An Analysis of the Ripple Effect for Disruptions Occurring in Circular Flows of a Supply Chain Network

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Abstract

This paper examines the ripple effect in supply chains due to circular flows embedded in supply chain design. Although supply chains are complex and nonlinear, circular flows exist in real-world supply chains but are often unknown or hidden to supply chain managers. These circular flows exist when a Tier 2 supplier is also a Tier 3 (or higher) supplier in the supply chain network. Additionally, a circular network can occur when a supplier is also a customer in the same network. In the presence of these types of supply chain network structures, supply chains may experience a ripple effect (or disruption propagation) in which disruptions impact supply chain performance. Using a real-world supply chain structure, we examine the effect of circular flows on the ripple effect and identify how this influences the supply chain's resilience to disruptions. We offer managers and researchers insights that improve the understanding of how circular flows exacerbate the ripple effect.

Keywords: Supply Chain Disruptions, Ripple Effect, Circular Flow Supply Chain Networks; Supply Chain Design, Supply Chain Risk

1. Introduction

A supply chain disruption is defined as an unanticipated event that disrupts the flow of goods and materials in the supply chain (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007), causing the supply chain to deviate from normal operations (Garvey, 2018). A disruption in the supply chain may impact not only the particular node where the disruption originated but may spread to other parts of the supply chain beyond the local node to affect large portions of the supply chain and degrade long term performance (Kinra et al., 2020; Craighead et al., 2007; Blackhurst Scheibe & Johnson, 2008). This propagation or spread of a disruption event has been discussed in research using terms such as cascading failures (Hearnshaw & Wilson 2013; Zobel & Khansa, 2014), contagion (Bellamy & Basole, 2013), and the ripple effect (Ivanov, Sokolov & Dolgui, 2014a; Ivanov, Sokolov & Pavlov, 2014b; Solokov, Ivanov, Dolgui, & Pavlov, 2016, Dolgui, Ivanov, & Sokolov, 2018), which describe how a disruption may spread or ripple out to other parts of the supply chain, often with increasingly adverse effects on supply chain performance metrics such as sales, service levels, and costs (Ivanov, Dolgui & Sokolov, 2019b).

As a disruption ripples to other nodes in the supply chain, the impact may intensify (Blackhurst, Dunn, & Craighead, 2011; Scheibe & Blackhurst, 2018). In other words, a minor disruption in one location may grow and spread in the network with increasingly negative effects (Fiksel, Polyviou, Croxton, & Pettit, 2015; Pettit, Croxton, & Fiksel, 2019). The ability to withstand, adapt, and recover from a disruption is the resilience of a supply chain. (Hosseini, Ivanov, & Dolgui, 2019; Dolgui, Ivanov, & Rozhkov, 2020). Despite the crucial importance of such effects, disruption propagation (i.e., the ripple effect) and supply chain resilience to disruptions remains poorly understood (Bhamra, Dani, & Burnard, 2011; Wu, Blackhurst, & O'Grady, 2007; Blackhurst et al. 2011; Ivanov et al. 2014a; Ivanov et al., 2014b).

Therefore, research to understand the ripple effect of supply chain disruptions is an ongoing effort. For example, Ivanov, Dolgui, Sokolov, & Ivanova (2017) note a shortage of research investigating how firms can recover from supply chain disruptions. Kinra et al. (2020) note that understanding the ripple effect can help identify previously hidden risk exposure in the supply chain and prioritize where to focus mitigation efforts. Others have called for further exploration of disruption propagation and impacts beyond simple dyads (Ghadge, Dani, & Kawalsky, 2012) and even how networks can interact, leading to unforeseen risk exposure (Ivanov, 2020a). Research has focused on the development of understanding of how structure affects supply chain performance (Kim, Choi, Yan, & Dooley, 2011; Nair & Vidal, 2011) and how examining the ripple effect at the network level, with all the intertwined structural relationships, can help researchers better understand risk and supply chain viability (Ivanov & Dolgui, 2021; Hosseini & Ivanov, 2020). Basole & Bellamy (2014) note that the structure of the supply chain, i.e., system architecture

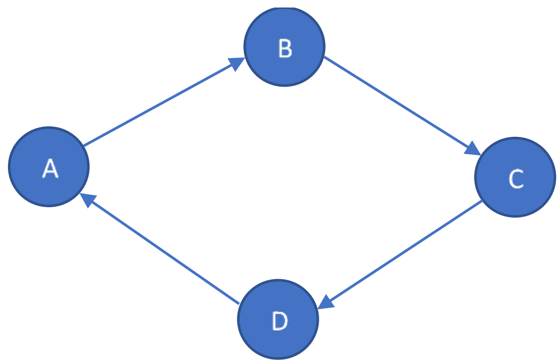
(Bellamy & Basole, 2013), has a significant impact on the spread of a disruption which can negatively influence the health of that supply chain. It is important to understand how systems react when hit with disruption and why it can ripple through the supply chain (Bellamy & Basole, 2013). Also, it has been noted that propagation (the ripple effect) is influenced by supply chain structure (Garvey, Carnovale, & Yeniyurt, 2015). The network structure can amplify the negative impacts of the disruption (Zhao, Zuo, & Blackhurst, 2019). Speier, Whipple, Closs, and Voss (2011) note that the design of a supply chain has risk management implications and emphasize that managers should be mindful of the role that supply chain design plays in risk exposure to disruptions. This research answers specific calls to understand which structures in a supply chain lead to higher susceptibility levels to the ripple effect of a disruption (Dolgui et al., 2018).

One underexplored supply chain network structural characteristic is circular linkages. Scheibe & Blackhurst (2019) present the concept of a cyclical (or circular) linkage (see Figure 1) where a disruption in Node A can propagate to Node B, which can then propagate to Node C and then to Node D, which, in turn, may exert a feedback effect onto Node A (Eisenberg & Noe, 2001), depending on the structure of the supply chain (Scheibe & Blackhurst, 2018). The real-world existence of circular linkages highlights that supply chain networks are complex and often lack neat linear flows, even though supply chain managers may not recognize such structures. Since circular linkages are capable of causing an interesting phenomenon in which a disruption evolves into a self-sustaining disaster (Ackermann, Eden, Williams, & Howick, 2007), supply chain managers and their partners should be vigilant in identifying these structural pitfalls in their supply chains (Scheibe & Blackhurst, 2018). Therefore, the research question we seek to answer is:

- How do circular supply chain structures impact both the ripple effect of supply chain disruptions and the supply chain's resilience?

To answer this question, we model a supply chain network based on real-world data and structures to examine 1) the impact of circular supply chain structures on the ripple effect and 2) how these structures influence supply chain resilience. Specifically, we present a prescriptive analysis to illuminate weaknesses in the supply chain that are often not visible to or poorly understood by supply chain managers and demonstrate how circular linkages in a supply chain structure pose "hidden dangers" to supply chain managers.

Figure 1: Circular linkages example in a supply chain network



The remainder of this paper is organized as follows. We first discuss literature related to supply chain disruptions and the ripple effect, and we introduce the concept of circular flows. Then, we present models for prescriptive analysis using both a simple network and a more complex network in a simulation model based on a real-world supply chain containing circular linkages. Next, we offer supply chain network performance measurements in terms of production level, demand satisfaction, and inventory levels. We then examine the impact of disruptions in supply chains with circular linkages regarding the robustness of the supply chain, the backlogged demand, and the overall recovery period. Finally, we address the influence of disruptions occurring at different supply chain locations (nodes), as well as those occurring at more than one location, and conclude with a discussion of how a better understanding of the effect of circular linkages on disruption propagation and supply chain resilience will help supply chain managers make better and more informed risk management decisions.

2. Literature Review

This section discusses how disruptions can spread through a supply chain and the impact of structure on disruption propagation. We also outline the particular supply chain structural characteristic of *circular linkages*, which is the focus of this study, and briefly discuss how supply chain risks, disruption, and resilience are analyzed in the existing literature.

2.1 Supply Chain Disruptions and the Ripple Effect

Disruptions occur in a supply chain, which can disrupt and alter the flow of goods and impact its performance. The propagation of disruptions, along with their impacts on the supply chain, is known as the “ripple effect” (Ivanov, Dolgui, & Sokolov, 2019a; Ivanov & Dolgui, 2020). Researchers have noted that the complexity, connectivity, and intertwined nature of supply chains can lead to disruptions that propagate or spread through a supply chain (Hearnshaw & Wilson, 2013; Fiksel et al., 2015; Zhao et al., 2019; Ivanov & Dolgui, 2020). As such, a disruption at one location in the supply chain can spread or ripple to other nodes in the supply chain. The ripple effect of a disruption leads to decreased performance and may even fail entire portions of the supply chain (Jüttner & Maklan, 2011; Ivanov et al., 2014a; Ivanov & Dolgui, 2020). This, in turn, affects the supply chain’s overall resilience (Ambulkar, Blackhurst, & Grawe, 2015; Kamalahmadi & Parast, 2015).

The structure of a supply chain may facilitate propagation and amplification of the negative impacts of a disruption, especially given that managers often fail to recognize or adequately understand this structure (Kim et al., 2011; Zhao et al., 2019), its impact on disruption propagation, and the notion of disruption propagation itself (Fiksel et al., 2015). Because of this generally insufficient understanding of how a disruption ripples through a supply chain at the system or supply chain level (Ghadge et al. 2012; Ivanov et al. 2014a; Ivanov et al., 2014b), researchers have called for work that better articulates how the structure of the supply chain impacts risk exposure and the ability to recover from a disruption (Wagner & Neshat, 2010; Mizgier, Juttner, & Wagner, 2013; Bellamy & Basole, 2013; Dolgui et al., 2020; Ivanov & Dolgui, 2020).

2.2 Complex Supply Networks

The complex, interdependent nature of supply chains increases the risk of disruption effects (Zhao et al., 2019). Complexity in the supply chain can be due to its structure, geographic proximities, or interconnections between the nodes in the supply chain network. This section discusses some of the supply chain complexities and how they influence supply chain disruption, risk transmission, and resilience.

Due to globalization, supply chain networks are becoming multinational, and such multinational supply chains are known as transactional supply chain networks. The dynamic trend of risk transmission in transactional supply chain networks is studied by Lei et al (2020) using an improved susceptible-improved-susceptible model. Supply chain networks are also considered complex adaptive systems to study disruption propagation and adaptive strategies to reduce the harmful effects of supply chain disruptions (Zhao et al., 2019). These studies suggest that complex supply chain networks make a firm more vulnerable to disruptions.

Complex supply chain networks may sometimes exhibit “nestedness.” Nestedness is a pattern that emerges when generalist suppliers also supply products supplied by specialist suppliers. Supply chain resilience in nested supply chains is studied using a tri-partite (product-supplier-buyer) network (Chauhan et al., 2021). The performance of a supply chain network can depend on the structure of the network. A disruption can propagate both forward and backward in a supply chain network, and the network structure can moderate its effect on disruption propagation behavior. Li et al. (2020a) showed that the forward and backward propagation rates interact with the supply chain network structure in determining a firm's vulnerability and network health.

