Article:

Chen, LM, Liu, YE orcid.org/0000-0003-2637-5890 and Yang, SJS (2015) Robust supply chain strategies for recovering from unanticipated disasters. Transportation Research Part E: Logistics and Transportation Review, 77. pp. 198-214. ISSN 1366-5545

https://doi.org/10.1016/j.tre.2015.02.015

Robust supply chain strategies for recovering from unanticipated disasters

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23 February 2015

Forthcoming in *Transportation Research Part E: Logistics and Transportation Review*

Abstract

Recovering from unanticipated disasters is critical in today's global market. This paper examines the effectiveness of popular recovery strategies used to address unpredictable disasters that derail supply chains. We create a formal model to portray dynamic operational performance among supply chain firms facing disruptions caused by natural and man-made disasters. Our analysis shows that a supply chain recovers best if member firms adopt a radical, rapid, costly recovery strategy that immediately resolves the disruption. This observation is robust to various resource consumption requirements. We apply our methodology in the case of Taiwan's 2011 food contamination scandal and provide managerial insights.

Keywords: Emergency management, supply chain disruptions, supply chain vulnerability, cellular automata, complex adaptive systems

1 Introduction

Today's global business landscape is characterized by increasing uncertainty and vulnerabilities. Recent years have brought unforeseeable disasters – man-made and natural – including terrorist attacks, computer viruses and 'hackings', financial crises, earthquakes, tsunamis, the SARS and Ebola epidemics, and nuclear reactor accidents, etc. Anecdotal evidence about the global production plummet due to Japan's March 2011 earthquake and nuclear reactor

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semi-meltdown shows that most serious, unpredictable disasters can disrupt the normal flow of goods and materials within and across supply chains. Such unpredictable disasters expose firms enormous operational and financial risks (Kleindorfer and Saad, 2005; Papadakis, 2006; Xiao and Yu, 2006; Bueo-Solano and Cedillo-Campos, 2014). Motivated by these real-world observations this paper examines the effectiveness of popular recovery strategies when a supply chain faces unpredictable, hazardous events, and then provides managerial insights for supply chain managers.

Historical data indicate that the total number of natural and man-made disasters has soared dramatically over the last two decades (see e.g., www.cred.be; www.munichre.com). For instance, Thailand's 2011 massive flooding affected the supply chains of computer manufacturers dependent on hard disk drives and of Japanese auto companies including Honda, Toyota, and Nissan with factories in Thailand (BBC, 13/10/2011), among others. The 2010 eruption of an Icelandic volcano caused flight disruptions across Europe that severely affected supply chains dependent on air-freighted imports and exports, such as food and flowers. BMW had to suspend auto production at three plants in Germany due to the parts supply interruptions resulting from this volcanic eruption (DailyMail, 19/04/2010). Empirical studies indicate that most supply chains tend to collapse during disruptions caused by major unanticipated disasters and many of them never recover afterwards (e.g., Eskew, 2004; Tang, 2006). The detrimental effects of various catastrophic disasters (Hendricks and Singhal, 2005; Green et al., 2011) motivate us to identify robust supply chain strategies that promptly and effectively address them – strategies enable supply chains to maintain their operations during and closely after disaster-caused disruptions.

To explore supply chain dynamics in the presence of major disasters, we construct a behavioral supply chain model using the cellular automata (CA), a simulation method that considers strategic interaction among neighboring firms and the resultant impact on the entire supply chain (Davis et al., 2007; Harrison et al., 2007; Nair et al., 2009; Yang and Chandra, 2013). Using the aforementioned floods in Thailand and the volcano eruption in Iceland as examples, we employ CA to model how an unanticipated disaster in a supply chain firm places the entire supply chain's operational and financial performance at risk, following the forest fire model in physical science (see Robertson and Caldart, 2008). In essence, our model mirrors many real-world supply chain disruption cases.

