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Abstract

Purpose – The purpose of this paper is to investigate different combinations of collaboration strategies to deal with different types of supply chain disruptions, find the best combination, and provide targeting suggestions for investments.

Design/methodology/approach – A system dynamics simulation is applied to study a supply chain with three tiers: a producer, a logistics service provider (LSP), and a retailer. There are three types of disruptions to simulate: a producer capacity disruption, an LSP capacity disruption, and a demand disruption. As each tier has the option to choose whether or not to collaborate with the other two tiers, eight ($2 \times 2 \times 2$) scenarios are generated to represent different combinations of collaboration strategies.

Findings – For a producer capacity disruption, both the producer and the LSP should collaborate by providing their surge capacities, while the retailer does not have to collaborate. For an LSP capacity disruption, the producer should not provide its surge capacity, while the LSP should do so; the retailer does not have to collaborate. For a demand disruption, both the producer and the LSP should not provide their surge capacities, while the retailer should not collaborate but play shortage gaming. Targeting suggestions for investments are provided.

Originality/value – Through system dynamics modeling, this study allows the discussion of surge capacity to help supply chain partners and the discussion of shortage gaming when products are oversupplied, in a disruption recovery system over time.

Keywords System dynamics, Collaboration, Supply chain disruptions, Disruption recovery, Shortage gaming, Surge capacity

Paper type Research paper

1. Introduction

Modern supply chains are becoming complex. Companies increasingly depend on a complicated network of global suppliers and partners to deliver products at the right time and place, in the right quantity, and under persistent cost pressures (Datta and Christopher, 2011). Unfortunately, complex and tightly coupled supply chains are usually slow to respond to changes in their environment, and hence, they are more vulnerable to supply chain disruptions (Tang and Tomlin, 2008). For instance, the Japanese earthquake and tsunami in 2011 caused not only a manufacturing slowdown in European and North American countries, but also a drop in the demand for those that deliver goods and services to Japanese industries. Such events adversely impacted companies by increasing their costs and delaying some parts of their production, even having more permanent impacts in some cases, e.g., shut down (MacKenzie *et al.*, 2012). However, the temporal perspective of managers and low possibility of supply chain disruptions lead to a need for supply chain recovery strategies that involve little extra cost and that provide immediate performance improvement after a disruption (Manuj and Mentzer, 2008). It is important to carefully evaluate supply chain recovery strategies before investing in them.

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Collaboration for recovery has been highlighted by recent literature, because it is important to quickly respond to supply chain disruptions and alleviate harmful impacts. A famous example is from Toyota keiretsu, which is a typical closely collaborative supply chain. If a disruption occurs, the keiretsu can band together by directing certain firms to produce more to replace the lost production at other facilities. The pace at which Toyota resumed production after the Japanese earthquake and tsunami in 2011 was quicker than many observers had expected (MacKenzie *et al.*, 2012). Remarkably, the further away the disruption is located, the more likely that the ultimate impact of the disruption will be influenced by collaborative actions taken at intervening stages (Melnyk *et al.*, 2009). It is not a priori clear which tier of the supply chain will benefit from increased collaboration activities for recovery (Wakolbinger and Cruz, 2011). Hence, we are motivated to investigate combinations of different tiers' willingness to collaborate for recovery, find the best combination, and provide targeting suggestions for investments. In particular, we will investigate the usage of surge capacity and shortage gaming in the context of collaboration for recovery, after an uncertainty becomes reality in the form of a major disruption.

Mathematic programming and simulation papers have provided thoughtful suggestions on limiting risks as well as improving performance. For example, Hsieh and Wu (2008) have analyzed the impact of the uncertainty-, cost-, and attitude-related parameters on coordination performance and provided corresponding suggestions. Yet, most prior research on recovery after supply chain disruptions has drawn on either case-based studies (e.g. Oke and Gopalakrishnan, 2009) or survey-based analyses (e.g. Bode *et al.*, 2011). Although such research has provided a better understanding for improved management of supply chain disruptions and initial frameworks of effective practices when dealing with such disruptions, the researchers are always constrained to the experiences of the respondents (Melnyk *et al.*, 2009). Furthermore, empirical research methods are static while supply chain disruptions always involve dynamic events developing over time (Akkermans and Van Wassenhove, 2013). This drawback is shared with traditional optimization models (e.g. Wu *et al.*, 2015; Zou *et al.*, 2004), which calculate the static equilibrium to search for an optimal solution for an operational problem (Datta and Christopher, 2011). System dynamics simulation will help study the behavioral dynamics and policy effects on supply chain operations after disruptions (Reddi and Moon, 2011). Other simulation methods, e.g. discrete event simulation and agent based modeling, are less feasible for this (Datta and Christopher, 2011).

This paper models a cheese supply chain of three tiers (i.e. a producer, a logistics service provider (LSP), and a retailer) with dyadic information sharing, both upstream and downstream, but bilateral. We aim to measure the impact of different combinations of collaboration strategies on each tier's performance after different types of supply chain disruptions. A system dynamics approach is used to build the simulation model. The rest of this paper is organized as follows: a literature review of supply chain disruptions, collaboration for recovery, and system dynamics is presented in the next section. Section 3 introduces the simulation model and the analysis methodology. The results are presented in Section 4. The paper ends with discussion and implications in Section 5.

2. Literature review

2.1 Supply chain disruptions

The discussion of supply chain disruptions starts from managing uncertainty on both the focal firm level and the whole supply chain level. Focussing on the weather-linked rebate of a manufacturer-retailer supply chain, Chen and Yano (2010) helped the manufacturer design contracts that are Pareto-improving and/or limit his risk in offering the contract. Through simultaneous optimization of both order processing time and order quantity, Zou *et al.* (2004) show that risk sharing and proper safety stock placement lead to better supply chain coordination and performance. In particular, integration of planning and decision making across the supply chain reduces the need for safety stock (Acar and Atadeniz, 2015). However, despite of firms' efforts on risk management, some risks still occur in the form of supply chain disruptions. Wagner and Bode (2008) have defined a supply chain disruption as the combination of first, an unintended, anomalous triggering event that materializes somewhere in the supply chain or its environment, and second, a consequential situation which significantly threatens normal business operations of the companies in the supply chain. Based on the definition, we identify some examples of sources of supply chain disruptions. These are, but are not limited to:

- Natural disasters: disruptions caused by nature, including earthquakes, tsunamis, hurricanes, etc.
- Socio-political issues: disruptions that occur directly as a result of socio-political activities, such as terrorism, strikes, and social unrest.
- Regulatory changes: disruptions caused by regulatory changes (e.g. trade and transportation laws).
- Financial issues: disruptions caused by adverse changes in the financial situation of any participant in the supply chain (e.g. bankruptcy or liquidation).