Studies have looked into how different network types influence resilience behavior. The scale-free network, the small-world network, and the random network are frequently studied (Basole & Bellamy, 2014; Kim et al., 2015; Nair & Vidal 2011; Zhao, Kumar, Harrison & Yen, 2011). Li et al. (2020b) suggest that studying such network types has limitations because real supply chain networks might not belong to one network type. Hence, using network characteristics is a more realistic option. Network characteristics provide greater insights than network types when tested on real-world supply chain networks. Some of these network characteristics can provide insights into circular linkages. Ledwoch et al. (2018) discuss various network characteristics using centrality metrics to assess supply chain risks. The six centrality measures are degree centrality, eigenvector centrality, hub and authority centrality, closeness centrality, radiality centrality, and betweenness centrality. Degree centrality measures the number of nodes connected to the node. It denotes the connectivity and influence of a node to the rest of the network. Eigenvector centrality measures the relative importance of a node. Hubs are nodes that point towards many authorities, and authorities are pointed to by many hubs. This measure is used in the supply chain context to identify if a firm has many customers or suppliers. The inverse of the mean distance from a node to other nodes is known as closeness centrality. A high closeness centrality value for a firm indicates that the firm has a small average distance to other parts of the network. The measure of how a node is connected and reachable within a network is radiality centrality. A high radiality centrality between two firms, “i” and “j,” indicates that firm i and j are not close partners. Betweenness centrality measures the extent to which a node lies on the path between other nodes. This metric measures the global importance of a node and the spread of a network, including intermediaries. Even though these network characteristics can define circular networks, they do not inherently discuss the cyclic flow in circular linkages.

Circular linkages can be considered an extension of intertwined supply networks (ISN) defined by Ivanov and Dolgui (2020). ISNs are a group of intersecting supply chains that are intertwined. The viability of ISN was demonstrated using the three-level trophic model developed in the area of ecological modeling. Ivanov and Dolgui (2020) call for more research examining ripple effects in ISNs. Our study investigates the ripple effect in networks having circular linkages focusing mainly of the flow of products.

2.3 Circular Linkages

Circular linkages can be considered as an extension of the concepts of triads in supply chain networks. Triads are the smallest unit with multiple links within a supply chain (Choi and Wu, 2009). Triads have been noted as fundamental building blocks of a network where link-based system dynamics can be studied (Autry, Williams, & Golicic, 2014). Much of the work in triads have focused on relationships and competition in the supply chain. For example, Choi and Wu (2009) discuss examples of a triad being a buyer (A) with two competing suppliers (B and C) for dual sourcing of a product. The connection of B and C forms a circular link to which this paper is referring may or may not take place – it depends on the coordination of the competing suppliers (Choi & Wu, 2009; Wynstra, Spring, & Schoenherr, 2015). This paper seeks to understand how circular linkages impact the ripple effect and supply chain resilience. These circular linkages exist in today’s complex and intertwined supply chain networks and can be overlooked or even unknown to a supply chain manager (for example, a supplier could also be a customer). Therefore, we note that circular linkages expand the concept of buyer-supplier-supplier triad and represent the complexities of real-world supply chain networks.

Despite the obvious presence of circular linkages in today's complex, global supply chains, in an investigation of the bankruptcy of supply chain partners, Yang, Birge, & Parker (2015) note that the impact of the structure of the supply chain on firm performance is not always obvious or intuitive. Thererfore, many firms may simply fail to recognize them. Circular linkages are evidenced, for example, by supply chain nodes that engage with products multiple times in different capacities or by those that serve as a supplier for one product and a customer for another product offered by the same firm (see, e.g., Scheibe & Blackhurst's (2018) discussion of such a case). Studies have considered circular flows as cycles in the form of triads as ego-networks (Choi & Wu, 2009; Garvey, 2018). Firms must consider the complexities of their supply chain structures given that one firm may fulfill multiple roles within a single chain, which may increase dependencies in an unknown manner.

Traditional supply chain risk management models tend to be overly simplistic and often fail to recognize hidden interactions within the supply chain network (Pettit et al., 2019). Therefore, decision tools are needed to prescribe what managers should do when facing disruptions in supply chain networks with circular linkages. For example, Adenso-Diaz, Mar-Ortiz, & Lazano (2018) studied the failure of links in the supply chain by investigating the percentage of demand that can be satisfied when links fail, which could assist managers in handling link failures. In contrast to their paper, we examine node failure, as opposed to link failure, and investigate supply chains with multiple tiers. Recently, Ivanov (2018) demonstrated that firms facing a disruption could respond by adapting metrics such as inventory levels or structures or by adding resources such as a backup supplier. We go beyond this by examining the impact of inventory levels and safety stocks and investigating how the utilization of resources can mitigate the impact of a supply chain disruption.

2.4 Supply Chain Simulation Analysis

Optimization and simulation are two common methods used to analyze the behaviors of supply chain networks. The complexity of supply chain networks can be reduced by using optimization methods to identify feasible solutions that can be implemented in a reasonable time frame. However, the randomness and time-related aspects of disruption and recovery are complex and may not be easily modeled in a closed-form equation. Thus, since simulations allow for the incorporation of randomness and the real-time effects of problem complexity, simulations can be used to model the dynamic nature of disruption and recovery policies and their effect on performance (Ivanov, 2017). Ivanov et al. (2017) conducted a review of disruption and recovery considerations in the supply chain literature. They confirmed that simulation is a suitable tool for analyzing the ripple effects of supply chain disruptions. Tordecilla, Juan, Montoya-Torres, Quintero-Araujo, & Pandero (2020) conducted a review of the literature on the simulation-optimization methods to study resilience in supply chain networks, and Dolgui et al. (2018) note that simulation is an effective tool for studying the ripple effect because it can handle complex problem settings and changes to the system over time.

In research using simulation to examine disruptions in the supply chain network, Tang, Jing, He, & Stanley (2016) analyzed the robustness of interdependent supply chain networks using a time-varying cascade failure model simulation. The simulation results show that interdependent supply chain networks collapse suddenly after a failure. Similarly, Ojha, Ghadge, Tiwari, & Bititci (2018) studied the behavior of risks in supply chain disruption propagation, and Ivanov (2019) used discrete event simulation to study the effect of revival policies (policies developed for a transition from recovery to disruption-free operation mode) on “disruption tails,” which constitute the backlogs and delay in orders that arise due to the disruption-driven changes in supply chain behavior. Garvey & Carnovale (2020) proposed the “rippled newsvendor” model by leveraging a Bayesian network to explore optimal inventory and production policy through the lens of risk severity objective. They conducted multiple simulation experiments to understand the nature of the objective function, optimality of the solution and sensitivity analysis. In another study by Ivanov (2020b), the COVID-19 epidemic outbreak is articulated as a disruption risk and its impacts on global supply chains are demonstrated through simulation experiments.

Moreover, simulations are also helpful in studying the ripple effect and supply chain resilience. Carvalho, Barroso, Machado, Azevedo, & Cruz-Machado (2012) used a simulation study investigating various supply chain scenarios to identify how to improve supply chain resilience. Likewise, Ivanov (2018) used a simulation-based study to identify how different sustainability factors influence ripple effects in supply chains and found that sustainable single sources increase ripple effects while facility fortification at major regional employers mitigate them. Because of the need to consider vulnerabilities and recovery capabilities at individual firms in a network, ripple effect assessment in multistage supply chains can be challenging. Hosseini, Ivanov, & Dolgui (2020) simulation study based on the discrete time Markov chain (DTMC) and the dynamic Bayesian network (DBN) demonstrated the disruption propagation behavior of suppliers in a multistage supply chain.

Simulation is a very useful tool for capturing multiple sources of uncertainties and incorporating various policies relating to decision-making surrounding complex phenomena (Meisel, & Bierwirth, 2014). Simulation can also be useful for studying supply chain risks and resilience, theory development, theory testing, and the description and exploration of various phenomena (Macdonald, Zobel, Melnyk, & Griffis, 2018). The ripple effect is one such phenomena. Five simulation perspectives have been used to analyze ripple effect – system dynamics (to simulate ripple effect in the supply chain), agent-based simulation and modeling (to model supply chain disruption and impact on supply chain performance), discrete event simulation (used in the area of severe supply chain disruption and resilience analysis), graph-theory based simulation (to analyze disruption propagation through the supply chain and evaluate its impact on performance), and optimization-based simulation (Ivanov, 2017). This study examines the ripple effect of supply chain disruption in circular networks using discrete event simulation.

3. Method

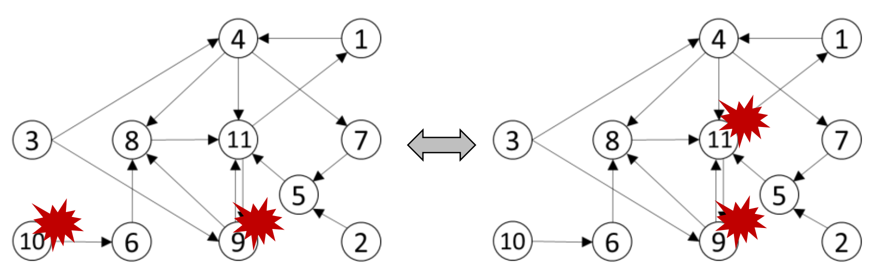
Whereas mathematical models or closed-form solutions may not be capable of handling complex problem settings (Dolgui, et al., 2018), simulation is an effective descriptive and prescriptive analytical tool for investigating phenomena and evaluating decision-making options. The most common simulation technique used in supply chain studies is discrete event simulation. Discrete event simulation models (DESM) are used to understand how systems react over time and compare their performance under different conditions (Borshchev & Filippov, 2004). Tako & Robinson (2012) provide a literature review using discrete event simulation model in logistic and supply chain literature. DESM is used to study and analyze various strategic, operational, and tactical issues in the supply chain, including supply chain structure, replenishment control policies, supply chain optimization, cost reduction, system performance, inventory planning and forecasting demand, production planning and scheduling, and dispatching rules. DESM is also used to analyze the ripple effect in supply chain networks. Dolgui et al. (2018) conducted a review of the literature on ripple effect analysis that summarizes the use of DESM in ripple effect studies. These studies analyze the effect of different strategies and policies on recovery, the performance impact of disruption, ripple effect and sustainability, and how performance varies under different disruption scenarios.

We analyze the impact of disruptions to circular flow supply chains using a discrete-event simulation. In our simulation, several parts (or subassemblies) are processed and moved between multiple companies (or nodes in the supply chain) within a supply chain system. We then introduce disruptions into the systems and analyze their impact on system performance. Using the simulation model developed in this section, we test multiple hypotheses (illustrated in Figure 2) and test the effects of circular and multiple disruptions and the disruptions' location in a given network. For the network in Figure 2 involving 11 companies, we assume that one circular flow exists (Company 9 → Company 11 → Company 9) for illustration purposes. The supply chain network used in our simulation study, introduced in Section 3.2.1, involves multiple circular flows.