Research that explores ways to mitigate supply chain disruptions has generally followed one of two streams: disruptions caused by anticipated and unanticipated disasters. In practice, a supply chain frequently faces disruptions with anticipated probability of occurrence and magnitude of impact, due to forecast errors caused by demand fluctuations, machine breakdown, and poor supplier performance (e.g., Hilletofth and Hilmola, 2008; Lättilä and Saranen, 2011). The first stream, anticipated disaster-caused disruptions, suggests that the disruption's adverse impact can be mitigated by taking steps to diminish the *likelihood* of a disruption (e.g., Chang et al., 2007); on this, Altay and Green (2006) offer a comprehensive literature survey. However, how can a firm reduce the chance of a disruption if the probability distribution of the hazards is *unknowable*, such as those caused by unpredictable, sudden-onset natural and man-made disasters? The first stream of research cannot address this thorny problem, which is important in global supply chain management of product production ranging from airplanes to consumer goods to chemicals (Sheffi, 2007; Simchi-Levi et al., 2014). But the second stream of research, unanticipated disaster-caused disruptions, attempts to address this problem of unforeseeable incidents.

In the past decade, managers of supply chains and operations have become much more concerned about the potential consequences of unanticipated disasters at their facilities and those of their supply chain partners (Sheu, 2007b; Kunz and Reiner, 2012). The increased concern is partly the result of greater inter- and intra-organizational complexity and increased exposure to unpredictable natural and man-made disasters. For instance, meteorologists are forecasting increased weather events – in terms of severity and incidence rates – due to global warming. These events will inevitably disrupt supply chains because shipping, air freight, trains, and other transportation modes along with fuel shortages, communication and electricity outages and electricity supply supply disruptions, will be greatly affected by increasingly extreme weather events. As noted earlier, in 2011 Honda had to cut its car production at six plants and postponed new model launches in the US and Europe due to a shortage of electrical and engine components from suppliers in flood-stricken Thailand; Kenyan farmers who relied on air-freighted exports to Europe had to destroy over 400 tons of flowers after two days of flights cancellations due to the eruption of an Icelandic volcano; and Japan's 2011 earthquake and tsunami halted Toyota's production at three plants for several days and damaged American dealerships (see Chopra and Sodhi (2004, 2014) for more details and examples).

To address the practitioners' and researchers' increased concern about unanticipated disasters, a second stream of research has recently emerged that explores the role of supply chain disruptions caused by unpredictable natural and man-made disasters (Sheu, 2007a). For instance, Bueno-Solano and Cedillo-Campos (2014) develop a system dynamics model to analyze the devastating effects of terrorist acts on global supply chain performance. Qi et al. (2004) examine a one-supplier-one-retailer supply chain experiencing demand disruptions and the resultant impacts on supply chain's coordination mechanisms in pursuit of maximum supply chain performance. Xiao and Qi (2008) extend Qi et al.'s (2004) analysis of a one-manufacturer-two-competing-retailers supply chain under disruption. However, most studies in this stream explore the effects of supply chain disruptions but fail to consider recovery strategies – the major focus of this work (see, Altay and Green, 2006; Sheu, 2010). We extend this research stream by developing a formal model of supply chain dynamics under unanticipated disasters and their effects on member firms over time. Also, we summarize several observations by carefully analyzing extensive simulation outcomes.

Our key findings are as follows. An incremental recovery strategy mitigates disruptions from unanticipated disasters by incrementally improving the supply chain's recovery performance; this strategy performs well when bringing the entire supply chain operations from a poor to good state consumes considerable resources. However, with the incremental recovery strategy, the supply chain may not perform as well as expected if the above condition – high resource consumption requirement – does not hold. As Lee (2004) highlights, a good supply chain strategy for recovery must perform at "triple-A" job by employing agility, adaptability, and alignment. Our computational analysis demonstrates that a radical (the most rapid) recovery strategy – one that contains the impact of a disaster within the effected firms and strives to immediately fix the disruption – is most robust. That is, in most disruptive cases, the radical recovery strategy consistently performs reliably. In contrast, strategies using the state-of-immediate-neighbors as a reference point are not as effective as the radical strategy to inhibit the contagion effect of disasters across the supply chain, leading to relatively low recovery performance. Their lack of efficiency is more significant when the supply chain is relatively large (e.g., the supply chain has ten echelons). These findings and insights under the supply chain structure generally hold in a stochastic setting in which a firm's recovery strategy is altered over time and in an extended supply network structure where each member firm has multiple upstream and downstream neighbors. We describe those conditions and strategies in detail, and justify these insights and other results in subsequent sections.