It should be recognized that these disruptions do not often occur independently, but all the disruptions will finally lead to one or several problems on three tiers (i.e. the producer, the LSP, and the retailer), as shown by the case of the Japanese earthquake and tsunami in 2011 (MacKenzie *et al.*, 2012). Thus our simulation model will be based on the ending problems on three tiers. For the producer and the LSP, only capacity shortages are considered in our model, because the impact of transportation disruptions on supply chain performance has already been demonstrated by Wilson (2007) through simulation. For the retailer, we only consider the situation of customer demand that is far below the available capacity, as the situation of customer demand that is far beyond the available capacity is similar to the bullwhip effect (Lee *et al.*, 1997), of which solutions have been well discussed (Disney and Towill, 2006; Lee *et al.*, 1997; Özbayrak *et al.*, 2007).

2.2 Collaboration for recovery

For a producer or an LSP facing a capacity shortage after a disruption, it is always a dilemma to decide whether to provide surge capacity to collaborate with firms of other tiers. For a producer, surge capacity may refer to its own excess capacity to deal with volatile or uncertain demand (Driver, 2000), or the capacity of a contract manufacturer that the producer can outsource the excess order to (Hsieh and Wu, 2008). For an LSP, surge capacity may refer to its own flexible capacity to give priority (Boulaksil *et al.*, 2011), or the capacity of other LSPs through horizontal cooperation (Cruijssen *et al.*, 2007), which is similar to Toyota keiretsu.

On the one hand, providing surge capacity will benefit the recovery of the whole supply chain. A famous example is from Philips in Albuquerque, New Mexico, USA, where a fire at the local plant site caused a production breakdown worldwide at various manufacturing sites. Ericsson lost $400 million in sales, because it employed this plant as a single source for several chips. Ericsson's production was disrupted for months, when the Philips' plant shut down after the fire. By contrast, Nokia, another major customer of the plant, collaborated with Philips to switch its chip orders to other Philips' plants to use their surge capacity. Because of this collaboration, Nokia suffered little during the crisis and even stole market shares from Ericsson (*Wall Street Journal*, 2001). On the other hand, surge capacity will generate extra costs, which may hurt financial performance (Chopra and Sodhi, 2004). In this example, more than ten million chips were replaced by a Philips' plant in Eindhoven, the Netherlands. Extra costs were then generated by overtime payments. Moreover, a special problem in this example is that, as surge capacity was limited and occupied by Nokia, it may have negatively influenced Philips' relationship with Ericsson. This may explain why Ericsson has signed on second suppliers for the chips made in Albuquerque since the fire (Norrman and Jansson, 2004). Therefore, in our study of surge capacity, we will explore the trade-off between order fulfilment and supply efficiency in the context of collaboration for recovery. Instead of focussing on a focal company (e.g. Boulaksil *et al.*, 2011; Driver, 2000; Hsieh and Wu, 2008), we will take a three-tier supply chain perspective, so we will look at each tier's performance and try to find a win-win combination, i.e. good for all tiers.

Retailers have their own way to deal with disruptions. "Shortage gaming" is the term used by Lee *et al.* (1997) to denote what downstream companies do when they perceive that a upstream company that they share with other companies is facing capacity shortages. Knowing that the upstream company will ration when the product is in short supply, downstream companies exaggerate their real needs when they order to "game" the potential rationing. However, shortage gaming will distort the demand information as it is transmitted up the chain. If the retailer is willing to collaborate, waiting (means not playing shortage gaming) is better for the whole supply chain to recover, although this will sacrifice some current demand. In our study, we will test whether shortage gaming is still an important issue with the presence of surge capacity or when customer demand is far below the available capacity.

2.3 System dynamics

System dynamics is a modeling technique used to model, study, and manage complex systems. Here, a "system" refers to a group of inter-dependent or autonomous components/entities working together for a common cause (Reddi and Moon, 2011). The complexity of supply chains, especially those which encompass several tiers, warrants a perspective that considers the supply chain structure and the feedback inherent in these structures, which is provided by system dynamics modeling (Wilson, 2007). This is different from some mathematic programming and simulation papers (e.g. Acar and Atadeniz, 2015; Boulaksil *et al.*, 2011; Sahin and Robinson, 2005), which model hierarchical structures that involve sequential decision makings. Although discrete event simulation can deal successfully with disruption events, agent based simulation, and system dynamics have the capability to reproduce the interaction of different system agents to improve the understanding of the real system. Compared to agent based simulation, system dynamics modeling takes less time to build and works better when the level of aggregation is high (Hilletofth and Lattila, 2012). For these reasons, we prefer using system dynamics modeling in this study.

System dynamics uses primarily stock (or level) and rate variables to represent the dynamic behavior of complex systems. In essence, a stock variable defines the state of a system over time, while a rate variable directly changes the rate of evolution of a stock variable (Zhang and Dilts, 2004). One of the simplest examples can be illustrated by a bathtub with an inlet and outlet (Sterman, 2001). The stock of the bathtub varies depending upon the flow through the inlet and outlet valves, while the stock level is also defined by the inflow and outflow rates. The stock of water in the bathtub is filled by the inflow and drained by the outflow. The stock level accumulates at a rate equal to the difference between the inflow and outflow rate. The modeling structure is shown in Figure 1. The stock is represented by a rectangle while the flows are represented by arrows pointing in and out of the stock, depicting the inflow and outflow, respectively. The valves on the arrows control the magnitude of the flows in and out of the stock. The source and sink are represented by a cloud symbol. The source has an arrow coming out, while the sink has an arrow going into the cloud (Reddi and Moon, 2011).

The bathtub example is known as a material delay, since it captures the physical flow of material (in this case, water) through a delay process, a process whose outflow lags behind its inflow in some fashion (Sterman, 2000). There is another kind of delay, which represents the gradual adjustment of a perception or belief. This is an information delay, a delay between the receipt of new information and the updating of one's belief. Because information, unlike material flows, is not conserved, a different structure is needed to capture an information delay (Figure 2). "Output" adjusts to the actual "Input" in proportion to the size of their difference in one's belief. "Adjustment time" determines how rapidly one's belief responds to the difference.