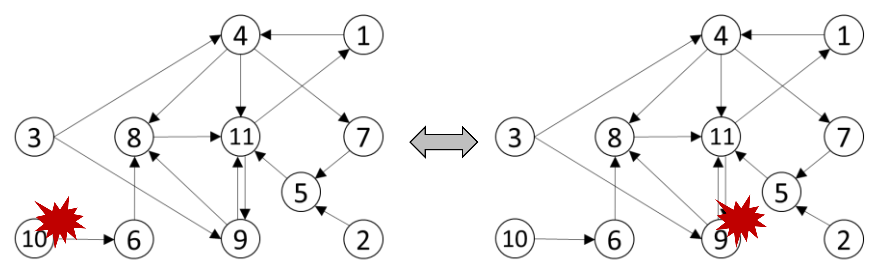
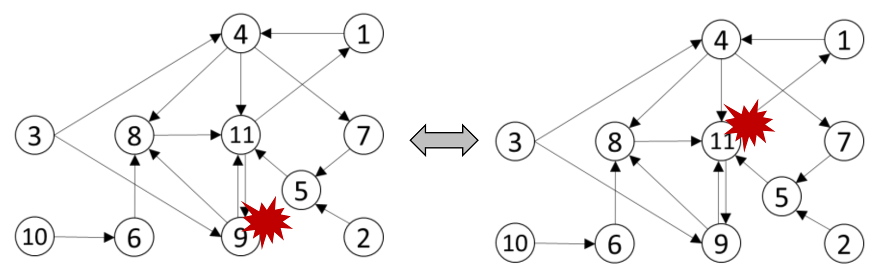
Figure 2: Illustration of hypotheses tested

H1. *Simultaneous disruptions that occur within circular linkages will have longer backlog and recovery periods compared with simultaneous disruptions occurring in noncircular linkages, all else being equal.*

Effect of multiple disruptions in circular flows (vs. noncircular) to backlog periods and recovery periods



H2. *Single disruptions that occur within circular linkages will have longer backlog and recovery periods compared with a disruption that occurs in noncircular linkages, all else being equal.*

<table>
<tr><td>Effect of single disruption in circular flows (vs. noncircular) to backlog periods and recovery periods</td><td></td></tr>
<tr><td colspan="2">H3. Disruptions that occur in different locations within the same circular flow will have different backlog and recovery periods.</td></tr>
<tr><td>Effect of disruption location to backlog periods and recovery periods</td><td></td></tr>
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Based on the hypotheses (which will be discussed below in more detail), we investigate: (1) how multiple disruptions affect the supply chain when the disruptions occur within circular flows, (2) how a single disruption affects the supply chain when the disruption occurs within the circular linkages, and (3) how the location of the disruption (in the same circular flow) affects the supply chain.

3.1 Model Development

To measure the impact of disruptions on system resilience and performance, we adapted the quantification of resilience expressed by Bruneau, Chang, Eguchi, Lee, O'Rourke, Reinhorn, Shinozuka, Tierney, Wallace, & Winterfeldt (2003), where they investigated the seismic resilience of communities. They state that resilient systems will have reduced failure probabilities, reduced consequences of failures, and reduced time to recovery to a normal performance level. We assessed the following three metrics and used them to derive performance measures:

- First, the *production level* computes the ratio between the production quantity and demand of the final product, defined as the production level = (production quantity) / demand.
- Second, the *demand satisfaction level* computes the cumulative demand percentage satisfied for the final product, defined as demand satisfaction level = (cumulative production quantity) / (cumulative demand).
- Third, the *relative inventory level* computes the ratio between the part inventory level and the safety stock, defined as relative inventory level = (part inventory) / (desired part safety stock inventory level). Note that the first two measures are defined only for the final product, and the last measure is defined for each part.

Figures 3 to 5 present the three metrics over time when a firm faces a disruption event. The figures are obtained by generalizing the simulation outputs using various settings. Figures 3 and 4 show the production level and demand satisfaction level, respectively, of the final product affected by the disruption event. Figure 5 shows the relative inventory level of a part affected by the disruption event.

Figure 3: Relative Production Level

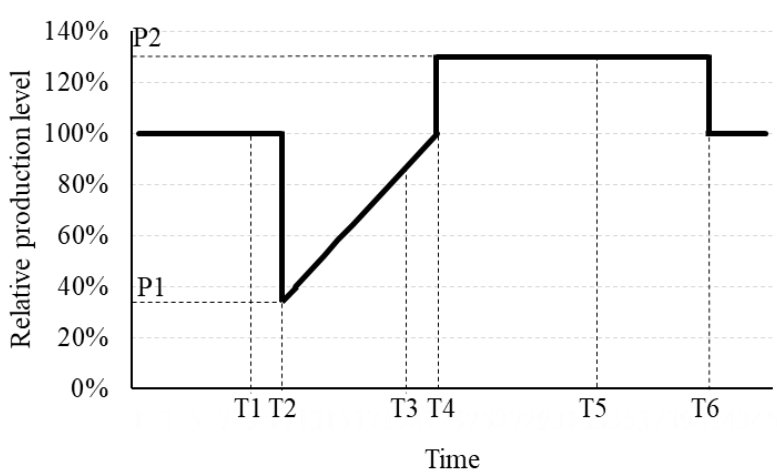


Figure 4: Cumulative Demand Satisfied

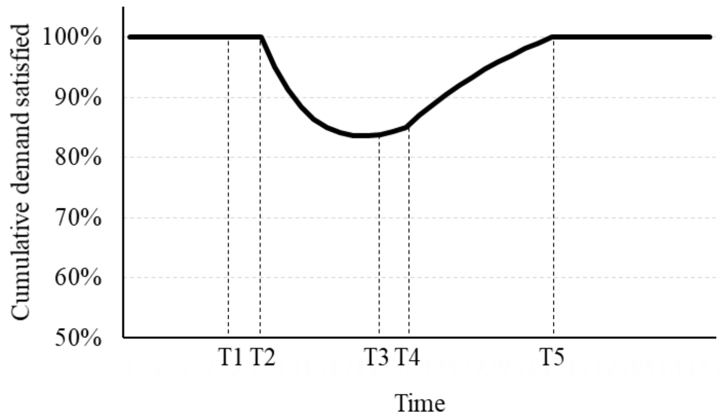
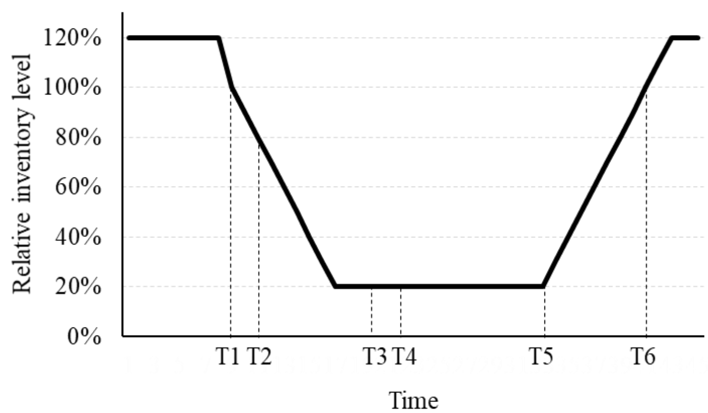


Figure 5: Relative Inventory Level



In our model, a disruption event has six distinct time phases:

1. Time T1: the time at which a disruption begins.
2. Time T2: the time at which all in-process units and safety stocks begin to show the effects of disruption.
3. Time T3: the time at which disruption ends.
4. Time T4: the time at which the network returns to normal capacity following the disruption event.
5. Time T5: the time at which all backlogged demands are satisfied.
6. Time T6: the time at which overproduction ends because safety stock levels have fully recovered from the disruption event.

Note that the triangle in Figure 3 with angles at T2 and T4 is slightly different from the resilience triangle of Bruneau et al. (2003) because our vertical axis indicates the relative production level. In contrast, Bruneau et al. (2003) use the infrastructure's quality for the vertical axis. In Figure 3, the effect of the disruption to the production level is delayed because (1) disruptions at earlier stages will slowly affect the production of the final product, and (2) the safety stock and in-process parts delay the effect of the disruptions, which explains the time difference between T1 and T2. Similarly, the production level is not 100% at the end of the disruption at T3. Instead, the effect of the disruption appears at T2 and disappears at T4 in Figure 3, while the actual disruption occurs from T1 to T3. However, during periods T2 through T4, demands are backlogged, and overproduction is needed following a disruption event to meet the unsatisfied demand. The overproduction starts immediately after removing the disruption (T3) and ends when all the backlogged demands are satisfied and all part inventory levels reach the baseline safety stock level (T6). The manager determines the overproduction level, P2, and the overproduction stops at T6 in Figure 3 because the relative inventory level reaches 100% at T6 in Figure 5, implying that the part inventory levels have reached the baseline safety stock level.

Supply chain literature uses a variety of performance metrics to analyze supply chain resilience. Han et al. (2020) provide a systematic review of literature on the various capabilities and performance metrics used in supply chain resilience. Based on Han, Chong, & Li (2020), the main performance metrics include fulfilling customer requirements, efficiency in completing supply chain processes, efficiency in recovery to normality, production performance, inventory, financial performance, and disruption damage. Many simulation studies investigating supply chains with disruptions address capacity degradation and recovery duration (Dolgui et al., 2018). In this paper, we focus mainly on the supply chain's ability to recover to normality. Hence, we evaluate supply chain resilience based on the performance measures derived from the three system quantities introduced below.

(1) *Robustness* is measured by the lowest relative production level (P1 in Figure 3—with 100% being normal). This measures the system's strength and ability to resist the impact of a disruption event (Bruneau et al., 2003; Nair & Vidal, 2011; Zobel & Khansa, 2014).

(2) The *backlogged period* is measured by the number of days from the day the disruption ends to the day when the demand satisfaction level reaches 1 for the first time (T5-T3). This shows the system's stability (Ivanov & Dolgui, 2020) by measuring the time required to meet the backlogged demand at the end of a disruption event. We measure the backlogged period because this shows that the system is now stable and meets demand. This is different than recovering backlog AND safety stock. Including safety stock is a measure to prepare for future disruptions rather than returning to a stable state with the downstream customer. This is measured in our next measure, the recovery period.

(3) The *recovery period* is measured by the number of days from the day the disruption ends to the day on which the relative inventory level reaches 1 for the first time (T6-T3). This also measures the stability of the system (Ivanov & Sokolov, 2013; Ivanov & Dolgui, 2020) by capturing the time required to return to the baseline safety stock level at the end of the disruption event. It is similar to the time to full system service resilience used in Pant, Barker, Ramirez-Marquez, & Rocco (2014).

Using the three performance measures, we assess: (1) how single or simultaneous disruptions at different locations affect performance, and (2) how manager decisions regarding the overproduction level (P2) and safety stock level affect performance.

3.2 Simulation Model

3.2.1 Example Supply Chain Network

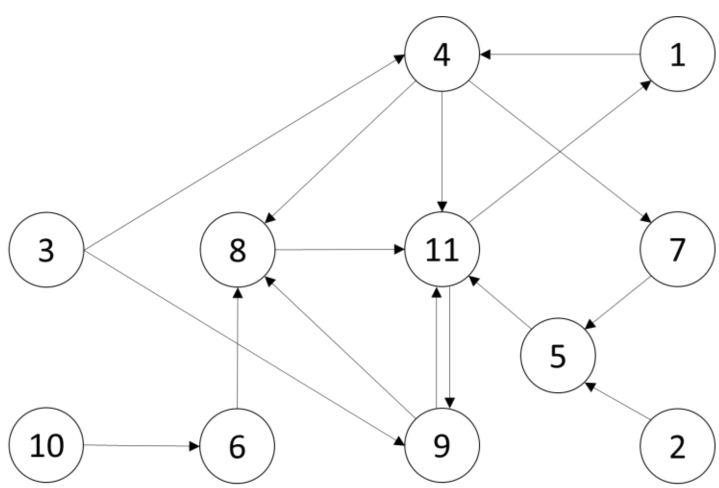
In our simulation study, we considered a supply chain network (presented in Figure 6) based on real-world supply chain data and structures—specifically, the Boeing supply chain structure extracted from the Mergent Horizon (Mergent Inc., n.d.) database. Companies included in the supply chain network are listed in Table 1 below.