This paper is organized as follows. Section 2 presents the model characteristics. Section 3 reports on a computational analysis to explore our model. Two extensions of the model – the stochastic setting and the supply network structure setting – are discussed in Section 4. Section 5 illustrates the validation of the proposed model in a recent real-world case. Section 6 summarizes our findings and develops several theoretical observations for future empirical research.

2 Model

While our model encompasses a wide range of technical systems (e.g., information systems, manufacturing processes), we focus on supply chains. A long tradition in the model-based literature on operations, supply chain, and organization (see, Cachon and Netessine, 2004; Davis et al., 2007; Harrison et al., 2007) leads us to conceptualize the supply chain as the interaction of all member firms each of which makes a number of interdependent decisions. Specifically, each firm follows its strategy to interact with its adjacent upstream and downstream neighbor firms; together their unique interactions influence the supply chain's overall performance.

2.1 Supply chain structure

In modeling a supply chain's evolution, the cellular automata (CA) framework assumes that each firm interacts within a supply chain following fixed, homogeneous rules. Since a supply chain consists of autonomous or semiautonomous business entities (i.e., firms) engaged in various independent and interdependent activities, CA is an ideal research methodology to explore supply-chain issues (Nair et al., 2009). The firms in our model populate a one-dimensional array; consider a supply chain in which every firm interacts with its adjacent upstream and downstream neighbors. (We extend this chain structure into a network structure in Section 4.2, where each firm has multiple upstream and downstream neighbors.) We refer to N as the *size* of the supply chain; thus N firms populate the supply chain. Without loss of generality, we number these firms consecutively $1, 2, \cdots, N$ so that firm 1 is the most upstream (the first or start) firm and thus firm N is the most downstream (the last or end) firm. As a result, firm 1 has only one (downstream) neighbor, firm 2, and firm N has also only one (upstream) neighbor, firm $N-1$.

2.2 Firm performance

In our stylized supply chain model, each firm's operational performance can be one of three states that we rate as *bad*, *normal*, and *good*, designated by 0, 1 and 2, respectively. We denote the state of firm i at period t by $s_i(t) \in \{0, 1, 2\}$, where $i = 1, 2, \cdots, N$ and $t = 1, 2, \cdots, T$. Parameter T indicates the simulation periods of each run. The supply chain's performance at period t is

$$S(t) = \sum_{i=1}^{N} s_i(t).$$

Accordingly, our model is a discrete dynamic system with discrete and integral space, time, and states (see Robertson and Caldart, 2009).

A firm's state can change due to an unanticipated disaster. Suppose that a disaster occurs. A bad state (0) represents major damage to terminal facilities and/or halted production. At the other extreme, a good state (2) indicates restored operations from disruptions, which represents the firm functioning well. The normal state (1) represents the intermediate status whereby day-to-day operations are not fully recovered yet still functional, for instance, the firm utilizes supply chain collaboration, inventory, and/or transportation rerouting to remain operational (Transportation Report Board, 2012).

For the sake of simplicity, each firm in the supply chain at each period has a probability f of being derailed when encountering an operations shutdown from "severe" disasters and a probability g of being affected by "mild" disasters. Note that our study focuses on sudden-onset disasters that arrive rapidly with little or no forewarning, such as tsunamis, earthquakes, acts of war, and terrorist attacks; slow-onset disasters such as famines and droughts are not sudden onset and thus are not considered in this study (Van Wassenhove, 2006; Iakovou et al., 2014). Specifically, upon encountering a mild disaster at period t, firm i's operational performance is

$$\xi_i(t) = \max\{s_i(t-1) - 1, 0\};$$

during disruption from a severe disaster at period t, firm i's operational performance post disaster at that time is

$$\xi_i(t) = 0,$$

irrespective of its state prior to encountering the disaster, $s_i(t-1)$.

2.3 Recovery strategy

Following CA modeling convention, we assume that each firm's behavior is controlled by an identical decision rule, and that this rule uses the firm's post-disaster state – bad (0), normal (1), or good (2) – and the post-disaster states of its two adjacent neighbors (upstream and downstream) to determine the recovery state. Theoretically, a decision rule is a mapping of each possible input state (i.e., post-disaster performance, $\xi_j(t)$, $j \in \{i-1, i, i+1\}$) to an output state (i.e, recovery performance, $s_i(t)$) for every firm in the supply chain. A decision rule thus specifies a supply chain 'strategy' to restore every member firm's performance to its pre-disruption state following a disaster .

