the sample may be subject to cross-sectional correlation. To account for this potential issue, we follow the Brown and Warner's (1985) adjustment of cross-sectional correlation. Hence, we first calculate the mean abnormal returns for the 200-day estimation period and then estimate the standard deviation from the mean daily abnormal returns for the period, $\widehat{S}(\overline{A}_t)$. This allows us to compute the test statistic for single-day event period as $\overline{A}_t/\widehat{S}(\overline{A}_t)$ and the test statistic for m-day event period as $\sum_{t_1}^{t_2} \overline{A}_t/\widehat{S}(\overline{A}_t)\sqrt{m}$.

To better control for estimation bias, event studies related to issues in the supply chain have mostly considered a short two-day interval consisting of the day of announcement (day 0) and the day before the announcement (day −1). This is mainly because for print media sample, the stock market could have been informed about firm events a day earlier (Kim *et al.*, 2019). In some cases, for the same reason, a three-day interval including the day after the announcement (day 1) is also considered (e.g. Liu *et al.*, 2020; Schmidt *et al.*, 2020). In our case, we have collected data from online version of the news publications, so any delay in the observation of the announcement is unlikely. Also, our study of the COVID-19-induced SCDs is highly uncertain and rare, so information diffusion about the severity of the SCD beforehand is less. Hence, we consider the event period from day 0 to day 1. Nevertheless, we report abnormal returns on other intervals as well.

4.3.2 Comparison analysis. A series of comparison analysis is conducted to test our hypotheses H1–H5. To this end, we first characterized our sample firms based on the hypothesized factors. Regarding the first hypothesis (H1), we compared the magnitude of pandemic-induced SCDs with that of SCDs under normal circumstances. To collect SCDs during the pre-pandemic period, we followed the same approach used in this study except for the COVID-specific keywords, and this led to 88 SCD events during 2018–2019. To make sure that the constituents of the two groups are not different, we conducted a χ^2 test for country ($\chi^2 = 2.72$, $p > 0.10$) and industry ($\chi^2 = 4.09$, $p > 0.10$) characteristics and t-test (Z-test for median) for firm statistics. As a result, we found no statistical differences.

To determine the role of the stringency measures (H2), we examine the SI developed by Hale *et al.* (2021) for all countries affected by the pandemic. The index is on a scale of 100 that are broadly based on nine parameters including school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transportation, stay-at-home requirements, restrictions on internal movements, restrictions on international travel controls, and public information campaigns. The SI for the SCD event used was that of the country the affected firms are headquartered. Following the prior study, we divided the events into severe (SI: $\geq$ 60) and non-severe groups. For the sake of robustness, we also check other possible severe groups (SI: $\geq$ 70, $\geq$80), as well as time effect of the SI.

For the supply- and demand-side comparison (H3), we examine the source of SCD event. SCDs that arise due to disruption in the supply of product, material, labor or support are grouped into supply-side (e.g. manufacturing delay, plant shutdown), whereas SCDs that occur due to disruptions in the demand (e.g. customer order change, order cancelation) are grouped into demand-side. In supplementary analyses, we provide additional insights by investigating major sub-groups of supply- and demand-side disruptions.

For determining firm position in the supply chain network (H4), we follow the approach by Osadchiy *et al.* (2021) and look into our sample firm's GICS industry codes to group them into upstream and downstream. However, several firms lie somewhere in the middle of the supply chain network, making harder to classify into the classification. Thus, to make the distinction clearer, we group the firms as "strictly upstream" and "strictly downstream" for comparison. For example, Osadchiy *et al.* (2021) suggest that GICS sectors 25–30 are strictly downstream. Similarly, strictly upstream firms belong to the GICS sectors 10–20. We also added sector pharmaceuticals, biotechnology and life sciences as their majority of operations are in the upstream stages. The industry groups are noted in Table 2.

The last comparison is related to firms' supply chain complexity (H5). Borrowing from social network analysis, we use the most relevant metric, degree centrality (i.e. total number of suppliers and customers), that exhibits complexity at the firm-level in a supply chain network (Borgatti and Li, 2009; Han *et al.*, 2020; Kim *et al.*, 2015). Thus, we first compare the firms based on high- and low-degree centrality as a proxy for supply chain complexity. As a robustness, we also consider other complexity measures such as in- and out-degree centrality, which indicates supplier- and customer-complexity respectively. The median value is used to distinguish between firms with high- and low-values, commonly used for comparison in event study analysis (e.g. Bose and Pal, 2012).