Table 1 List of companies in the supply chain network

Company #	Company Name	Company #	Company Name
Company 1	Alcoa Corporation	Company 7	United Technologies Corp
Company 2	Zodiac Aerospace	Company 8	General Dynamics
Company 3	Hexel Corp	Company 9	TransDigm Group
Company 4	General Electric	Company 10	Korea Aerospace
Company 5	Mitsubishi	Company 11	Boeing
Company 6	Triumph Group		

Note that two circular relationships are indicated here: Companies 9 and 11 provide parts to each other and Companies 1, 4, and 11 form a cycle.

Figure 6: Example real-world supply chain network structure



We consider a final product produced at Company 11 within this network. The required parts and flow for producing each part are listed in Table 2. Each row of the table shows how the part is produced and indicates the production rate for all companies involved. Parts 5a and 5b are combined to produce Part 5, supplied to Company 11. When Company 11 holds ten units of Parts 1, 2, and 3 and five units of Parts 4 and 5, one unit of the final product is produced. Hence, one unit of the final product is produced per day without considering delivery delays per day on average.

Table 2: Parts and flows required for the production of the final product

Part type	Flow	Regular production rate (units per day)	Number of units required for each final product
Part 1	1 – 4 – 7 – 5 – 11	10	10
Part 2	2 – 5 – 11 – 9 – 11	10	10
Part 3	3 – 4 – 8 – 11	10	10
Part 4	4 – 11 – 1 – 4 – 11	5	5
Part 5a	10 – 6 – 8*	5	5
Part 5b	3 – 9 – 8* – 11	5	5

*Note: * indicate that Parts 5a and 5b are required to produce Part 5 at Company 8.*

3.3 Simulation Experiment Settings

3.3.1 Supply Chain System Settings

In our simulation, we assume batch production in a push-based supply chain[1]. The production or processing of a part is scheduled when the number of parts needed exceeds the sum of the parts contained in the safety stock and the batch production number. The production is scheduled in batches, where the batch size is equal to the regular production rate (in our simulation, either 5 or 10 units per day). The production time (in days) to produce a batch is modeled as a normally distributed random variable with a mean of 1 and a standard deviation of 0.1. The

[1] In a push-based system, products are pushed through the process, from the raw materials to finished goods. The production levels are set by the manufacturer in advance in accord with historical ordering or demand patterns.

deliveries are scheduled with larger-sized batches: 2 * production batch size. We assume that the companies do not hold the inventories they produce and schedule delivery when the number of parts in the inventory exceeds the sum of the safety stock and delivery batch size. The time (in days) to deliver a delivery batch (of two production batches) is modeled as a normally distributed random variable with a mean of 1 and a standard deviation of 0.1. The production and delivery are scheduled every hour rather than in real-time, which means the production and delivery can be delayed up to one hour even if all requirements are met in the simulation.

3.3.2 Disruption Settings

A disruption occurs between randomly generated start and end dates. To check the effect of various disruption durations, we use the uniform distributions to generate disruption lengths in a wide range instead of using a fixed-length or several discrete duration lengths (Ivanov, 2020b; Olivares-Aguila & ElMaraghy, 2020) or a firm-specific formula (Schmitt & Singh, 2009). The start date follows a uniform distribution between Day 180 and Day 220, and the end date follows a uniform distribution between Day 280 and Day 320. Hence, the average length of the disruption is 100 days, with the shortest and longest disrupted lengths being 60 days and 140 days, respectively. When a disruption occurs, the disrupted company's production rate is reduced, and the reduction rate follows a uniform distribution between 20% and 80%. For example, if Company 1 is disrupted with a reduced rate of 50%, the production rates of Parts 1 and 4 at Company 1 become 5 and 2.5 units per day, respectively. Similar to the generated disruption durations, our generation procedures cover various disruption rates in a wide range. Our generation procedures for the disruption durations and rates consider much more disruption scenarios than using a fixed value or multiple discrete values. To model the linearly increasing production rate immediately after a disruption, the reduced production rate linearly increases until the date on which the disruption ends. The delivery time is also affected by the disruption. With a disruption rate of 50%, the mean delivery time is doubled; i.e., the delivery time would be extended from 1 day to 2 days. Conversely, during the overproduction period, delivery times are reduced—e.g., an overproduction rate of 30% would reduce the normal delivery time from 1 day to 0.77 days. A summary of the simulation settings and parameters is found in Table 3.

Table 3: Simulation settings and parameters

	Descriptions	
System settings	• Push-based supply chain • Backlogged final product • Batch productions and deliveries scheduled every hour Deliveries are scheduled when the stock level exceeds the sum of safety stock and delivery batch size	
	Variable	Corresponding value or distribution
Decisions	Overproduction levels	{20%, 30%, 40%}
	Safety stock levels	{2 days, 3 days, 4 days}
Scenarios	D-j: 11 Single disruption scenarios	Company j is disrupted
	D-(j,k): 55 Two disruptions scenarios	Companies j and k are disrupted
Parameters	Number of replications	200 simulations per scenarios and decision alternative
	Number of simulation days	1000 days
	Warm-up period	150 days
	Regular production rate	5 or 10 units per day
	Production batch size	Regular production rate
	Production time	Normal (mean = 1, sd = 0.1)
	Delivery batch size	2*production batch size
	Time to deliver	Normal (mean = 1, sd = 0.1)
	Disruption start date	Uniform(180, 220)
	Disruption end date	Uniform(280, 320)
	Reduction rate of production (after disruption)	Uniform(20%,80%)
	Production rate recovery	Recovered linearly during the disrupted periods
Performance measures	Backlogged period	# days to reach demand satisfaction level 1
	Recovery period	# days to reach relative inventory level 1
	Robustness	Minimum production level due to disruption

3.3.3 Performance Measures and Scenarios

Based on the simulation study, we assess the three performance measures of robustness, backlogged period, and recovery period introduced in Section 3.1. To calculate the performance measures, the following three values were calculated for each simulation day and each part:

average production level = (10 days production quantity) / (10 days demand); demand satisfaction level = (cumulative production quantity) / (cumulative demand); and relative inventory level = (part inventory level) / (desired safety stock inventory level). We used these three values to calculate the performance measures robustness, backlogged period and recovery period. In all of the simulation experiments, we considered the following two types of scenarios:

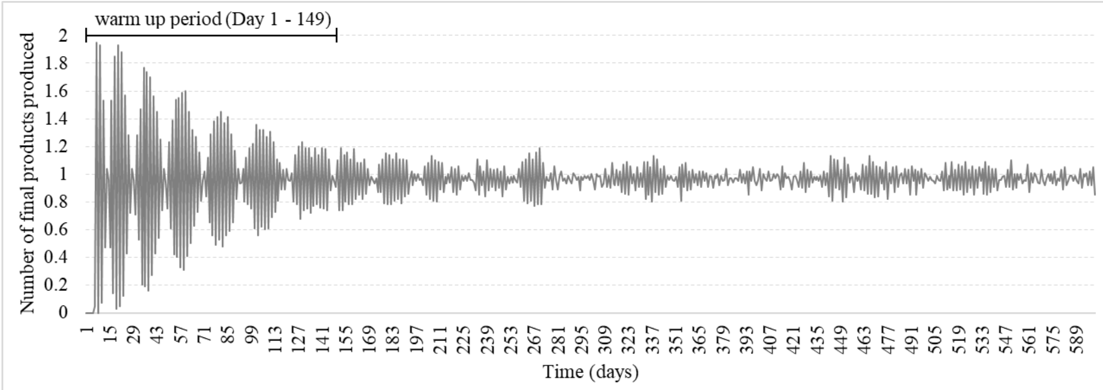
(1) Single disruption scenario, where one company, Company j, faces a disruption, which is denoted as D-j.

(2) Simultaneous disruptions scenario, where two companies, Companies j and k, face disruptions, which is denoted as D-(j,k).

3.3.4 Other Simulation Parameters

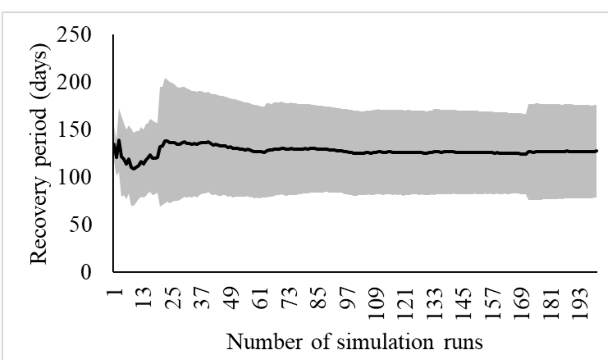
Finally, we discuss the setup of the simulation parameters summarized in Table 3, such as the number of days, the number of simulation runs, and warm-up periods. To observe how the system works without a disruption, we conducted a pilot study that ran a 1000-day simulation 200 times for the network in Figure 6 with a fixed safety stock level of 3 days and an overproduction rate of 30%. In Figure 7, the number of final products produced on each day is displayed over time. Each value in the series was obtained by averaging the number of final products produced during one day using over 200 replications. Because the daily production level fluctuates in the warm-up period (Day 1-149) and stabilized, we discarded all the records collected during the warm-up period. The average number of final products produced each day was 0.967, which is the value used as the daily demand in our simulation.

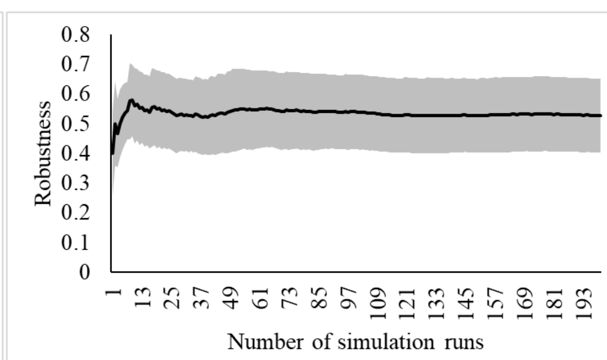
Figure 7: Number of final products produced in each day (average of 200 replications)



To determine the length of each simulation run, we conducted a pilot study and concluded that a 1000-day simulation is sufficient. To determine the number of simulation runs, we conducted a pilot study with two randomly disrupted companies (uniform distribution is used) in each simulation run. Because 11 companies exist in the network, there are 55 simultaneous disruptions scenarios. To obtain the average performance for each scenario, we averaged the output from multiple simulation runs with randomly created pairs of disrupted companies. In Figure 8, the average recovery periods and robustness values are plotted for increasing numbers of simulation runs. The plain black line represents the average values, and the shaded areas indicate the upper and lower bounds; the bounds are defined as one standard deviation from the mean.