3. The simulation model and analysis methodology

3.1 Research background

Our simulation model is derived from a business simulation game (www.bedrijfssimulaties.nl) that was developed by a Dutch university. The game was used by the second author for academic and executive teaching. The game uses data that

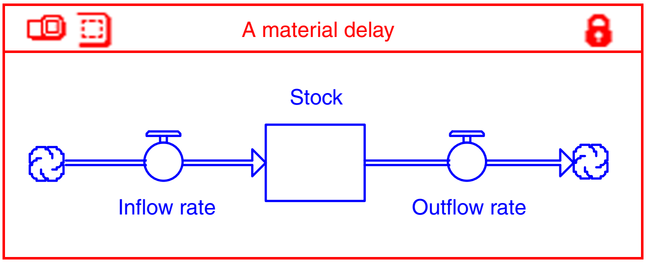

Figure 1.
The structure of a material delay

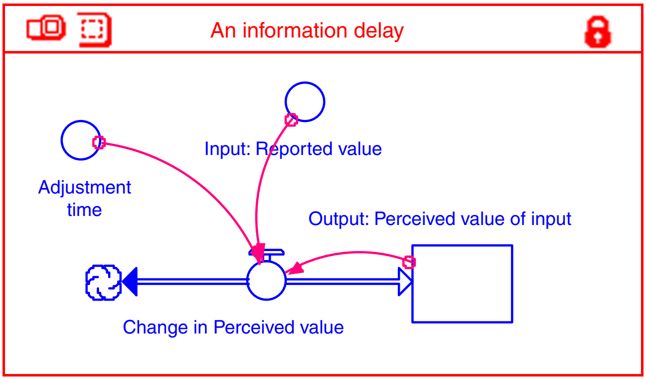

Figure 2.
The structure of an information delay

were collected from real life practice of a large multinational dairy firm. The game's learning objectives are strongly related to supply chain collaboration. Through playing the game, one can explore the trade-offs between supply chain goals (i.e. supply efficiency and order fulfillment) and individual company interests (i.e. the usage of surge capacity and shortage gaming). Furthermore, the game adopts a supply chain structure with three tiers. Our simulation model resembles the gaming model, but emphasizes the role of collaboration for disruption recovery. Therefore, our research used original parameter values from the game as well as adjusted parameter values that are related to disruptions. The software that was used to build our simulation model is STELLA.

The focus of this paper is on the cheese industry. From a supply chain's point of view, the cheese industry is special: production start-up is pull, i.e. demand driven. The main inbound resource is milk, of which supply is assumed abundant. Once started, however, the process becomes push. After milk is pasteurized, it is curdled and gets its typical molded shape. Next, it is salted, which takes one to five days. The entire process takes around a week. However, most of the production lead time involves waiting. Depending on the type of cheese, the product has to mature for two to sixteen weeks. Despite its long production time, cheese is perishable. If it is not delivered to customers in time, it does not have value any more.

3.2 Model structures and assumptions

The cheese supply chain in our model consists of three tiers: a producer, an LSP, and a retailer. Infinite milk and other resources are available for the producer. The producer produces a cheese product with six weeks production time and the finished products are immediately delivered to the LSP. When ready, the cheese product has a remaining shelf life of six weeks. The LSP keeps inventory, but it is the ordering policy of the retailer and the production volume pushed by the producer that determine the actual inventory level. This is beyond control of the LSP. The LSP serves multiple retailers and will ration when facing capacity shortages. The retailer sells the products to customers. The sales time is one week.

The structure of how the producer organizes production is illustrated in Figure 3. It consists of two information delays (for "Perceived channel demand rate" and "Perceived real customer demand rate") and one material delay (for "Producer order backlog"). We assume that the producer can only realize "Real customer demand rate" one week after its managers receive "Channel demand rate" from the LSP, because they need time to analyze "Channel demand rate" with other information they get to perceive "Real customer demand rate." We set "Alpha" as 0.5, which means that one half of "Product demand rate" is from "Perceived channel demand rate" and the other half (equals 1–"Alpha") results from "Perceived real customer demand rate." "Product shipment rate" is the minimum value between "Producer desired shipment rate" and "Producer base capacity."

Figure 4 presents the structure of the LSP's operation simulation model. There are two material delays (for "Order backlog" and "LSP inventory"). "LSP shipment rate" is the minimum value of "LSP base capacity", "LSP desired shipment rate", and "LSP inventory"/"LSP target shipment time." "Workload" will be used by the retailer to judge the LSP's ability to deliver order on time. "Workload" equals "LSP inventory"/"LSP target shipment time"/"LSP base capacity." "LSP shipment time" will be used in the retailer's order fulfillment simulation model. "LSP shipment time" is equal to "LSP inventory" divided by "LSP shipment rate."