Given that each firm has three possible states, a fully specified rule will map the 27 ($= 3^3$) possible combinations of actions that the firm and its two neighbors can take to achieve the firm's new state. Because the rule must designate one of three possible states for each of the 27 situations, 3^{27} possible rules could direct a firm's behavior. Therefore, searching for optimal strategies is unrealistic and impractical in most CA models (Miller and Page, 2007). Following the modeling practice for complex adaptive systems (Miller and Page, 2007; Gintis, 2009), we choose ten possible rules (or strategies) based on their similarity to real-world decision making for supply chain recovery activities. Table 1 illustrates the ten decision rules selected, which determine the state of firm i at period t given $\xi_i(t)$ $\forall i$.

Table 1 Recovery strategies (decision rules) considered.

	Mathematical representation	**Remark**
DR1	$s_i(t) = 2$. Firm i will return to the good state (2) no matter what states its upstream and downstream neighbors held post disaster.	This rule can be considered a *radical* recovery strategy to reach the best state recovered from a disaster-caused disruption. A real-world example is Japan's semiconductor supply chain responding to the 2011 earthquake/tsunami, where each supply chain firm worked to successfully repair damaged facilities and fix the electrical power supply interruptions that had hindered chemical plants and fabs (SEMI, 2011).
DR2	$s_i(t) = 2$ if $\max\{\xi_{i-1}(t), \xi_i(t), \xi_{i+1}(t)\} = 2$; otherwise $s_i(t) = 1$. Firm i will return to the good state (2) if it had a good-state neighbor post disaster; otherwise, the recovery will be to the normal state (1).	This rule can be considered a *benchmarking* recovery strategy since it returns a firm to the best state of its neighboring firms. A real-world example is following the 2011 earthquake/tsunami when Toyota paid its workers to help its hard-hit suppliers in Japan return to functional production, leading to a quick supply chain disruption recovery (The Guardian, 11/03/2012).
DR3	$s_i(t) = 2$ if there are any two $j \in J = \{i-1, i, i+1\}$ such that $\xi_j(t) = 2$: at least two firms have a good state (the value of 2) in the set J; otherwise $s_i(t) = 1$. Firm i will return to the good state (2) if there are two good-state firms among the neighbors and itself post disaster; otherwise, the firm will recover to the normal state (1).	This rule is less likely to return a firm to a good state (2) than DR2. A real-world example is Entergy New Orleans's slow restoration following hurricanes Katrina and Rita in 2005, when flooding destroyed gas facilities and equipment of its domiciled response contractors, and brought massive damage to its supply chain's logistics and communications; that is, both Entergy New Orleans and its upstream contractors were not in the good post-disaster state. It took Entergy New Orleans two years of bankruptcy protection and numerous efforts to recover fully.
DR4	$s_i(t) = 2$ if $\xi_{i-1}(t) + \xi_i(t) + \xi_{i+1}(t) = 6$; otherwise $s_i(t) = 1$. Firm i will return to the good state (2) if it and both of its adjacent neighbors (up- and down-stream) had been in a good state (2) post disaster; otherwise, the firm will recovery to the normal state (1).	This rule is the least likely to return the firm to a good state (2) compared to DR2 and DR3. A real-world example: Malaysian Airline had difficulties in coping with the catastrophic losses of Flight 370 that went missing over the Indian Ocean in May 2014 and Flight 17 shot down over Ukraine in July, 2014.