Figure 8: Average of recovery periods (plain black line in the left figure) and robustness values (plain black line in the right figure) and the upper and lower bounds (shaded area)



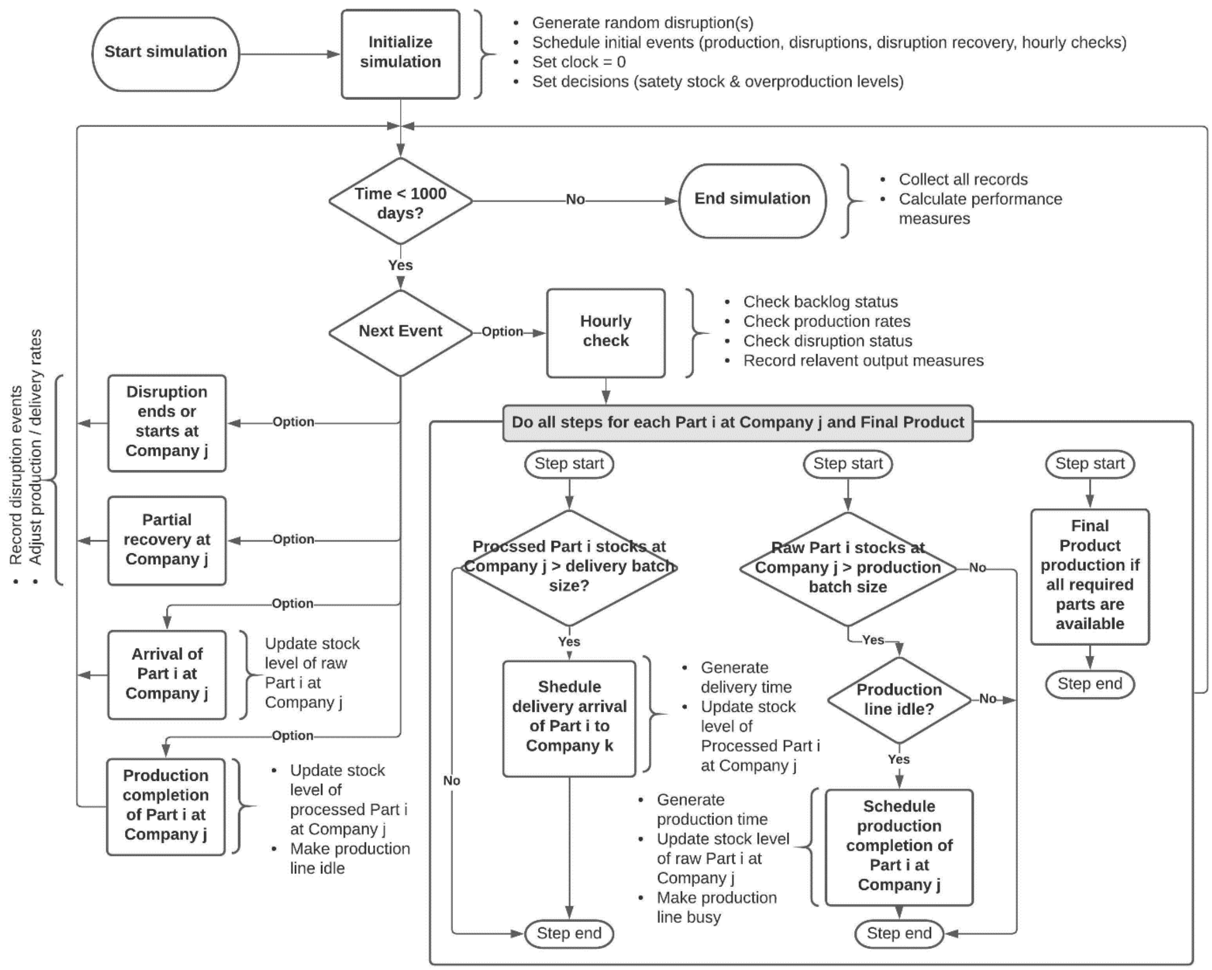


The standard deviations are relatively large compared to the averages because the disrupted locations are randomly selected, and the disruption rates follow a uniform distribution of between 20% and 80%, which yields large variances. However, the averages and standard deviations become stable quickly, within 50 simulation runs. To generate more stable results, we ran approximately 200 simulations for each disruption scenario for the network in Figure 6. For the single disruption cases, in which only one company was disrupted, we ran 19,800 simulations (i.e., 11 scenarios of single disruptions * 200 replications * 9 decision alternatives), where each run randomly selected a company to be disrupted. Hence, each scenario corresponded to 200 simulation runs on average. For the multiple disruption cases in which two companies were simultaneously disrupted, we ran 99000 simulations (i.e., 55 scenarios of two simultaneous disruptions * 200 replications * 9 decision alternatives), where each run randomly selected two companies to be disrupted. Hence, for each scenario, we had an average of 200 simulation runs.

3.3.5 Simulation Implementation and Flows

We implement our simulation experiment in C#. In Figure 9, the flowchart of the simulation steps is presented. The bullet points next to each box briefly explain the steps executed. Note that some events are represented as a single event in the diagram for simplicity (e.g., events defined for multiple companies). The hourly check event enumerates all steps needed (productions, deliveries, updates, and records) for each Part i at Company j and the Final Product.

Figure 9 Simulation Flowchart



3.4 Simulation Experiment Results

We test the supply chain network in Figure 6 using the simulation settings discussed in the previous section. Based on our results, we observed that: (1) the recovery period depends significantly on the overproduction-rate decision; (2) simultaneous multiple disruptions decrease the robustness of the system—the average robustness values for the single and multiple disruptions scenarios are 0.588 and 0.523, respectively. However, because there are numerous scenarios (594 scenarios = 66 single and multiple disruption cases * 9 decision alternatives), rather than presenting the aggregated result according to the scenario, we focus on testing the hypotheses for this model as explained below. For all of the hypothesis tests conducted in this section, we use Welch's t-test, or unequal variances t-test, for comparing the means of two populations (e.g., circular vs. noncircular, company A vs. B). To further validate our conclusion, we provide a regression analysis for the hypotheses in the appendix.

3.4.1 Effect of multiple simultaneous disruptions in circular flows

In Figure 6, there are two circular flows: 4 – 11 – 1 – 4 – 11 and 11 – 9 – 11. According to the analysis in this section, two simultaneous disruptions are simultaneous circular disruptions if the two disrupted companies are part of any circular flows. That is, disruptions D-(1,4), D-(1,9), D-(1,11), D-(4,9), D-(4,11), and D-(9,11) are considered simultaneous circular disruptions. All other pairs are defined as simultaneous disruptions in noncircular flows. The performance differences between multiple simultaneous disruptions in circular and noncircular flows are presented in Table 4.

Table 4: Average performance measures for multiple disruptions in circular/noncircular flows

Circular or Not	Safety Stock	Over-production	Robustness AVG	Robustness SD	Backlogged Periods AVG	Backlogged Periods SD	Recovery Periods AVG	Recovery Periods SD
0	2 days	20%	0.525	0.128	168	46	169	46
0	2 days	30%	0.525	0.128	117	31	117	32
0	2 days	40%	0.525	0.128	88	24	89	24
0	3 days	20%	0.525	0.128	168	46	188	89
0	3 days	30%	0.525	0.128	116	31	127	52
0	3 days	40%	0.525	0.128	88	24	97	42
0	4 days	20%	0.525	0.128	168	46	273	245
0	4 days	30%	0.525	0.128	116	31	203	220
0	4 days	40%	0.525	0.128	88	24	169	215
1	2 days	20%	0.508	0.124	175	46	180	46
1	2 days	30%	0.508	0.124	122	32	125	32
1	2 days	40%	0.508	0.124	92	24	95	25
1	3 days	20%	0.508	0.125	175	47	268	177
1	3 days	30%	0.508	0.125	121	32	176	129
1	3 days	40%	0.508	0.125	92	24	139	102
1	4 days	20%	0.508	0.125	175	46	532	363
1	4 days	30%	0.508	0.125	121	32	439	364
1	4 days	40%	0.508	0.125	91	24	379	351

We observed that simultaneous multiple disruptions decreased the robustness of the system but not significantly. The average robustness values for the multiple disruption scenarios in circular and noncircular flows are 0.500 and 0.525, respectively.

H1a. *Simultaneous disruptions that occur within circular linkages will have longer backlog periods compared with simultaneous disruptions occurring in noncircular linkages, all else being equal.*

H1b. *Simultaneous disruptions that occur within circular linkages will have longer recovery periods compared with simultaneous disruptions occurring in noncircular linkages, all else being equal.*

Conversely, backlogged and recovery periods are significantly different across different disruption scenarios. For example, we compare the average backlogged and recovery periods for disruptions in circular and noncircular flows, given a fixed safety stock level of 2 days and an overproduction rate of 20%. For the average backlogged period, the null and alternative hypotheses are H1a0: mean(backlogged period for circular disruptions) = mean(backlogged period for noncircular disruptions) and H1a1: mean(backlogged period for circular disruptions) != mean(backlogged period for noncircular disruptions). For this test, we calculate:

$$\mathrm{t} = \frac{175.4-167.9}{\sqrt{\frac{45.9^2}{1197}+\frac{46.2^2}{9803}}} = 5.361 > 1.962 = \mathrm{t}_{\frac{0.05}{2},930.8}.$$

Hence, we reject H1a0 and conclude that the mean backlogged periods are different. For the recovery period, the null and alternative hypothesis are H1b0: mean(recovery period for circular disruptions) = mean(recovery period for noncircular disruptions) and H1b1: mean(recovery period for circular disruptions) ≠ mean(recovery period for noncircular disruptions). For this test, we calculate:

$$\mathrm{t} = \frac{180.3-169.0}{\sqrt{\frac{46.5^2}{1197}+\frac{46.3^2}{9803}}} = 7.933 > 1.963 = \mathrm{t}_{\frac{0.05}{2},928.9}.$$

Hence, we reject H1b0 and conclude the mean recovery periods are different.

3.4.2 Effect of single disruptions in circular flows

Similar to the definitions of the disruptions for circular and noncircular flows, we use the two circular flows in the network: 4 – 11 – 1 – 4 – 11 and 11 – 9 – 11. For this single disruption case, companies involved with any of the circular flows are considered to be single disruptions in circular flows: disruptions D-1, D-4, D-9, and D-11. All the other single disruptions D-2, D-3, D-5, D-6, D-7, D-8, and D-10 are considered single disruptions in noncircular flows. The performance differences between single disruptions in circular and noncircular flows are presented in Table 5. There are significant differences regardless of management decisions.

Table 5 Average performance measures for single disruption in circular/noncircular flows

Circular	Safety	Over-	Robustness		Backlogged Periods		Recovery Periods	
or Not	Stock	production	AVG	SD	AVG	SD	AVG	SD
0	2 days	20%	0.594	0.149	135	51	135	51
0	2 days	30%	0.594	0.150	94	35	94	35
0	2 days	40%	0.594	0.150	71	26	71	26
0	3 days	20%	0.594	0.149	135	51	135	51
0	3 days	30%	0.594	0.150	94	35	94	35
0	3 days	40%	0.594	0.150	71	26	71	26
0	4 days	20%	0.594	0.149	135	51	135	51
0	4 days	30%	0.594	0.150	94	35	94	35
0	4 days	40%	0.594	0.150	71	26	71	26
1	2 days	20%	0.577	0.151	143	52	144	52
1	2 days	30%	0.577	0.151	100	36	101	36
1	2 days	40%	0.577	0.151	76	27	76	27
1	3 days	20%	0.577	0.151	144	52	156	63
1	3 days	30%	0.578	0.151	100	36	107	38
1	3 days	40%	0.577	0.151	76	27	82	31
1	4 days	20%	0.577	0.151	143	52	252	225
1	4 days	30%	0.578	0.151	100	36	176	169
1	4 days	40%	0.578	0.151	75	27	143	164

H2a. *Single disruptions that occur within circular linkages will have longer backlog periods compared with a disruption that occurs in noncircular linkages, all else being equal*

H2b. *Single disruptions that occur within circular linkages will have longer recovery periods compared with a disruption that occurs in noncircular linkages, all else being equal*

Let us consider a fixed-decision pair with two days of safety stock and 20% overproduction. We use the same hypothesis tests, and the null hypotheses are the equal average hypotheses. For the backlogged period, we calculate:

$$t = \frac{143.3-135.1}{\sqrt{\frac{51.9^2}{800}+\frac{51.4^2}{1400}}} = 3.614 > 1.961 = t_{\frac{0.05}{2},1647.8}.$$

Hence, we reject H2a0 and conclude that the mean backlogged periods are different. For the recovery period, we calculate:

$$t = \frac{144.2-135.1}{\sqrt{\frac{52.1^2}{800}+\frac{51.4^2}{1400}}} = 3.990 > 1.961 = t_{\frac{0.05}{2},1643.8}.$$

Therefore, we reject H2b0 and conclude the mean recovery periods are different.