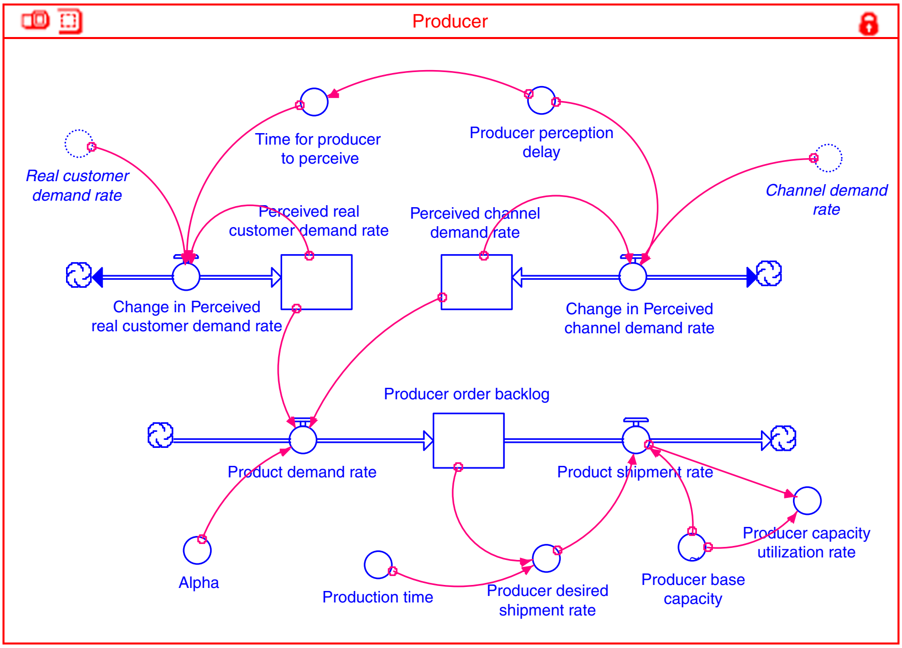

Figure 3. Producer's production simulation model

Figure 5 shows the structure of the retailer's order fulfillment simulation model. It consists of two material delays (for "Retailer inventory" and "Cumulative demand") and two information delays (for "Communicated lead time" and "Perceived delivery reliability"). "Customer demand rate" is a sum of "Real customer demand rate" and "Customer backlog adjustments." The retailer's managers will align the actual backlog with what they want it to be ("Desired channel backlog"), over a certain delay ("Time to adjust backlog"). "Desired channel backlog" is equal to "Real customer demand rate" × "LSP lead time expectation" × "Shortage gaming multiplier." The calculation of "LSP lead time expectation" is similar to that of "Product demand rate" in the producer's production simulation model, so the value of "Beta" is also set to be 0.5. "Inferred lead time" is equal to "LSP target lead time" × "Inferred capacity shortage." "Inferred capacity shortage" equals 1/"Perceived delivery reliability." "Current delivery reliability" is equal to "Normal delivery reliability" divided by the maximum value between 1 and "Workload." We also assume that the retailer can only realize "Workload" one week after its managers perceive "LSP shipment time" from the LSP. "Shortage gaming multiplier" is equal to "LSP lead time expectation" divided by "LSP target shipment time."

3.3 *Simulation inputs, types of disruptions, and strategies*

Table I shows the initial simulation inputs. Please note that, all the values in this paper are reported in *E* notation. For "Real customer demand rate", the value is a normal distribution with mean of 1.28E6 kg/week and standard deviation of 1.00E5 kg/week.

There are three types of disruptions that we will simulate: a producer capacity disruption, an LSP capacity disruption, and a demand disruption. For each disruption, we simulate a process in 24 weeks: in the first nine weeks, all the variables are stable;

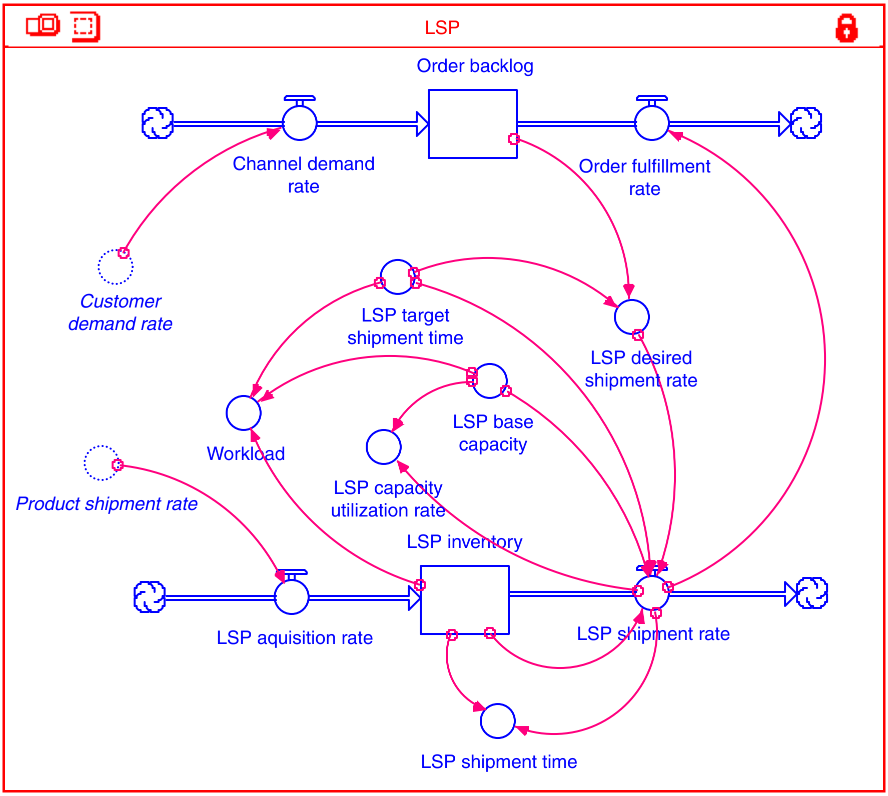

Figure 4. LSP's operation simulation model

at the end of Week 9, a disruption happened and caused a base capacity or demand drop of 640,000 kg/week; at the end of Week 12, the base capacity or demand recovers 320,000 kg/week; at the end of Week 15, the base capacity or demand recovers another 320,000 kg/week – back to the starting level, until the end of simulation.

Table II shows eight different combinations of collaboration strategies. Each tier has the option to choose whether or not to collaborate with the other two tiers independently. The corresponding actions are also shown in the table. The action "Base and surge capacity" means that "Producer base capacity" will be replaced by "Producer base capacity"+"Producer surge capacity" in the simulation model. The action "Prioritizing" means that "LSP base capacity" will be displaced by "LSP base capacity"+"LSP surge capacity" in the simulation model. This is not applied to the calculation of "Workload", as "Workload" is calculated by the retailer, who does not know in advance whether or not the LSP will use its surge capacity. The action "Waiting" means that there is no "Shortage gaming multiplier" in the simulation model. All scenarios of a producer capacity disruption are reported. For an LSP capacity disruption, there is little value to simulate the situation which the producer uses both base and surge capacity. This is because such choice cannot help the LSP recover from the disruption, but rather puts pressure on the LSP. Our deduction is verified by our initial simulation results. To simplify our discussion, we only report the results of Scenarios 1, 3, 5, and 7 of an LSP capacity disruption. Similar logic applies to a demand disruption: we only compare Scenario 1 and 5 in the results.