Continued on next page

	Mathematical representation	Remark
DR5	$s_i(t) = 1$ if $\xi_{i-1}(t) + \xi_i(t) + \xi_{i+1}(t) = 6$; otherwise $s_i(t) = 2$. DR5 is similar to DR1 except for one situation in which firm i's state will change from good (2) to normal (1).	A member firm in a supply chain adopting this rule does not just reinstate what the disaster had destroyed, but improves the supply chain over its post-disaster state.
DR6	$s_i(t) = \max\{\xi_{i-1}(t), \xi_i(t), \xi_{i+1}(t)\}$. Firm i will recover to the best post-disaster state of its adjacent neighbors and of itself.	This rule can be considered a *matching* recovery strategy because it matches the state of its up- and down-stream neighbors. A real-world example is the Unitited States Enrichment Corporation (USEC), one of the biggest suppliers of uranium to Tokyo Electric Power (TEPCO), who maintains the Fukushima reactor before the meltdown caused by Japan's 2011 earthquake/tsunami. Its recovery activities were largely constrained by the lack of demand from the downstream firm in the supply chain, TEPCO, and the low market prices.
DR7	$s_i(t) = \min\{\xi_i(t) + 1, 2\}$. Firm i will recover its post-disaster state incrementally, going from bad (0) to normal (1), normal (1) to good (2), or maintain the good state (2).	This rule can be considered an *incremental* recovery strategy. Real-world examples are small- and medium-size-firms' recovery activities that are hindered by no or little access to capital, resulting in a slower recovery than expected.
DR8	$s_i(t) = \xi_{i-1}(t)$ if $\xi_i(t) \neq \xi_{i-1}(t)$; otherwise $s_i(t) = \min\{\xi_i(t) + 1, 2\}$. Firm i will adjust its recovery state to its adjacent upstream neighbor's post-disaster state when its state differs from that of its upstream neighbor post disaster; otherwise, the firm will recover its state by one additional unit.	A member firm in a supply chain adopting this rule follows the post-disaster state of its upstream neighbor. This strategy, similar to the *reverse bullwhip effect*, implies that upstream firms are more powerful to initiate recovery activities after disasters and this action will correctly align the rest of the chain.
DR9	$s_i(t) = \xi_{i+1}(t)$ if $\xi_i(t) \neq \xi_{i+1}(t)$; otherwise $s_i(t) = \min\{\xi_i(t) + 1, 2\}$. This rule suggests that firm i will adjust its recovery state to its immediate downstream neighbor's post-disaster state when a difference exists between its state and that of its downstream neighbor post disaster; otherwise, the firm will improve its state by one unit.	A member firm in a supply chain adopting this rule follows the state of its downstream neighbor. This strategy, similar to the *bullwhip effect*, assumes that downstream firms have more power to initiate recovery activities after disasters.

Continued on next page

	Mathematical representation	Remark
DR10	$s_i(t) = \max\{\xi_{i-1}(t), \xi_{i+1}(t)\}$ if $\xi_i(t) \neq \max\{\xi_{i-1}(t), \xi_{i+1}(t)\}$; otherwise $s_i(t) = \min\{\xi_i(t)+1, 2\}$. This rule suggests that firm i will adjust its recovery state to match the highest post-disaster state of its adjacent downstream and upstream neighbors; otherwise, the firm will improve its state by one unit.	A member firm in a supply chain adopting this rule follows the post-disaster state of its neighbor immediately before and after it. This strategy assumes that firms in the literal centre of the chain have more power to initiate recovery activities after disasters.

To sum up, a recovery strategy represents a firm's option to change its state (i.e., operational performance). The action set, however, is limited and localized to the firm itself and two of its adjacent upstream and downstream neighbors. In this sense, our model can be viewed as a modeling framework of behavioral game theory similar to nonlinear dynamic systems, following the principle of cognitive limits in human and organizational decision-making and judgement (see Gintis, 2009; Robertson and Caldart, 2009).

2.4 Resource consumption

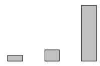
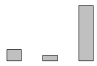
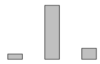
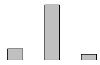
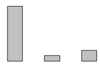
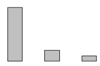
Undoubtly, a firm needs to consume a degree of resources to increase its post-disaster operational performance. We thus assume that the firm does not need to consume any resources for decreases in its performance. The resource consumption function for firm i with post-disaster state $\xi_i(t)$ to reach recovery state $s_i(t)$ is given by:

$$C(\xi_i(t), s_i(t)) = \begin{cases} c_1 & \text{for } \xi_i(t) = 0 \text{ and } s_i(t) = 1, \\ c_2 & \text{for } \xi_i(t) = 1 \text{ and } s_i(t) = 2, \\ c_3 & \text{for } \xi_i(t) = 0 \text{ and } s_i(t) = 2, \end{cases}$$

where c_3 is the resource amount spent to recover from a severe disaster at one time unit, c_2 is the resource amount spent to recover from a mild disaster, and c_1 is the resource amount needed to find alternatives, such as another supplier and a substitute route, in order to maintain day-to-day operations following a severe disaster. We consider six scenarios of resource consumption, listed in Table 2, where $c_1, c_2, c_3 \in \{1, 2, 10\}$ and $c_1 \neq c_2 \neq c_3$. (Results on additional sets of resource consumption function, C, are available upon request from the corresponding author. Our results are insensitive to the choice of C in the experiments.)