3.4.3 Effect of disruption locations

Company 9 is the fourth company processing Part 2, Company 11 represents the third and fifth company processing Part 2, and Part 2 includes a circular flow (11-9-11). Therefore, to illustrate the effect of the locations within the same circular flow, we present the performance differences between single disruptions at Company 9 (D-9) and single disruptions at Company 11 (D-11) in Table 6.

Table 6 Average performance measures for disruptions at Companies 9 and 11

Disrupted company	Safety stock	Over-production	Robustness		Backlogged periods		Recovery periods	
			AVG	SD	AVG	SD	AVG	SD
9	2 days	20%	0.587	0.154	135	50	135	50
9	2 days	30%	0.587	0.154	94	35	94	35
9	2 days	40%	0.587	0.154	71	26	71	26
9	3 days	20%	0.587	0.154	135	50	135	50
9	3 days	30%	0.587	0.154	94	35	94	35
9	3 days	40%	0.587	0.154	71	26	71	26
9	4 days	20%	0.587	0.154	135	50	135	50
9	4 days	30%	0.587	0.154	94	35	94	35
9	4 days	40%	0.587	0.154	71	26	71	26
11	2 days	20%	0.567	0.153	146	52	148	52
11	2 days	30%	0.567	0.153	101	35	103	35
11	2 days	40%	0.567	0.153	77	26	78	26
11	3 days	20%	0.567	0.153	146	52	186	78
11	3 days	30%	0.567	0.153	101	35	124	40
11	3 days	40%	0.567	0.153	76	27	97	35
11	4 days	20%	0.567	0.153	145	52	499	311
11	4 days	30%	0.567	0.153	101	35	361	246
11	4 days	40%	0.567	0.153	76	27	317	252

H3a. *Disruptions that occur in different locations within the same circular flow will have different backlog periods*

H3b. *Disruptions that occur in different locations within the same circular flow will have different recovery periods*

Let us consider a fixed-decision pair with two days of safety stock and 20% overproduction. The null hypotheses are the equal average hypotheses. For the backlog period, we calculate:

$$\mathrm{t} = \frac{145.6-134.8}{\sqrt{\frac{51.9^2}{199}+\frac{50.0^2}{200}}} = 2.122 > 1.966 = \mathrm{t}_{\frac{0.05}{2},396.3}.$$

Hence, we reject H3a0 and conclude that the mean backlog periods are different. For the recovery period, we calculate:

$$\mathrm{t} = \frac{147.7-134.8}{\sqrt{\frac{52.0^2}{199}+\frac{50.0^2}{200}}} = 2.515 > 1.966 = \mathrm{t}_{\frac{0.05}{2},396.2}.$$

We reject H3b0 and conclude that the mean recovery periods are different.

4. Discussion of Results

There are several aspects of the results that warrant attention and discussion. First, a disruption’s ripple effect is more severe when it occurs inside circular flows than a disruption occurring outside circular flows. It is expected that when multiple disruptions occur in a supply chain network, the impact of the disruptions should be greater than if a single disruption occurs, given that the disruptions occur in similarly prominent network locations. Of course, when a disruption occurs at a critical point in a network, the disruption’s effect can be greater than multiple disruptions at non-critical points. Thus, understanding the supply chain structure can make a difference in planning mitigation strategies for ripple effects. Specifically, when disruptions occur inside networks with circular flows, the effect will ripple further, creating longer backlog periods to meet demand and longer recovery periods.

Second, like hypotheses H1a and H1b, hypotheses H2a and H2b show that supply chains can experience different ripple effects caused by a single disruption simply on whether that disruption occurs inside or outside of circular flowing portions of the network. This highlights the influence of circular flows in a network as the effect of a single disruption would be expected to be less than multiple disruptions in a similar network. Thus, to show an increased ripple effect even with a single disruption demonstrates the importance of the network structure in terms of circular flows. In our experiments, disruptions that occurred in circular flows led to longer backlog periods and longer recovery periods than those that occurred outside of circular connections. Thus, compared to similar flows without circular relationships, when a disruption occurs in a supply chain, the ripple effect is greater when it occurs within a circular flow.

Third, when disruptions occur in similarly complex flows but in different circular flows, the ripple effect can be greater. For example, when comparing disruptions at different locations in circular flows, we showed that the backlogs are significantly different when safety stock levels and overproduction rates are unequal. However, when safety stock levels and overproduction rates are similar, but they exist in different circular flows, the ripple effect is less pronounced. Lastly, when a disruption occurs at different companies in the same circular flow, the disruption causes the ripple effect to be significantly different, even though the companies are in the same flow.

4.1 Managerial Implications

It is essential to understand the supply chain structure to mitigate the ripple effect's risk when circular flows are present. Unfortunately, it may be impossible to remove circular flows. When that is the case, supply chain managers may help the mitigation process by multi-sourcing a part and thus remove a potential dependency in a circular flow. They may also increase safety stock to buffer the effect of a disruption.

A difficulty in recognizing circular flows is they may be present unbeknownst to the supply chain manager. When building our real-world supply chains for this research, we found circular flows to be a common occurrence. It is often the case that details in a supply chain network are obscure beyond two levels up. Thus, a company may know who their suppliers and their suppliers' suppliers are, but beyond that, it is impractical or impossible to know, let alone manage those relationships. Therefore, it would be beneficial if managers clearly understood the structure of their supply network so that they could ascertain whether there were circular flows in the network, which would allow them to adjust their safety stock or overproduction capabilities in circular flow areas to mitigate the risk of disruption ripple effects. This is in line with recent calls to understand the impact of the ripple effect in supply chains that are complex and intertwined (Ivanov & Dolgui, 2021; Ivanov 2020a). Circular linkages exacerbate complexity and can lead to intertwined networks. Because our research articulates the influence of ripple effects in supply chains with circular flowing networks, it could help managers better understand risk in their supply chains and facilitate the development of insights to bolster supply chain resilience.

Given improved understanding among supply chain managers regarding the structure of their networks, network analysis using a simulation approach like the one employed here could help identify appropriate resiliency measures. However, managers must understand that the organization's location within that circular flow can generate different ripple effects.

4.2 Research Implications

Supply chain disruptions have long been of interest to both practitioners and researchers and continue to be relevant due to the growing complexity of supply chains in a highly connected world. Suppliers across the globe engage with partners that are not geo-proximate. Consequently, supply chain risks such as the ripple effect are prominent, and researchers must continue investigating means and methods to mitigate these types of risk. Analytic capabilities are growing in supply chains, giving decision makers greater ability to predict disruptions (Hazen, Skipper, Ezell, & Boone, 2016; Wang, Gunasakaren, Ngai, & Papadopulos, 2016). Our research improves the understanding of supply chain exposure through simulation, which is an effective prescriptive analytic technique that can also allow decision makers to perform "what-if" analyses in varying scenarios to determine the influence and effectiveness of disruption mitigation strategies.

We show that disruptions inside circular flows have a greater ripple effect than those occurring outside circular flows. The ripple effect is greater when multiple disruptions occur and even when a single disruption occurs. We also show that the location of a disruption within a circular flow will influence the ripple effect, even when the disruptions occur within the same circular flow. Finally, our research delves into supply chain operations' resilience (Choi, Chan, & Yue, 2017). Specifically, we demonstrate that the network structure, in terms of circular versus noncircular flows, has a significant influence on supply chain resiliency. We demonstrate that the length of time it takes to return to normal operating levels and safety stock levels is extended following disruptions occurring in networks with circular linkages.

5. Conclusion

Sheffi & Rice (2005) propose eight phases of a firm's response to a disruption: preparation, the disruptive event, first response, initial impact, full impact, preparation for recovery, recovery, and long-term impact. This study investigates preparation vis-à-vis the relationship between circular flows within a supply chain network and the ripple effect of disruptions. Our results show that disruptions that occur within circular flows experience more substantial ripple effects than those without. Supply chain managers should consider whether their networks contain the hidden danger of circular flows. If they do, they should take steps to reduce the potential for ripple effects by adjusting their safety stocks and/or overproduction rates. Our main finding indicates that circular linkages are associated with challenges, particularly in the preparation phase of supply chain planning. These circular linkages are often unobserved yet significantly impacting a supplier's resiliency to disruptions. Zobel and Khansa (2014) argue that multiple characteristics of a system's response should be simultaneously measured to reflect system performance better and more effectively characterize resilient behavior. However, our research demonstrates one characteristic that has not previously been measured—the ripple effect caused by circular linkages. Future supply chain resiliency research should consider further investigation of this characteristic. Specifically, as observed during the COVID-19 pandemic, supply chain resilience, disruptions, and the ripple effect need even greater study (Ivanov & Dolgui, 2021; Hosseini, Ivanov, & Blackhurst, 2020; Ivanov, 2020b; Ivanov & Dolgui, 2020).

This research is not without limitations. First, to articulate the impact of disruptions on circular flowing networks, we derived a simplified network and used simulated disruptions. We assumed certain distributions for duration, severity, and reduction rates and attempted to model these distributions based on the supply chain literature, but actual networks will vary. Additionally, we considered a single final product, again for clarity and demonstration, although actual supply chains are more complex and have multiple final products. While the derived networks were modeled using actual networks and real-world connections, the influence of disruptions on circular flow networks is likely understated, given that authentic networks may be more complex than those modeled here.

Furthermore, the database containing the actual network connections did not list every dependency level (Mergent Inc., n.d.). For example, the database listed suppliers with a high percentage of business dealing with a focal firm but did not list values for lesser importance suppliers. Thus, it is challenging to model true and complete networks based on these data. Lastly, our experiment consisted of a single supply chain network with disruptions occurring inside and outside circular linkages. However, it is well known that disruptions can and do propagate to other portions of the network (Basole & Bellamy, 2014; Li et al., 2020a; Zhao et al., 2019). Thus, even though disruptions may occur inside circular linkages, the ripple effect can travel to nodes outside those circular flows and vice versa. Despite this weakness, we have shown a significant effect of the location of the disruption in circular linkages via the ripple effect on a supply chain network.

An important focus of this research is the supply chain structure, particularly when there are loops that may provide a level of feedback that increases the ripple effect. These looping structures exist in real-world supply chains, but many supply chain decision makers are unaware of their presence, let alone their potential influence on the network. As managers strive to increase coordination, efforts to mitigate the ripple effect in circular flowing networks should be further examined not only by increasing safety stock and overproduction rates but also by investing in coordination and control efforts.

6. References

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Appendix A: Regression Analysis

In this section, we test the six hypotheses in Section 3.4 based on regression analysis. Let $\boldsymbol{y}^{\boldsymbol{backlog}}$ and $\boldsymbol{y}^{\boldsymbol{recover}}$ be the backlog and recovery periods, respectively, used as dependent variables in the regression models. Let us also define the following independent variables for notational convenience.