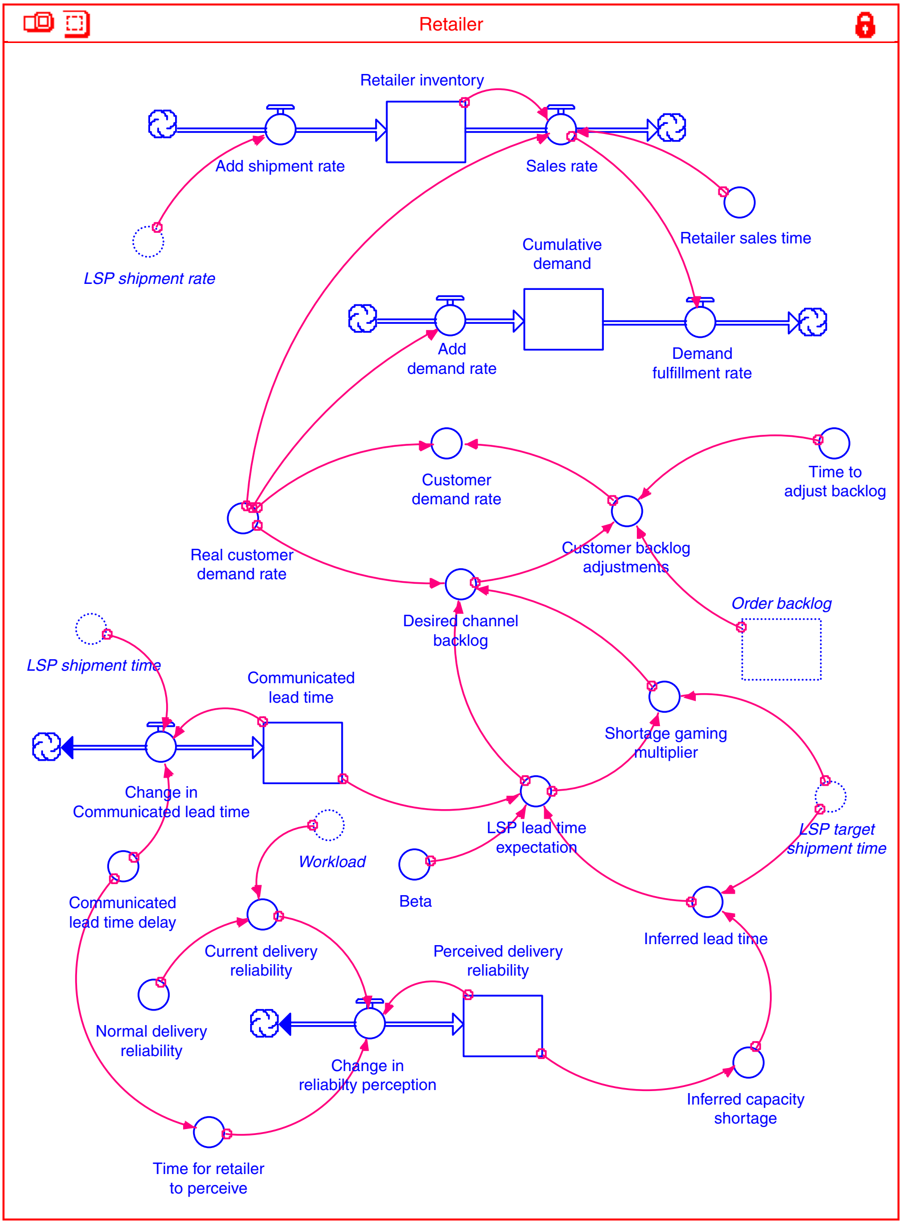

Figure 5.
Retailer's order fulfillment simulation model

3.4 Analysis methodology

We use a multiple analysis of variance (MANOVA) to compare the average of performance measures across multiple scenarios for different combinations of collaboration strategies after different disruptions. MANOVA is a generalized form of univariate analysis of variance (ANOVA) which is used in cases where there are two or more dependent variables (Revilla and Sáenz, 2014; Wang and Lee, 2013). In this

Table I.
Simulation inputs with value

Simulation input	Value
Producer order backlog	7.68E6 kg
Production time	6 weeks
Alpha, Beta	0.5
Producer base capacity, LSP base capacity	1.28E6 kg/week
Producer surge capacity, LSP surge capacity	3.20E5 kg/week
Order backlog, LSP inventory, Cumulative demand	1 kg
LSP target shipment time, Retailer sales time	1 week
Retailer inventory	2.56E6 kg
Time to adjust backlog	2 weeks
Normal delivery reliability	0.95
Real customer demand rate	Normal(1.28E6, 1.00E5) kg/week

Table II.
Combinations of collaboration strategies

	Producer		LSP		Retailer	
	Willingness to collaborate	Action	Willingness to collaborate	Action	Willingness to collaborate	Action
Scenario 1	No	Just base capacity	No	Rationing	No	Shortage gaming
Scenario 2	Yes	Base and surge capacity	No	Rationing	No	Shortage gaming
Scenario 3	No	Just base capacity	Yes	Prioritizing	No	Shortage gaming
Scenario 4	Yes	Base and surge capacity	Yes	Prioritizing	No	Shortage gaming
Scenario 5	No	Just base capacity	No	Rationing	Yes	Waiting
Scenario 6	Yes	Base and surge capacity	No	Rationing	Yes	Waiting
Scenario 7	No	Just base capacity	Yes	Prioritizing	Yes	Waiting
Scenario 8	Yes	Base and surge capacity	Yes	Prioritizing	Yes	Waiting

study, we select two performance measures as the dependent variables for each tier: one focusses on supply efficiency (that based on capacity utilization rate and costs), the other focusses on order fulfilment (that based on product quality and quantity). The selected six performance measures are: "Producer capacity utilization rate", "LSP capacity utilization rate", and "Retailer inventory" for supply efficiency; "Producer order backlog", "LSP shipment time", and "Cumulative demand" for order fulfillment. For "Producer capacity utilization rate" and "LSP capacity utilization rate" to evaluate the results of a producer/LSP capacity disruption, the higher the value, the better the performance. This is because higher capacity utilization rate justifies the investments in capacity. For "Producer capacity utilization rate" and "LSP capacity utilization rate" to evaluate the results of a demand disruption, the closer to 0.91 (which is the average value of "Real customer demand rate"/"Producer (or LSP) base capacity"), the better the performance. This is because extra capacity will not fulfill real customer demand, but generate extra costs. For the rest four performance measures to evaluate all the results of three disruptions, the lower the value, the better the performance. The relative-precision procedure is used for sample size determination (Bienstock, 1996). Ten runs for each of the eight scenarios at 5 percent relative-precision level are suitable. We have controlled our simulation inputs to ensure that the following three assumptions are not violated: first, the observations must be independent, second, the observations on the depend variables must follow a multivariate normal distribution in each group, and third, the population covariance matrices for the dependent variables are equal (Stevens, 2002). A Duncan test will be used to identify significant differences in the mean values of a performance measure when more than two scenarios are compared (Nutt, 2008).