5. Results

This section presents the results of hypotheses tested. We first calculate the stock market reaction on SCDs caused by pandemic through estimating CARs, which is followed by robustness checks. The results are then tested against all the hypotheses using a subsample comparison analysis.

5.1 Results of event study analysis

For the 206 SCD events, we first examine the abnormal return on and around the event dates. As shown in Table 3, we observe the mean (median) CAR during the event period is −2.16% (−1.10%), which is significantly different from zero at the 1% level. 63.59% of the CAR are negative, which is significantly lower than 50%. The mean (median) abnormal return on day 0 is −1.60% (−0.87%) and on day 1 is −0.56% (−0.33%), both of which are significant at the 5% level. Overall, the magnitude of the consequence of pandemic-induced SCDs is found to be similar to those during the pre-pandemic period that shows a decrease in shareholder value of 1–4% (cf. Table 1).

To ensure the robustness of our results, we run a series of robustness checks. First, to make sure that our model choice for the event study does not drive the results, we estimate the CAR using the market-adjusted model and mean-adjusted model as alternatives (Brown and Warner, 1985). Second, there is a possibility that our estimation period can distort the results, as the objective of the study is to capture the effect of pandemic-caused SCDs. To overcome this, we estimate the CARs based on estimation period before January 2020 (i.e. before the COVID-19 outbreak). As a result, we find the mean (median) CAR of −3.28% (−1.76%) for mean-adjusted, −2.15% (−1.06%) for market-adjusted, and −2.16% (−1.01%) for pre-pandemic estimation period, all of which are similar to our main results.

Moreover, to ensure that our event study analysis is not affected by country-dependent factors, we examined the difference in the stock market reaction of US-based and non-US-based firms, as well as of developed economies and others. As a result, we found that both tests are insignificant, supporting our main results.

5.2 Results of comparison analysis

A comparison analysis is conducted to test our hypotheses H1–H5. The results are presented in Table 4. First, we test H1 indicating that pandemic-induced SCDs would be more severe

Event day	Mean (%)	*t*-statistic	Median (%)	*Z*-statistic[a]	% negative	*Z*-statistic[b]
Day −5	−0.18	−0.93	−0.25	−1.03	55.34	−1.46
Day −4	0.10	0.50	0.24	1.075	46.12	1.05
Day −3	−0.22	−1.16	−0.18	−0.73	52.91	−0.77
Day −2	−0.28	−1.50	−0.33	−1.81	58.25	−2.30
Day −1	−0.24	−1.25	−0.23	−1.01	53.88	−1.05
Day 0	−1.60***	−8.43	−0.87***	−4.76	62.62***	−3.55
Day 1	−0.56***	−2.96	−0.33**	−2.02	56.80*	−1.88
Day 2	0.36*	1.90	−0.08	0.35	52.43	−0.63
Day 3	0.50***	2.62	0.19	1.46	47.57	0.63
Day 4	0.34*	1.81	0.03	0.52	48.06	0.49
Day 5	0.17	0.91	−0.11	−0.05	51.46	−0.35
Days [−1, 0]	−1.83***	−6.84	−0.84***	−4.07	62.14***	−3.41
Days [0, 1]	−2.16***	−8.05	−1.10***	−4.37	63.59***	−3.83
Days [−1, 1]	−2.39***	−7.29	−1.09***	−4.29	63.59***	−3.83

Note(s): n = 206. [a]Wilcoxon-signed rank *Z*-statistics for median; [b]binomial sign *Z*-statistics for % negative; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3. Abnormal returns for SCDs due to COVID-19