Specifically, resource consumption scenarios 1 (RC1) and 2 (RC2) illustrate the cases that restoring a firm to a good state (2) following a major, severe disaster is much more costly than

Table 2 Six resource consumption scenarios.

	Recovery Degree			
Scenario	0→1 (c_1)	1→2 (c_2)	0→2 (c_3)	Graph
RC1	1	2	10	
RC2	2	1	10	
RC3	1	10	2	
RC4	2	10	1	
RC5	10	1	2	
RC6	10	2	1	

recovering from a mild disaster (i.e., $c_3 > c_2$); yet it is less expensive to find alternative resources to carry out day-to-day operations possible (i.e., $c_3 > c_1$). The four other resource consumption scenarios (RC3 – RC6), on the other hand, suggest an innovative option: the use of resources to respond to severe disasters such that $c_3 < c_1 + c_2$. That is, member firms in a supply chain consider the recovery process an opportunity to foster innovation and bring a simple, cheap response to a disastrous event. For instance, a supply chain might permanently change its production locations and/or transportation routing after a major disaster because it could be too much effort to fix them (Transportation Report Board, 2012); hence, a disruption becomes an impetus for a supply chain's structural change. In addition, RC3 and RC4 depict cases that reinstate the disrupted supply chain at a high cost, despite low resource consumption to maintain day-to-day operations, $c_2 > c_1$. A real-world example is the 2012 Evonik plant explosion in West German that disrupted worldwide automakers' supply chains dependent on its specialty resin called PA-12, used to make fuel and brake lines (Simchi-Levi et al., 2014). Although the automakers in this case utilized their inventories to maintain day-to-day operations, in general, seeking alternatives to fully recover a compromised production capacity is highly resource-consuming (BBC, 19/04/2012). Finally, RC5 and RC6 consider that for some disasters, such as the 9/11 world trade center terrorist attack and Thailand's 2011 floods, the region's destroyed infrastructure and traffic disruptions require an enormous amount of resources to restore daily operations; once this step is achieved, it is relatively inexpensive to recover to the good state (i.e., $c_1 > c_2$).

Firm i's resource amount at period t is $R_i(t)$; there is an increase Δ in resources per period. Parameter Δ can be thought of as a firm's investment in risk mitigation in each period. So firm i's resource level at period t is