4. Results

First of all, the Box's test results for all three types of disruptions (Table III) are significant ($p < 0.001$) and indicate that homogeneity of variance-covariance is violated. So Pillai's trace statistic will be used in interpreting the MANOVA results (Mertler and Vannatta, 2002). All three Pillai's traces are significant ($p < 0.001$) and will be shown in Tables IV-VI for each type of disruptions.

For the first two types of disruptions, we will pay more attention to order fulfilment measures ("Producer order backlog", "LSP shipment time", and "Cumulative demand"), as the main problem of these disruptions is the lack of capacity, leading to delayed orders and/or low quality products. By contrast, supply efficiency measures ("Producer capacity utilization rate", "LSP capacity utilization rate", and "Retailer inventory") are the main concerns for a demand disruption.

The MANOVA results for a producer capacity disruption are shown in Table IV. Except for "Retailer inventory", all the other five performance measures are found to be significantly different among eight scenarios ($p < 0.001$). Through a Duncan test, we group similar scenarios and arrange the groups from low to high performance (Chang, 2009). The same logic applies to the Duncan test results for an LSP capacity disruption in Table V. There is no significant difference between the scenarios that the retailer is not willing to collaborate (Scenarios 1, 2, 3, and 4) and the corresponding scenarios that the retailer is willing to collaborate (Scenarios 5, 6, 7, and 8). The results of three order fulfilment measures ("Producer order backlog", "LSP shipment time", and "Cumulative demand") show that Scenarios 4 and 8 are the best combinations of collaboration strategies to deal with a producer capacity disruption. There is no significant distinction between Scenario 4 and 8 on the other three performance measures.

Table V illustrates the MANOVA results for an LSP capacity disruption. "Producer order backlog", "LSP capacity utilization rate", and "LSP shipment time" are found to be significantly different among four scenarios with $p < 0.001$. "Retailer inventory" and "Cumulative demand" are found to be significantly different among four scenarios with $p < 0.01$. The Duncan test results of three order fulfilment measures ("Producer order

	Producer capacity disruption	LSP capacity disruption	Demand disruption
Box's M	1.68E3	6.42E2	1.91E2
F	8.11	6.99	5.74
df1	1.47E1	6.30E1	2.10E1
df2	6.28E3	3.04E3	1.19E3
p-value	0.000***	0.000***	0.000***

Note: ***$p < 0.001$

Table III. Box's test of equality of covariance matrices

Table IV. The MANOVA results for a producer capacity disruption

Performance measures	Mean (SD) Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	*F*	*p*-value	Duncan (scenarios in groups)
Producer capacity utilization rate	1.00 (0.01)	0.89 (0.05)	1.00 (0.01)	0.88 (0.04)	1.00 (0.01)	0.88 (0.04)	0.99 (0.01)	0.88 (0.04)	3.59E1	0.000***	(2 4 6 8, 1 3 5 7)
Producer order backlog	9.37E6 (9.13E5)	8.33E6 (6.46E5)	9.37E6 (9.14E5)	8.26E6 (5.60E5)	9.35E6 (9.31E5)	8.21E6 (5.62E5)	9.35E6 (9.31E5)	8.22E6 (9.26E5)	5.91	0.000***	(1 3 5 7, 2 4 6 8)
LSP capacity utilization rate	0.90 (0.01)	0.98 (0.03)	0.72 (0.01)	0.81 (0.04)	0.90 (0.02)	0.98 (0.03)	0.72 (0.01)	0.80 (0.04)	1.53E2	0.000***	(3 7, 4 8, 1 5, 2 6)
LSP shipment time	1.03 (0.07)	1.33 (0.21)	1.03 (0.06)	1.05 (0.05)	1.05 (0.11)	1.32 (0.18)	1.05 (0.11)	1.12 (0.09)	1.05E1	0.000***	(2 6, 1 3 4 5 7 8)
Retailer inventory	1.32E6 (3.17E5)	1.56E6 (5.26E5)	1.33 E6 (3.26E5)	1.73E6 (4.50E5)	1.30E6 (2.70E5)	1.53E6 (4.57E5)	1.30E6 (2.70E5)	1.64E6 (3.96E5)	1.99	0.068	(2 4 6 8, 1 2 3 5 6 7 8)
Cumulative demand	3.06E6 (1.97E6)	9.34E5 (1.34E6)	3.06E6 (1.97E6)	6.67E5 (8.64E5)	3.06E6 (1.97E6)	9.46E5 (1.34E6)	3.06E6 (1.97E6)	6.77E5 (8.67E5)	5.70	0.000***	(1 3 5 7, 2 4 6 8)

Notes: Overall test Pillai's trace = 2.73 ($F = 8.59$, $p < 0.001$). *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Performance measures	Mean (SD) Scenario 1	Scenario 3	Scenario 5	Scenario 7	F	p-value	Duncan (scenarios in groups)
Producer capacity utilization rate	1.00 (0.01)	0.99 (0.03)	0.99 (0.03)	0.99 (0.03)	0.24	0.87	(1 3 5 7)
Producer order backlog	1.00E7 (1.04E6)	8.67E6 (8.79E5)	8.34E6 (8.50E5)	8.37E6 (8.36E5)	7.93	0.000***	(1, 3 5 7)
LSP capacity utilization rate	1.00 (0.01)	0.87 (0.02)	0.99 (0.01)	0.87 (0.02)	2.02E2	0.000***	(3 7, 1 5)
LSP shipment time	2.55 (0.05)	1.22 (0.03)	2.55 (0.07)	1.25 (0.08)	1.55E3	0.000***	(1 5, 3 7)
Retailer inventory	1.32E6 (2.89E5)	1.78E6 (5.44E5)	1.29E6 (2.20E5)	1.73E6 (4.29E5)	4.48	0.009**	(3 7, 1 5)
Cumulative demand	3.12E6 (1.93E6)	1.21E6 (1.25E6)	3.16E6 (1.89E6)	1.24E6 (1.22E6)	4.73	0.007**	(1 5, 3 7)

Notes: Overall test Pillai's trace = 2.07 (F = 1.22E1, $p < 0.001$). *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table V. The MANOVA results for an LSP capacity disruption