Panel A: SCDs due to COVID-19	Pre-COVID-19	COVID-19	Difference
Mean CAR (%)	−1.64***	−2.16***	0.52
t-statistic	−7.21	−8.05	0.70
Median CAR (%)	−0.79***	−1.10***	0.31
Z-statistic[a]	−3.52	−4.37	0.40
% negative	69.32***	63.59***	
Z-statistic[b]	−3.83	−3.52	
n	88	206	
Panel B: severity of COVID-19	**Non-severe**	**Severe (SI: ≥ 60)**	**Difference**
Mean CAR (%)	−2.45***	−1.84***	−0.61
t-statistic	−8.86	−4.07	−0.64
Median CAR (%)	−1.05***	−1.11**	0.06
Z-statistic[a]	−3.46	−2.60	0.25
% negative	63.55***	64.00***	
Z-statistic[b]	−2.71	−2.61	
n	107	99	
Panel C: sources of disruption	**Supply-side**	**Demand-side**	**Difference**
Mean CAR (%)	−2.64***	−0.43	−2.21**
t-statistic	−8.33	−1.10	−2.03
Median CAR (%)	−1.23***	0.01	−1.22**
Z-statistic[a]	−4.84	0.38	−2.07
% negative	68.42***	49.01	
Z-statistic[b]	−4.46	0.00	
n	152	54	
Panel D: position in supply chain	**Strictly upstream**	**Strictly downstream**	**Difference**
Mean CAR (%)	−1.57**	−2.08***	0.51
t-statistic	−2.19	−9.00	0.35
Median CAR (%)	−0.95	−1.08***	0.13
Z-statistic[a]	−1.08	−3.62	0.90
% negative	63.04	64.70***	
Z-statistic[b]	−1.62	−3.12	
n	46	119	
Panel E: supply chain complexity	**Low (by median)**	**High (by median)**	**Difference**
Mean CAR (%)	−2.98***	−1.34***	−1.66*
t-statistic	−6.95	−4.88	−1.75
Median CAR (%)	−1.29***	−0.79**	−0.50*
Z-statistic[a]	−3.89	−2.23	−1.71
% negative	66.34**	60.78**	
Z-statistic[b]	−3.24	−2.08	
n	104	102	

Note(s): Sample size varies due to additional (Panel A) or missing (Panel D) data for analyses; [a]Wilcoxon signed-rank *Z*-statistics for medians, and Mann–Whitney *Z*-statistics for median difference; [b]binomial sign test for % negative; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4.
CAR [0, 1] difference for pandemic, severity, source, position and complexity

than pre-pandemic SCDs in term of market reaction. As shown in Panel A of Table 4, we find no significant difference between the mean (median) CAR of the two groups. Surprisingly, we find the mean (median) CAR of SCDs during normal circumstances is −1.64% (−0.79%), which is somewhat consistent with that of prior SCD studies summarized in Table 1. This evidence does not support H1, a counterintuitive finding that warrants discussion that we will return to later.

Next, we test H2 that the severity effect of COVID-19 on stock market reaction on SCDs would be less negative due to increasing noises in a signaling environment. The result shown in Panel B of Table 4 reveals that the mean (median) CAR during severe stringent period (SI: ≥ 60) is significantly indifferent from those during non-severe stringent period. This indifferent result is the same when we tested other possible severe groups (SI: ≥ 70 and ≥ 80). To check whether the stringency measures are not time-dependent, we compared the difference of stock market reaction between observations of 2020 and 2021, as well as between first four months and last four months of our observation period and found negligible differences. Overall, we find no support for H2.

For H3, we test whether supply-side disruptions are associated with a more negative stock market reaction than demand-side SCDs during the pandemic. As shown in Panel C of Table 4, there is a significant difference between the two categories. On average, supply-side disruptions decrease the mean CAR by 2.21% than demand-side SCDs. Comparison of the median CARs of the two categories also suggest that the difference is significant, lending strong support for H3. Similarly, we test H4 if strictly downstream firms are affected more negatively than strictly upstream firms (Panel D of Table 4). The mean (median) CAR for strictly downstream areas is more negative than upstream ones; however, we find no significant difference between them, rejecting H4.