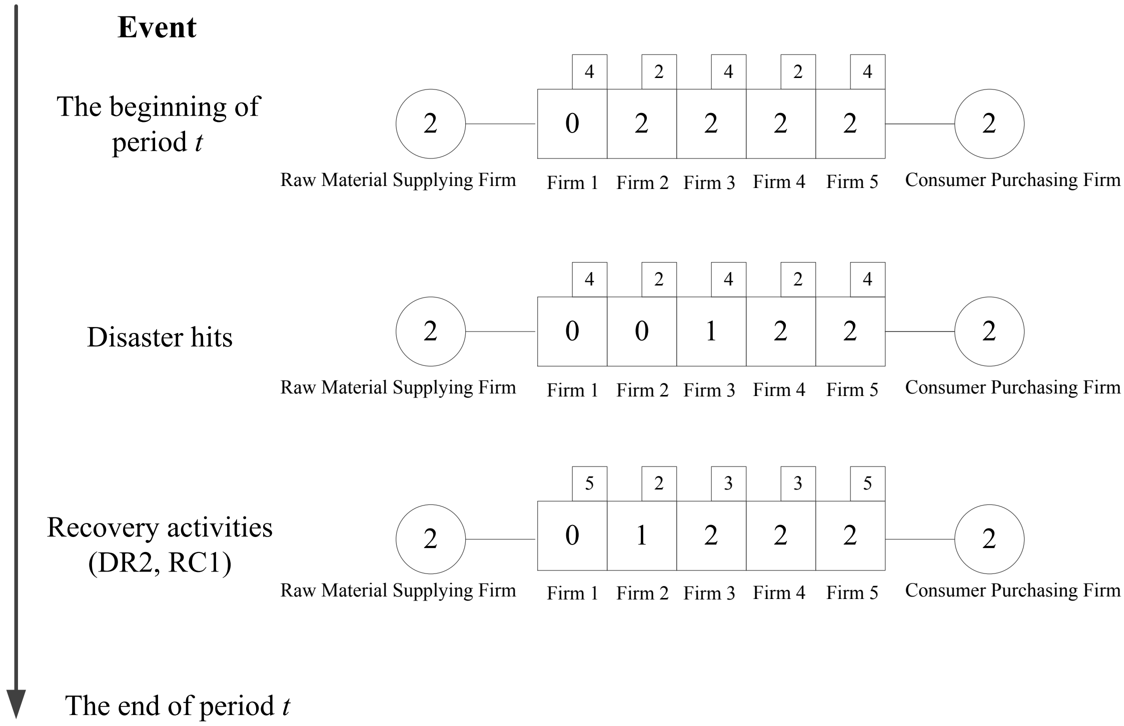
$$R_i(t) = \begin{cases} R_i(t-1) + \Delta - C(\xi_i(t), s_i(t)) & \text{if } \xi_i(t) < s_i(t), \\ R_i(t-1) + \Delta & \text{otherwise.} \end{cases}$$

2.5 Simulating the model

The simulation procedure for the proposed model is as follows. At period 0, we assign the recovery strategy, the resource consumption scenario, the probabilities of disasters (f and g), and the initial state for each firm. Since firm 1 has no upstream neighbor and firm N has no downstream neighbor, we assume that either firm 1's upstream neighbor or firm N's downstream neighbor is in a good state, or has the value of 2. (This assumption does not impact our outcomes since these two firms are outside the boundaries of our framework.) The simulation is executed until time T is reached. Next, we calculate the supply chain's performance by adding up the state of each member firm to evaluate the robustness of the ten recovery strategies employed by the N supply chain firms.

Figure 1 illustrates a recovery procedure at time period t: this simple example of five firms shows how recovery dynamics operate in our supply chain model. The numbers in the five large squares in the bottom row stand for state or operational performance, the numbers in the five small top-row squares present the level of the remaining resources, and the two firms denoted by circles present firm 1's upstream supplier and firm 5's downstream customer. DR2 and RC1 are applied to the recovery strategy and resource consumption scenario; and, each firm obtains one unit of resource at the start of each time period. Note that recovery actions following a strategy require adequate resources for implementation; that is, if the resource level is too low to execute the recovery strategy, the firm will remain in its post-disaster state (see Firm 1 as an example).

Fig. 1. Illustrated recovery procedure from time $t-1$ to time t.



2.6 Methodology and justification

Our objective is to consider the model in which recovery strategies reflect popular disaster response patterns in practice and to capture the interactions among supply chain members, to assess how such strategies can influence a firm's seemingly counterintuitive behaviors in supply-chain dynamics, and particularly in response to unanticipated disasters. Our ultimate goal is to gain insights into supply-chain emergency management strategies under unanticipated disaster-caused disruptions. As Robertson and Caldard (2009) note, CA is a dynamic network found in nature. We simulated our CA model in a MATLAB program.

Davis et al. (2007), Harrison et al. (2007), and Miller and Page (2007) note that when a study does not aim to predict the outcome of a particular set of equations, as in our study, a computational model using a set of parameter values is a valid experimental process if it satisfies the problem's general conditions and shows a property of general interest. Therefore, in this study, we employ the best practice for developing management theory through computer simulations and deriving insights for supply chain managers to formulate strategies for recovering their firms' operations from disruptions caused by unanticipated disasters.