Performance measures	Mean (SD) Scenario 1	Scenario 5	F	p-value
Producer capacity utilization rate	0.98 (0.04)	0.96 (0.04)	0.95	0.344
Producer order backlog	8.05E6 (7.66E5)	7.74E6 (6.75E5)	0.94	0.346
LSP capacity utilization rate	0.94 (0.02)	0.93 (0.03)	1.24	0.280
LSP shipment time	1.70 (0.06)	1.85 (0.17)	7.01	0.016*
Retailer inventory	2.28E6 (7.98E5)	2.07E6 (6.77E5)	0.39	0.541
Cumulative demand	4.08E5 (7.67E5)	4.29E5 (8.08E5)	0.00	0.954

Notes: Overall test Pillai's trace = 1.00 (F = 3.51E2, $p < 0.001$). *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table VI. The MANOVA results for a demand disruption

backlog", "LSP shipment time", and "Cumulative demand") show that Scenarios 3 and 7 are the best combinations of collaboration strategies to deal with an LSP capacity disruption. No significant distinction is found between Scenario 3 and 7 on the rest three performance measures. Compared to Scenario 1, Scenario 5 outperforms on "Producer order backlog" with $p < 0.001$.

The MANOVA results for a demand disruption are presented in Table VI. Only "LSP shipment time" is found to be significantly different between two scenarios with $p < 0.05$. As "LSP shipment time" does not belong to supply efficiency measures ("Producer capacity utilization rate", "LSP capacity utilization rate", and "Retailer inventory"), the difference of "LSP shipment time" means that Scenario 1 is slightly better than Scenario 5 to deal with a demand disruption.

5. Discussion and implications

5.1 Discussion

This paper simulates eight scenarios. Each scenario contains a certain combination of collaboration strategies to deal with three types of supply chain disruptions (Table II). For each type of disruption, different scenarios are found most suitable. We will elaborate them below.

For a producer capacity disruption, Scenarios 4 and 8 contain the best combinations of collaboration strategies. Both Scenario 4 and 8 contain the use of surge capacities for recovery. It is important for the producer to use its surge capacity for recovery, because the producer's surge capacity serves as the precautionary buffer to protect products supply (Driver, 2000). It is also important for the LSP to use its surge capacity to support the producer's recovery. Our results reveal that such action shortens "LSP shipment time." According to Schmitt and Singh (2012), it will alleviate the impact of non-supply by accelerating goods-in-transit. Note that, it is not important for the retailer to decide whether or not to collaborate, as our results show that whether playing shortage gaming or waiting will not make a significant difference in performance measures. Our findings are consistent with Hsieh and Wu's (2008) analysis that the producer's and the LSP's willingness to collaborate improve the probability of meeting customer demand as well as their profits after a producer capacity disruption, while the retailer's willingness to collaborate does not make a distinction. Our research is different from Hsieh and Wu's (2008) research regarding the LSP's and the retailer's collaborative efforts. In our study, the LSP collaborate by applying its own surge capacity, while the LSP in Hsieh and Wu's (2008) paper collaborates by waiting for the producer to recover from the capacity disruption. Our main concern is whether or not the retailer will play shortage gaming, while Hsieh and Wu's (2008) study pays attention to the retailer's efforts on price adjustment.

For an LSP capacity disruption, the best combinations of collaboration strategies are Scenarios 3 and 7. Scenarios 3 and 7 are different from Scenarios 1 and 5 in the usage of the LSP's surge capacity for recover. It is similar to what the producer would do when facing a producer capacity disruption. This is in line with Boulaksil *et al.* (2011) that the LSP's surge capacity serves as a first aid to alleviate the impact of capacity disruption. However, as Scenarios 3 and 7 do not differ with respect to order fulfilment measures ("Producer order backlog", "LSP shipment time", and "Cumulative demand"), the retailer does not have to determine whether or not to collaborate. If the LSP provides its surge capacity, such surge capacity will lessen the burden of capacity shortage, so that the retailer will not perceive it seriously to trigger shortage gaming (Lee *et al.*, 1997). By contrast, if the LSP has not provided its surge capacity (Scenarios 1 and 5), it is better for the retailer to choose waiting strategy (Scenario 5). A significant distinction is found in "Producer order backlog" between Scenario 1 and 5, meaning that there is a bullwhip effect caused by shortage gaming in Scenario 1. The purpose of the retailer's shortage gaming is to keep product supply to its customers (Lee *et al.*, 1997), but there is no significant difference found in "Cumulative demand" between Scenario 1 and 5. There is even no significant difference in "Retailer inventory" between Scenario 1 and 5, meaning that the retailer cannot benefit from shortage gaming in this case. On the other hand, distorted demand information that is generated by shortage gaming leads to more "Producer order backlog" in Scenario 1. Also considering that there is no significant difference in the LSP's performance measures ("LSP capacity utilization rate" and "LSP shipment time") between Scenario 1 and 5, we can conclude that this bullwhip effect is harmful for the whole supply chain. This is because after the LSP capacity disruption, all retailers tend to order more than they really need through shortage gaming, which will generate order amplification upstream (which is reflected by "Producer order backlog" in Scenario 1). However, since the LSP knows this is happening, it will ration the orders so that the retailer in our case still receives similar amount (Lee *et al.*, 1997). The only way to prevent this amplification from happening is that the retailer can trust the LSP to wait for its capacity recovery (Scenario 5) (Akkermans *et al.*, 2004).

For a demand disruption, the best combination of collaboration strategies is Scenario 1. At first glance, it is counter-intuitive that "LSP shipment time" of Scenario 1 (1.70 weeks) is significantly lower than that of Scenario 5 (1.85 weeks), because the bullwhip effect caused by shortage gaming usually leads to worse upstream performance (for both the producer and the LSP) (Lee *et al.*, 1997). The reason for our finding may lie in that, generally, shortage gaming is a strategy used by the retailer to deal with undersupply. In our case, the situation is that the demand disruption causes oversupply. By playing shortage gaming, the retailer sends more orders to the LSP and the producer, so that they can keep the same working pace as if there is no demand disruption. Our reasoning is also supported by the results that "Producer capacity utilization rate", "Producer order backlog", and "LSP capacity utilization rate" of Scenario 1 are higher than those of Scenario 5, although the difference is not significant. Also considering that there is no significant difference in the retailer's performance measures ("Retailer inventory" and "Cumulative demand"), we can conclude that this bullwhip effect is different from the one caused by an LSP capacity disruption. This bullwhip effect is beneficial for the whole supply chain. This finding is in line with Gonçalves *et al.*'s (2005) finding that an unresponsive capacity utilization policy that does not lower production level due to a decrease in demand will likely provide a higher service level. The only difference is that the unresponsive capacity utilization policy in our research is generated by the retailer's shortage gaming, while the unresponsive capacity utilization policy in Gonçalves *et al.*'s (2005) research is based on Intel Corporation (that is similar to the producer in our paper)'s own production policy.