- DL: disruption length (averaged if two disruptions are involved)
- DR: disruption rate (averaged if two disruptions are involved)
- CD: 1 if simultaneous disruptions (single disruption) occurs in a circular flow for testing H1 (H2), 0 otherwise
- SS: safety stock level
- OP: overproduction level
- CP_j: 1 if a disruption occurs at company j for testing H3, 0 otherwise

The regression data sets are obtained from the output of the 99,000 simulation runs of simultaneous disruption scenarios (for M1a and M1b) and the output of the 19,800 simulation runs of single disruption scenarios (for the other regression models). The regression models for the six hypotheses are summarized in Table A1. In the regression analysis, either $y^{backlog}$ or $y^{recover}$ are used as dependent variables. Note that disruption length (DL), disruption rate (DR), safety stock level (SS), and overproduction level (OP) are included as independent variables for all models. For testing the impact of simultaneous disruptions in a circular flow (Hypotheses H1a and H1b), Models M1a and M1b additionally include CD in the independent variable sets. For testing the impact of single disruption in circular flows (Hypotheses H2a and H2b), CD is added to the independent variable sets for Models M2a and M2b. To test the impact of different disrupted companies in the same circular flow (H3a and H3b), we build a regression model for each circular flow and dependent variable pair. For the circular flow 4-11-1-4-11, Models M3aX and M3bX have CP_1, CP_4, CP_{11} in the independent variable sets. For the circular flow 11-9-11, Models M3aY and M3bY use CP_9 and CP_{11} as independent variables.

Table A1 Regression models

Model #	Hypothesis	Dependent Variable	Independent variables								
			DL	DR	SS	OP	CD	CP_1	CP_4	CP_9	CP_{11}
M1a	H1a	$y^{backlog}$	1	1	1	1	1				
M1b	H1b	$y^{recover}$	1	1	1	1	1				
M2a	H2a	$y^{backlog}$	1	1	1	1	1				
M2b	H2b	$y^{recover}$	1	1	1	1	1				
M3aX	H3a	$y^{backlog}$	1	1	1	1		1	1		1
M3bX	H3b	$y^{recover}$	1	1	1	1		1	1		1
M3aY	H3a	$y^{backlog}$	1	1	1	1				1	1
M3bY	H3b	$y^{recover}$	1	1	1	1				1	1

From the eight regression models in Table A1, the following independent variables are used to check the hypotheses.

- H1a and H1b: CD
- H2a and H2b: CD
- H3a and H3b (for cycle 4-11-1-4-11): CP_1, CP_4, and CP_{11}
- H3a and H3b (for cycle 11-9-11): CP_9 and CP_{11}

The results for all regression models are presented in Table A2. In all models, DL, DR, SS, and OP show face validities: Disruption length (DL) shows positive effects; Disruption rate (DR), where lower rates imply severe disruptions, has negative effects; Overproduction (OP) reduces the backlogged and recovery periods; Safety stock (SS) reduces the backlogged periods while it increases the recovery periods. From the result of Models M1a and M1b, we observe that the simultaneous disruptions in a circular flow (CD) positively impact the backlogged and recovery periods, which support the hypotheses H1a and H1b. From the result of Models M2a and M2b, single disruption in a circular flow (CD) increases the backlogged and recovery periods, which confirm the hypotheses H2a and H2b. From the result of Models M3aX and M3bX, we observe that different companies (CP_1, CP_4, and CP_{11}) in the circular flow 4-11-1-4-11 have different coefficients showing positive impacts on the backlogged and recovery periods. From the result of Models M3aY and M3bY, the two companies (CP_9 and CP_{11}) in the circular flow 11-9-11 have different signs in the coefficients. The results of Models M3aX, M3bX, M3aY, and M3bY provide evidence for the hypotheses H3a and H3b.

Table A2 Regression results

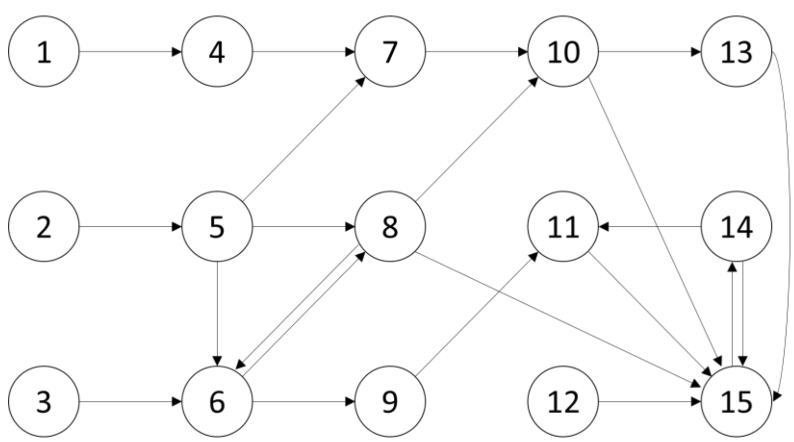
Hypothesis (Models)	Independent Variable	Dependent Variable = $y^{backlog}$			Dependent Variable = $y^{recover}$		
		Estimate	t-statistic	Pr(>|t|)	Estimate	t-statistic	Pr(>|t|)
H1 (M1a, M1b)	(Intercept)	241.78	333.66	0.00	147.47	39.77	0.00
	CD (circular disruption)	5.56	21.82	0.00	123.88	94.98	0.00
	DL (disruption length)	1.08	189.52	0.00	1.01	34.36	0.00
	DR (disruption rate)	-211.49	-390.59	0.00	-187.99	-67.86	0.00
	SS (safety stock)	-0.13	-1.55	0.12	43.91	105.92	0.00
	OP (over production)	-399.64	-493.19	0.00	-446.67	-107.74	0.00
	Adjusted R^2		0.8139			0.2761	
H2 (M2a, M2b)	(Intercept)	202.83	221.87	0.00	169.25	48.63	0.00
	CD (circular disruption)	6.46	29.61	0.00	34.13	41.08	0.00
	DL (disruption length)	0.92	140.44	0.00	0.88	35.64	0.00
	DR (disruption rate)	-194.32	-319.34	0.00	-187.62	-80.99	0.00
	SS (safety stock)	-0.01	-0.08	0.94	13.29	27.14	0.00
	OP (over production)	-326.02	-253.51	0.00	-347.79	-71.04	0.00
	Adjusted R^2		0.9037			0.4343	
H3 (M3aX, M3bX)	(Intercept)	202.79	223.81	0.00	170.55	53.81	0.00
	CP_1 (Company 1)	7.77	21.19	0.00	7.67	5.98	0.00
	CP_4 (Company 4)	9.51	26.01	0.00	29.48	23.05	0.00
	CP_{11} (Company 11)	6.90	18.79	0.00	98.12	76.38	0.00

	DL (disruption length)	0.92	141.64	0.00	0.87	38.31	0.00
	DR (disruption rate)	-194.10	-321.54	0.00	-186.43	-88.29	0.00
	SS (safety stock)	-0.01	-0.08	0.94	13.29	29.78	0.00
	OP (over production)	-326.02	-255.58	0.00	-347.79	-77.94	0.0
	Adjusted R^2		0.9053			0.5300	
H3 (M3aY, M3bY)	(Intercept)	204.98	221.23	0.00	174.85	54.57	0.00
	CP_9 (Company 9)	-0.74	-1.99	0.05	-3.01	-2.34	0.02
	CP_{11} (Company 11)	5.10	13.62	0.00	94.09	72.72	0.00
	DL (disruption length)	0.91	137.77	0.00	0.87	37.83	0.00
	DR (disruption rate)	-194.25	-313.89	0.00	-187.00	-87.38	0.00
	SS (safety stock)	-0.01	-0.08	0.94	13.29	29.38	0.00
	OP (over production)	-326.02	-249.30	0.00	-347.79	-76.90	0.00
	Adjusted R^2		0.9004			0.5173	

Appendix B: Result for 15-Companies Network

In this section, we test the hypotheses in the main section with a different larger network to improve the robustness of the conclusions and to claim that the conclusions are not network specific. We consider a supply chain network with 15 companies presented in Figure B1.

Figure B1: Supply chain network structure with 15 companies



Note that the network in Figure B1 has a completely different structure and flows from the network in Figure 6, while both networks have circular flows. We consider a final product produced at Company 15 within this network, and the required parts and flow for producing each part are summarized in Table B1.

Table B1 Parts and flows required for the production of the final product

Part Type	Flow	Regular production rate (units per day)	Number of units required for each final product
Part 1	1 – 4 – 7 – 10 – 15	10	10
Part 2	5 – 8 – 15 – 14 – 15	10	10
Part 3	6 – 8 – 6 – 9 – 11 – 15	10	10
Part 4	12 – 15 – 14 – 11 – 15	5	5
Part 5	5 – 6 – 8 – 10 – 13 – 15	5	5
Part 6a	2 – 5 – 7 – 10*	5	5
Part 6b	3 – 6 – 8 – 10* – 15	5	5

*Note: * indicate that Parts 6a and 6b are required to produce Part 6 at Company 10*

Note that there are three circular flows in the network: (i) 15 – 14 – 15 for Part 2, (ii) 6 – 8 – 6 for Part 3, and (iii) 15 – 14 – 11 – 15 for Part 4. This gives us the following set of multiple simultaneous disruptions: D-(6,8), D-(6,11), D-(6,15), D-(8,14), D-(8,15), D-(11,14), D-(11,15), and D-(14,15). All other simulation settings and parameters are identical to those in the main section experiment with the 11-companies network.

We ran 216,000 simulations, 200 replications for each scenario and decision alternative pair: 189,000 for two simultaneous disruptions (i.e., 105 scenarios of two simultaneous disruptions * 200 replications * 9 decision alternatives) and 27,000 for single disruptions (i.e., 15 scenarios of single disruptions * 200 replications * 9 decision alternatives). Then, we analyze the results following the procedure in the main section. We present the summarized hypothesis test results in Table B2 for a fixed safety stock level of 2 days and overproduction rate 20%. For H1a and H1b, we consider multiple simultaneous disruptions in circular flows (average performances presented in Table B3). For H2a and H2b, we study single disruption in circular flows (average performances presented in Table B4). For H3a and H3b, we compare single disruption at

Companies 14 and 15 (average performances presented in Table B5). The t-statistic values in Table B2 are greater than 2 for all hypothesis tests and the p-values are significantly smaller than 0.05. This indicates all our hypotheses hold for this new network.