Finally, we check H5, whether the market reaction is influenced by supply chain complexity. As shown in Panel F of Table 4, the mean (median) CAR for high degree centrality is less negative than low-degree centrality, which is marginally significant in difference. We further checked the mean (median) CAR for in-degree and out-degree centrality measures. The mean (median) CAR for high in-degree centrality was −1.38% (−0.91%) and low in-degree centrality was −2.29% (−1.24%), showing no significant difference in magnitude. However, the mean CAR for high out-degree centrality (−1.12%) is significantly ($p < 0.05$) less negative than low out-degree centrality (−3.04%), albeit no significant difference in median (−0.79% for high out-degree centrality and −1.30% for low out-degree centrality). This finding indicates that the marginal support of H5 is mainly driven by customer complexity. Overall, this evidence provides a partial support for H5.

5.3 Supplementary analysis

An analysis of market reaction to pandemic-induced SCD subcategories would offer additional nuances onto the effect of COVID-19. Among the reasons of disruptions during the pandemic, four reasons with high representation are observed. First, the highest contributor (42%) of SCDs during the pandemic is attributed to shutdowns. Shutdowns imply temporary closure of the working area leading to loss of production or sales. Factories, manufacturing units, assembly units, stores, or suspension of services are considered as shutdowns. This occurred mostly due to preventive orders of the concerned government. Second, approximately 9% of pandemic-induced SCDs were governed by reasons mentioning manufacturing delays. This could be an outcome of other reasons like shortage of component, labor, infection spread inside workplace etc. Third, customers' order cancelation account for 4% of the total sample, which is observed as one major reason for SCDs due to the pandemic. Order cancelations indicate pandemic-induced SCD events when buyers decide to cancel their order because of the repercussion of the pandemic. Finally, "panic consumer" such as panic-buying, panic-hoarding, and price-gouging is another subcategory of SCD due to COVID-19.

This subcategory is unique to the pandemic and limited to retailers only. As the pandemic spreads, end consumers started buying staple items in unreasonable amounts and hoarding in fear of shortage in the future. Price-gouging and rationing were seen on products with unusually high demand. This category covers 9% of the total sample.

As observed from Table 5, all the four categories are associated with significant stock price changes. Shutdowns, which own maximum share of SCDs due to pandemic, cause a strong negative mean (median) CAR of −2.39% (−1.25%). Manufacturing delay leads to more severe negative market reaction with the mean (median) CAR of −5.45% (−1.72%). The negative market reaction is also the case for the order cancelation subcategory, with the mean (median) CAR of −3.20% (−2.38%). Most intriguing, however, is the SCD events associated with panic consumers such as panic-buying, panic-hoarding, price-gouging, which lead to a significant positive market reaction with the mean (median) CAR of 1.08% (0.52%). Overall, these results support somewhat our main event study findings that supply-side disruptions (shutdowns and manufacturing delays) are more negative than demand-side disruptions (order cancelations and panic consumers) due to the pandemic.

6. Discussion and conclusion

Our study adds a timely and additional value to the literature of SCD and more broadly SCRM. The COVID-19 pandemic is a unique setting, having the propensity to cause irreversible damages in a supply chain network. In the light of our analysis, we summarize our main findings and its relevant discussions as follows.

First, the SCDs caused by COVID-19 are associated with a significant reduction in shareholder value of −2.16%. Contrary to expectations, yet, we found that this magnitude is indifferent from that of pre-pandemic SCDs (−1.64%, $n = 88$). This means that despite being extremely disruptive for supply chains (Flynn *et al.*, 2021), the overall financial impact of the pandemic-induced SCD is less severe than thought. This counterintuitive finding could be explained by the role of signaling environment (Connelly *et al.*, 2011). During the pandemic, multiple SCDs have occurred at the same time across almost every sector of the global economy for a long period. Therefore, SCDs during COVID-19 may be abundant in information that created noises around the actual signals, which causes distortion when received by receivers like shareholders. This is different from SCDs during normal times where those disruptions are observed in isolation and easy for shareholders to assess the information.