To test the "robustness" of our results, we further apply four post hoc sensitivity analyses by changing variables for trust ("Alpha" and "Beta") and information sharing (Producer perception delay" and "Communicated lead time delay"). The range of variables for trust ("Alpha" and "Beta") is set from 0 to 1. The range of variables for information sharing (Producer perception delay" and "Communicated lead time delay") is set from one week to three weeks. The key results from these sensitivity analyses are: first, for a producer capacity disruption, "Alpha" and "Producer perception delay" have significant impacts on "LSP shipment time", "Retailer inventory", and "Cumulative demand." When "Alpha" or "Producer perception delay" is increased, the gaps between groups from the Duncan test results are significantly narrowed. However, the gaps remain significant on "LSP shipment time" and "Cumulative demand", thus the best combinations of collaboration strategies (Scenarios 4 and 8) are not changed. Second, for an LSP capacity disruption, "Beta" has a significant influence on "Producer order backlog." When "Beta" is increased, the gap between groups from the Duncan test results is significantly narrowed, leading to a non-significant gap. However, the significant differences on "LSP shipment time" and "Cumulative demand" still support our conclusion that Scenarios 3 and 7 are the best combinations of collaboration strategies to cope with an LSP capacity disruption. Third, for a demand disruption, "Beta" has a significant impact on "LSP shipment time" and "Retailer inventory." When "Beta" is increased, the gaps between groups from the Duncan test results are significantly enlarged. However, the difference on "Retailer inventory" is still not significant, thus the best combination of collaboration strategies remains Scenario 1. "Communicated lead time delay" has a significant influence on "Producer order backlog" and "LSP shipment time." When "Communicated lead time delay" is increased, the gaps between groups from the Duncan test results are significantly narrowed. However, the difference on "Producer order backlog" is still not significant and the gap on "LSP shipment time" is still significant, therefore the best combination of collaboration strategies remains Scenario 1.

5.2 Academic contributions

Our study contributes to the literature of supply chain disruption recovery in two ways. Our first contribution stems from our research design. Empirical research methodologies (e.g. case study and survey) always measure causal relationships at a given point (Sun *et al.*, 2009). Similarly, given their roots in military and government-related activities, optimization techniques are usually based on static "just in case" philosophies (Natarajarathinam *et al.*, 2009). Instead of these methodologies, we use system dynamics to capture complex real world situations, which include delays and feedback mechanisms (Helo, 2000). Through system dynamics modeling, our paper sheds light on the interactions of key system parameters (that reflect whether or not to collaborate for recovery) in a disruption recovery system over time. Furthermore, system dynamics contributes to areas where uncertainty dominates, but nevertheless the need for simulation and scenario analysis is clearly apparent (Akkermans and Van Oorschot, 2004). This applies to our study, as no supply chain disruptions are identical. Though there are no comparable data for different combinations of collaboration strategies, they can be learned and compared via simulation, as shown in this study.

Our second contribution is theoretical in nature. In previous literature, surge capacity is always considered as a strategic asset that is used by the focal firm itself (e.g. Boulaksil *et al.*, 2011; Driver, 2000; Hsieh and Wu, 2008), while shortage gaming is always discussed when products are undersupplied (e.g. Akkermans *et al.*, 2004; Lee *et al.*, 1997). In contrast, our research allows for the discussion of surge capacity to help supply chain partners recover from a disruption (i.e. after a producer capacity disruption) and the discussion of shortage gaming when products are oversupplied (i.e. after a demand disruption). Hence, our study focusses on recovery strategies after a disruption, instead of managing demand uncertainty upfront. We find that the LSP's surge capacity can accelerate the physical flow to help the whole supply chain recover from a producer capacity disruption. We also find that shortage gaming is not always a negative strategy from the whole supply chain perspective. It helps the producer maintain production speed to achieve a higher service level after a demand disruption.

5.3 Managerial implications

There is no single optimal combination of collaboration strategies that is able to tackle all three types of disruptions at once. Companies should thus prepare to switch strategies when they find themselves faced with different types of disruptions. As surge capacity involves extra investments, such decisions should be carefully made by balancing regular aspects of business, e.g., extra benefits to deal with volatile demand or a price fluctuation, the carrying cost of unused capacity, or the efforts to find a proper contract manufacturer/LSP. Based on our results, we can further provide managers with targeting suggestions on where to invest. To deal with a producer capacity disruption, both the producer's and the LSP's surge capacity are useful for recovery and thus are worth investments. All three tiers will benefit from such investments, thus the investments should be joint. Especially for the LSP and the retailer, they should be aware of their benefits and share the investments. The same situation applies to the handling of an LSP capacity disruption. The LSP's surge capacity is essential for recovery, which will benefit all three tiers. Firms should jointly invest in the LSP's surge capacity, as such investment will not contradict any tier's own interest. For a demand disruption, no extra investments are needed, as shortage gaming just involves decision making.

5.4 Limitations and future research

Our findings are based on a specific simulation model of a three-tier supply chain with specific problem assumptions and parameter settings. By changing some of the inputs, future research can investigate more issues on collaboration for recovery. First, it is recommended to include a raw material provider (e.g. a milk or package provider) to add more complexity to the simulation. Four tiers are also the typical inputs for the "Beer Distribution Game" (Sterman, 1989) to discuss the bullwhip effect. Second, the antecedents of collaboration for recovery (i.e. surge capacity and shortage gaming) are our own interpretations. To contribute to theory-building, we suggest future research to stabilize the vocabulary and present clear categorization. Third, in our study, collaboration decisions are made by individual firms. Collective decision making on collaboration is worth researching. For instance, Disney and Towill (2003) have investigated the effect of vendor managed inventory (VMI) on the bullwhip effect in supply chains. It will be interesting to apply the discussion of VMI in the context of disruption recovery. On the other hand, in this paper, we pay more attention to the behavioral dynamics of each tier's decision making with a strategic perspective. The research therefore reports the effectiveness and robustness of each scenario. Based on our results, mathematic programming and simulation may help optimize on the tactical and operational level. Such research will contribute to optimizing the efficiency of each scenario in the future.

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