Table B2 Hypothesis test results (with safety stock = 2 days, overproduction=20%)

Hypothesis	Disruption type	Performance measures	t-statistic	p-value
H1a	Multiple in circular flows	Backlogged periods	3.7708	0.0017
H1b	Multiple in circular flows	Recovery periods	8.2002	<0.0001
H2a	Single in circular flows	Backlogged periods	3.6804	0.0002
H2b	Single in circular flows	Recovery periods	4.088	<0.0001
H3a	Disruption location (14 vs 15)	Backlogged periods	2.6725	0.0078
H3b	Disruption location (14 vs 15)	Recovery periods	3.3156	0.0010

Table B3 Average performance measures for multiple disruptions in circular/noncircular flows

Circular	Safety	Over-	Robustness		Backlogged Periods		Recovery Periods	
or Not	Stock	production	AVG	SD	AVG	SD	AVG	SD
0	2 days	20%	0.526	0.129	172	47	173	47
0	2 days	30%	0.526	0.129	120	32	121	32
0	2 days	40%	0.527	0.129	91	24	92	24
0	3 days	20%	0.527	0.129	172	47	193	107
0	3 days	30%	0.527	0.129	120	32	134	79
0	3 days	40%	0.527	0.129	91	24	103	71
0	4 days	20%	0.526	0.129	172	47	255	225
0	4 days	30%	0.526	0.129	120	32	193	215
0	4 days	40%	0.527	0.129	91	24	160	212
1	2 days	20%	0.511	0.124	178	48	186	52
1	2 days	30%	0.511	0.124	124	33	130	35
1	2 days	40%	0.511	0.124	93	25	99	27
1	3 days	20%	0.511	0.124	177	48	323	266
1	3 days	30%	0.511	0.124	123	33	232	220
1	3 days	40%	0.511	0.124	93	25	190	199
1	4 days	20%	0.511	0.124	177	48	545	369
1	4 days	30%	0.511	0.124	123	33	482	385
1	4 days	40%	0.511	0.124	93	25	439	394

Table B4 Average performance measures for single disruption in circular/noncircular flows

Circular	Safety	Over-	Robustness	Backlogged Periods	Recovery Periods

or Not	Stock	production	AVG	SD	AVG	SD	AVG	SD
0	2 days	20%	0.596	0.149	139	52	139	52
0	2 days	30%	0.597	0.149	98	35	98	35
0	2 days	40%	0.597	0.150	74	27	74	27
0	3 days	20%	0.596	0.149	139	52	139	52
0	3 days	30%	0.597	0.149	98	35	98	35
0	3 days	40%	0.597	0.150	74	27	74	27
0	4 days	20%	0.596	0.149	139	52	139	52
0	4 days	30%	0.597	0.149	98	35	98	35
0	4 days	40%	0.597	0.150	74	27	74	27
1	2 days	20%	0.579	0.150	146	52	147	52
1	2 days	30%	0.579	0.150	103	36	103	36
1	2 days	40%	0.579	0.150	78	27	78	27
1	3 days	20%	0.579	0.150	147	52	161	80
1	3 days	30%	0.579	0.150	103	36	109	50
1	3 days	40%	0.579	0.150	78	27	83	35
1	4 days	20%	0.579	0.150	147	52	234	220
1	4 days	30%	0.579	0.150	103	36	176	201
1	4 days	40%	0.579	0.150	78	27	138	179

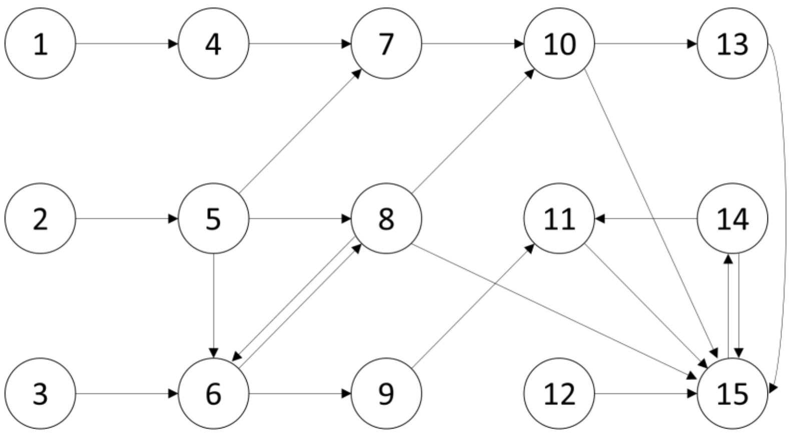
Table B5 Average performance measures for disruptions at Companies 14 and 15

Disrupted	Safety	Over-	Robustness		Backlogged periods		Recovery periods	
company	stock	production	AVG	SD	AVG	SD	AVG	SD
14	2 days	20%	0.590	0.153	134	51	134	51
14	2 days	30%	0.590	0.153	94	35	94	35
14	2 days	40%	0.590	0.153	71	26	71	26
14	3 days	20%	0.590	0.153	134	51	134	51
14	3 days	30%	0.590	0.153	94	35	94	35
14	3 days	40%	0.590	0.153	71	26	71	26
14	4 days	20%	0.590	0.153	134	51	134	51
14	4 days	30%	0.590	0.153	94	35	94	35
14	4 days	40%	0.590	0.153	71	26	71	26
15	2 days	20%	0.565	0.150	147	52	151	51
15	2 days	30%	0.565	0.150	103	35	106	35
15	2 days	40%	0.565	0.150	78	26	80	26
15	3 days	20%	0.565	0.150	148	51	211	130
15	3 days	30%	0.565	0.150	102	35	133	81
15	3 days	40%	0.565	0.150	78	26	104	52
15	4 days	20%	0.565	0.150	148	51	557	316
15	4 days	30%	0.565	0.150	103	35	451	318
15	4 days	40%	0.565	0.150	78	26	365	304

Appendix B: Result for 15-Companies Network

In this section, we test the hypotheses in the main section with a different larger network to improve the robustness of the conclusions and to claim that the conclusions are not network specific. We consider a supply chain network with 15 companies presented in Figure B1.

Figure B2: Supply chain network structure with 15 companies



Note that the network in Figure B1 has a completely different structure and flows from the network in Figure 6, while both networks have circular flows. We consider a final product produced at Company 15 within this network, and the required parts and flow for producing each part are summarized in Table B1.

Table B1 Parts and flows required for the production of the final product

Part Type	Flow	Regular production rate (units per day)	Number of units required for each final product
Part 1	1 – 4 – 7 – 10 – 15	10	10
Part 2	5 – 8 – 15 – 14 – 15	10	10
Part 3	6 – 8 – 6 – 9 – 11 – 15	10	10
Part 4	12 – 15 – 14 – 11 – 15	5	5
Part 5	5 – 6 – 8 – 10 – 13 – 15	5	5
Part 6a	2 – 5 – 7 – 10*	5	5
Part 6b	3 – 6 – 8 – 10* – 15	5	5

*Note: * indicate that Parts 6a and 6b are required to produce Part 6 at Company 10*

Note that there are three circular flows in the network: (i) 15 – 14 – 15 for Part 2, (ii) 6 – 8 – 6 for Part 3, and (iii) 15 – 14 – 11 – 15 for Part 4. This gives us the following set of multiple simultaneous disruptions: D-(6,8), D-(6,11), D-(6,15), D-(8,14), D-(8,15), D-(11,14), D-(11,15), and D-(14,15). All other simulation settings and parameters are identical to those in the main section experiment with the 11-companies network.

We ran 216,000 simulations, 200 replications for each scenario and decision alternative pair: 189,000 for two simultaneous disruptions (i.e., 105 scenarios of two simultaneous disruptions * 200 replications * 9 decision alternatives) and 27,000 for single disruptions (i.e., 15 scenarios of single disruptions * 200 replications * 9 decision alternatives). Then, we analyze the results following the procedure in the main section. We present the summarized hypothesis test results in Table B2 for a fixed safety stock level of 2 days and overproduction rate 20%. For H1a and H1b, we consider multiple simultaneous disruptions in circular flows (average performances presented in Table B3). For H2a and H2b, we study single disruption in circular flows (average performances presented in Table B4). For H3a and H3b, we compare single disruption at Companies 14 and 15 (average performances presented in Table B5). The t-statistic values in Table B2 are greater than 2 for all hypothesis tests and the p-values are significantly smaller than 0.05. This indicates all our hypotheses hold for this new network.

Table B2 Hypothesis test results (with safety stock = 2 days, overproduction=20%)

Hypothesis	Disruption type	Performance measures	t-statistic	p-value
H1a	Multiple in circular flows	Backlogged periods	3.7708	0.0017
H1b	Multiple in circular flows	Recovery periods	8.2002	<0.0001
H2a	Single in circular flows	Backlogged periods	3.6804	0.0002
H2b	Single in circular flows	Recovery periods	4.088	<0.0001
H3a	Disruption location (14 vs 15)	Backlogged periods	2.6725	0.0078
H3b	Disruption location (14 vs 15)	Recovery periods	3.3156	0.0010

Table B3 Average performance measures for multiple disruptions in circular/noncircular flows

Circular	Safety	Over-	Robustness		Backlogged Periods		Recovery Periods	
or Not	Stock	production	AVG	SD	AVG	SD	AVG	SD
0	2 days	20%	0.526	0.129	172	47	173	47
0	2 days	30%	0.526	0.129	120	32	121	32
0	2 days	40%	0.527	0.129	91	24	92	24

0	3 days	20%	0.527	0.129	172	47	193	107
0	3 days	30%	0.527	0.129	120	32	134	79
0	3 days	40%	0.527	0.129	91	24	103	71
0	4 days	20%	0.526	0.129	172	47	255	225
0	4 days	30%	0.526	0.129	120	32	193	215
0	4 days	40%	0.527	0.129	91	24	160	212
1	2 days	20%	0.511	0.124	178	48	186	52
1	2 days	30%	0.511	0.124	124	33	130	35
1	2 days	40%	0.511	0.124	93	25	99	27
1	3 days	20%	0.511	0.124	177	48	323	266
1	3 days	30%	0.511	0.124	123	33	232	220
1	3 days	40%	0.511	0.124	93	25	190	199
1	4 days	20%	0.511	0.124	177	48	545	369
1	4 days	30%	0.511	0.124	123	33	482	385
1	4 days	40%	0.511	0.124	93	25	439	394

Table B4 Average performance measures for single disruption in circular/noncircular flows

Circular	Safety	Over-	Robustness		Backlogged Periods		Recovery Periods	
or Not	Stock	production	AVG	SD	AVG	SD	AVG	SD
0	2 days	20%	0.596	0.149	139	52	139	52
0	2 days	30%	0.597	0.149	98	35	98	35
0	2 days	40%	0.597	0.150	74	27	74	27
0	3 days	20%	0.596	0.149	139	52	139	52
0	3 days	30%	0.597	0.149	98	35	98	35
0	3 days	40%	0.597	0.150	74	27	74	27

0	4 days	20%	0.596	0.149	139	52	139	52
0	4 days	30%	0.597	0.149	98	35	98	35
0	4 days	40%	0.597	0.150	74	27	74	27
1	2 days	20%	0.579	0.150	146	52	147	52
1	2 days	30%	0.579	0.150	103	36	103	36
1	2 days	40%	0.579	0.150	78	27	78	27
1	3 days	20%	0.579	0.150	147	52	161	80
1	3 days	30%	0.579	0.150	103	36	109	50
1	3 days	40%	0.579	0.150	78	27	83	35
1	4 days	20%	0.579	0.150	147	52	234	220
1	4 days	30%	0.579	0.150	103	36	176	201
1	4 days	40%	0.579	0.150	78	27	138	179

Table B5 Average performance measures for disruptions at Companies 14 and 15

Disrupted	Safety	Over-	Robustness		Backlogged periods		Recovery periods	
company	stock	production	AVG	SD	AVG	SD	AVG	SD
14	2 days	20%	0.590	0.153	134	51	134	51
14	2 days	30%	0.590	0.153	94	35	94	35
14	2 days	40%	0.590	0.153	71	26	71	26
14	3 days	20%	0.590	0.153	134	51	134	51
14	3 days	30%	0.590	0.153	94	35	94	35
14	3 days	40%	0.590	0.153	71	26	71	26
14	4 days	20%	0.590	0.153	134	51	134	51
14	4 days	30%	0.590	0.153	94	35	94	35
14	4 days	40%	0.590	0.153	71	26	71	26
15	2 days	20%	0.565	0.150	147	52	151	51

15	2 days	30%	0.565	0.150	103	35	106	35
15	2 days	40%	0.565	0.150	78	26	80	26
15	3 days	20%	0.565	0.150	148	51	211	130
15	3 days	30%	0.565	0.150	102	35	133	81
15	3 days	40%	0.565	0.150	78	26	104	52
15	4 days	20%	0.565	0.150	148	51	557	316
15	4 days	30%	0.565	0.150	103	35	451	318
15	4 days	40%	0.565	0.150	78	26	365	304

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