Second, we extend prior findings (e.g. Wagner and Bode, 2008) by observing a differential effect of stock market reaction to supply- and demand-side disruptions during the pandemic. This suggests that sources of disruptions carry information along with the SCD signals, which are relevant during the pandemic when signaling environment is noisy. Based on our empirical results, it could be inferred that shareholders view supply-side disruptions as

	Shutdown	Manufacturing delay	Order cancelation	Panic consumer
Mean CAR (%)	-2.39^{***}	-5.45^{***}	-3.20^{*}	1.08^{*}
t-statistic	−7.66	−4.52	−1.98	1.89
Median CAR (%)	-1.25^{***}	-1.72^{***}	−2.38	0.52^{***}
Z-statistic[a]	−2.68	−2.77	−1.36	2.68
% negative	62.07^{**}	83.33^{***}	66.67	55.55^{**}
Z-statistic[b]	−2.14	−2.59	0.667	2.14
n	87	18	9	18

Note(s): [a]Wilcoxon signed-rank *Z*-statistics for medians; [b]binomial sign test for % negative; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5.
CAR [0, 1] for subcategories of SCDs due to COVID-19

having greater potential to impede future growth than demand-side disruptions. This is further supported by our supplementary analysis, showing a more negative market reaction for supply-side SCDs like shutdowns and manufacturing delay.

Third, we found that firms with complex supply chains experience less negative stock market reactions. This is contrary to Hendricks *et al.* (2009) who find that firms that have more complex supply chains experience more negative market reactions for SCDs under normal circumstances. Indeed, redundancies matter during COVID-19. Firm's redundancy in suppliers provide the ability to adjust resources like facilities, inventory and production and respond to disruptions (Ali *et al.*, 2017; Birkie and Trucco, 2020; Wiedmer *et al.*, 2021). Particularly, high number of customers facilitate continuous stream of revenue and orders, which is of paramount importance during the pandemic. Supply chain complexity would indicate more supply chain risks (Choi and Krause, 2006; Bode and Wagner, 2015). However, shareholders are more concerned with a firm's redundancy capability that may minimize the negative impact against SCDs under extreme conditions like COVID-19.

Finally, contrary to expectations, we found no significant roles of the severity of COVID-19 and supply chain position for the stock market reaction to pandemic-induced SCDs. Although our "non-severe" and "strictly downstream" categories are marked with a more negative market reaction than their counterparts, the differences in magnitude are insignificant. This suggests that regardless of the COVID-19 severity and whether firms are in upstream or downstream parts of the supply chain network, the uncertainty caused by pandemic-induced SCDs remain high. This high uncertainty may create noises in a signaling environment, making the stock market difficult to capture SCD signals during the pandemic.

6.1 Theoretical implications

Findings from this study hold substantial value for research, which lead to following theoretical contributions. First, to our knowledge, we are the first to provide empirical evidence of the financial effect of SCDs caused by the pandemic. The study adds to the SCRM, particularly to the SCD literature in the category of events with extreme conditions that differ from normal challenges caused by SCDs. Interestingly, our findings suggest that the overall stock market reaction does not support the widespread acceptance of the pandemic being an extreme disruptor of supply chains. Rather, the magnitude of pandemic-induced SCDs is comparable to that of pre-pandemic SCDs, which can be explained by signal observability that is different between the two periods.

Our second contribution is the expansion of the application of signaling theory by adding the context of signaling environment. As explained by Spence (1978), shareholders are found to interpret pandemic-induced SCD as harmful and react negatively to the signals. This study then introduces moderators that stimulate the signaling strength in a unique setting of pandemic, which highlights the importance of signaling environment (Connelly *et al.*, 2011). In this setting, receivers like shareholders seek out for more information relevant to the pandemic-induced SCDs like its sources, or the firm's centrality measures. This behavior is characteristic of a noisy signaling environment (Connelly *et al.*, 2011).

Our study also expands the application of EST to a supply chain context. EST is mainly developed within organizational settings, which suggests two key catalysts for firm behavior changes caused by events: event time and space (Morgeson *et al.*, 2015). We examine SCDs due to COVID-19 as a signaling environment, which are moderated by the severity of COVID-19, sources of disruptions, firm position in supply chain, and supply chain complexity, all of which reflect event time and space. Despite its potential, EST has received relatively less attention in supply chain research on the COVID-19 pandemic (Craighead *et al.*, 2020). Our study is one of the first attempts to show promise.

Moreover, this study confirms the efficient market hypothesis assumption (Fama, 1970) that stock prices are adjusted immediately to the knowledge of pandemic-caused SCDs affecting firms. Our finding is consistent with prior SCD studies (e.g. Hendricks and Singhal, 2003; Zsidisin *et al.*, 2016; Schmidt *et al.*, 2020). Particularly, our study is among few that confirm the assumption, where multi-country observation on the impact mechanism of SCDs due to COVID-19 is considered.

Finally, our study makes the first attempt to estimate the financial impact of pandemic-induced SCDs by factoring supply chain complexity, an important concept for the context of supply chain (Carter *et al.*, 2015). This implies shareholders' growing concern of the firm's resilience. Conceptual framework of supply chain resilience (Ali *et al.*, 2017) suggests that during SCDs, adaptive ability is a capability obtained through flexibility and redundancy that are required to cope with the shock. Our findings show that during the pandemic, shareholders see adaptive ability as a preferable characteristic. This adds to the SCRM literature where the negative side of supply chain complexity is often highlighted.

6.2 Managerial implications

Several practical implications can be drawn from this study. First, our findings suggest that pandemic-induced SCDs are damaging indicators of firms' performance, leading to the loss of market value. Thus, firms should invest in developing supply chain resilience, which can help to increase the performance, as well as to find abnormal increase in stock return on their efforts (Liu *et al.*, 2020). This could offset any loss of market value due to the disruption. Since the pandemic is an extreme black swan event and developing prevention capability for such unknown disruptions is difficult, quick post-disruption management is important. As found in our study, firms with complex supply chains that act as a buffer are better to cope with SCDs during the COVID-19 pandemic. Therefore, redundancy and flexibility are capabilities that firms should not trade off with efficiency and agility.

Next, managers should be concerned over supply-side disruptions when multiple SCDs occur simultaneously across the supply chain. Therefore, in post-pandemic recovery, supplier selection should be carried with caution by conducting diverse risk assessments, with location being a key factor. As noted by Choudhary *et al.* (2021), suppliers that are dispersed to multiple countries and regions can alleviate the risk of supply break-down during an extreme condition like COVID-19. Selective reshoring or near-shoring (Baraldi *et al.*, 2018) may be effective in managing the right balance, which need to be considered in practices.

In addition, our study indicates that shareholders prefer firms to have high number of supply chain partners, particularly customers, against pandemic-induced SCDs. However, this aspect may be specific to extreme events like COVID-19. Supply chain scholars have noted the ill effects of managing a large pool of supply chain partners on firm's performance (Choi and Krause, 2006; Lu and Shang, 2017). Therefore, managers should be cautious about our finding that shows only one side of supply chain complexity that acts as a buffer for SCDs during the COVID-19 pandemic.

Finally, the central focus of this study is to build consciousness of the financial impact of extremely disruptive events outside the supply chain. We observe that during the pandemic, SCDs do not erode drastic shareholder's value. That said, resources should be exploited to identify and manage such events that can disrupt multiple supply chains now and in the future. Some of other extreme events may not even have the surprise financial effect like COVID-19. Yet, gradual causes like climate change, biodiversity loss, and geopolitical tension may prove detrimental to the whole supply chain network of firms, which need to be reviewed carefully.

6.3 Limitations and future research directions

Our study comes with several limitations, which can be addressed in future studies. First, the shareholder value is only one aspect of a firm's financial performance. Future studies can look into other aspects of financial performance such as operating income, return on sales, and return on assets in quarters following pandemic-induced disruptions. Second, to better understand the financial effect of pandemic-caused SCDs, we selected the severity of COVID-19, sources of disruption, supply chain position and supply chain complexity as event time and space factors that moderate the signaling environment. Future studies could extend our findings by exploring other potential time and space factors that may also play a significant role in shaping the signaling environment during the pandemic such as event timing. Third, we touched upon a small aspect of network measures as a proxy for supply chain complexity and explored its impact on the stock market reaction on SCDs during COVID-19. Other complexity measures that require extensive visibility of sub-tier firms in the supply chain may also offer interesting avenues, which we leave it for future investigation. Finally, in this study, we focused on pandemic-caused SCDs that were observed only by news publications during the period of 2020–2021. Hence, our main focus was its short-term implications, which could be extended by future studied with a longer perspective.

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