In practice, supply chain firms' recovery activities for unanticipated disasters must satisfy two prerequisites: 1) desirability (i.e., the motivation to restore operations is reflected in the recovery strategies considered), and 2) feasibility (i.e., the ability to meet the resource consumption requirements for execution of the recovery strategy). We consider both desirability and feasibility of the recovery strategies aimed to help supply chains recover from unanticipated disasters. Our model setting thus mimics the behavioral aspects of supply-chain emergency management by considering the motivation behind recovery strategies and the limits of resource consumption (Sheu, 2007a; 2007b; 2010). In the next section, we unpack the robustness of recovery strategies for supply chains facing disruptions caused by unanticipated natural and man-made disasters using a careful computational analysis.

3 Analysis

3.1 Base case

Prior to running an extensive experimental analysis, and based on simulation research practice, we perform a base case in a pilot study: $N = 5$, $T = 365$, $R_i(0) = 3$, and $\Delta = 1$. We set $g = 134/365$ and $f = 17/365$ for the probabilities of mild and severe disasters occurring during a year based on Sheffi's (2007) empirical analysis, thus, these values are also fixed in our experimental study. Each firm's operational performance at period 0 is either a good state ("good" setting) or randomly assigned – bad (0), normal (1), or good (2) – state ("random" setting) for the outcome reliability. Every parameter instance is repeated 200 times for outcome reliability; we observe that the firm's initial state does not significantly impact the robustness of recovery strategies. Specifically, panels 1 to 3 in Table 3 show the average of supply chain performance S per period, the average of $(S/S_{\max}) \times 100\%$ per period, and the standard deviation of S per period. $S_{\max}$ is the upper bound of supply chain performance, which is 10 ($= N \times 2$) in the base case.

In the supply chain disruption and emergency management arenas, we are primarily concerned about worst-case-scenarios rather than average and optimistic scenarios of unanticipated disasters (Tang, 2006). Thus, Table 4 cannot identify which recovery strategy best addresses routine disruptions and major disruptions caused by unanticipated disasters (e.g., a 7.5 Richter scale earthquake at a major production plant) because the measure is the average number of all simulated events across a supply chain. Following risk analysis and management best practices (e.g., Myerson, 2004), we address this concern by reporting the 25th percentile, 5th percentile, and 1st percentile of supply chain performance S among the 200 simulations (see Table 4). These three performance measures result in very similar ranking outcomes across all the ten strategies considered. Hence, we use the 1st percentile as the only performance measure to rank recovery strategies since it provides a strict standard by which to evaluate the performance of strategies used to recover disruptions caused by unanticipated disasters.

Tables 3 and 4 show that in the base case, only two of the ten strategies, DR1 and DR7, achieve the first place; that is, they are the most robust recovery strategies. Notice that the incremental recovery strategy, DR7, is ranked first but only under either RC1 or RC2. The common characteristic of these two resource consumption scenarios is $\max\{c_1, c_2, c_3\} = c_3$; that is, to return the firm's state from a bad to good state after a disaster is highly resource-consuming. If this condition for resource consumption does not hold, the performance of the incremental recovery strategy is not as good as most other strategies. Based on our results, the radical recovery strategy, DR1, can achieve success under many resource consumption scenarios; that is, it is the most robust strategy because its worst performance still achieves the top place among nine others. Following this logic, we examine the mean rankings of each recovery strategy across all six resource consumption scenarios for the robustness analysis. We find that a highly ranked strategy can effectively restore the supply chain performance following unanticipated disasters.

3.2 Experimental design

To characterize the range of recovery performance after unpredictable disasters and to assess the impact of each parameter, we analyze the proposed model under a variety of parameter instances (Montgomery, 1991). Hence, a full factorial design is employed to explore the proposed model and to check whether the insights derived from the base case are applicable in other circumstances as well. We examine 12 ($= 2 \times 3 \times 2$) parameter instances consisting of every combination in Table 5. These parameter instances are selected to provide a wide range of possible scenarios (i.e., a low-to-high resource increment per period, Δ, a small, medium, or large supply chain size, N, and short-to-long simulated periods, T). We run each parameter instance 200 times to achieve statistical reliability. This computational analysis enables us to identify the underlying conditions for one recovery strategy to dominate another.

Table 3 Base case results for the average and standard deviation of supply chain performance per period.

	RC1		RC2		RC3		RC4		RC5		RC6	
	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random
Panel 1. Average of supply chain performance (*S*) per period												
DR1	7.606	7.531	9.740	9.651	8.025	8.026	8.175	8.171	10.000	10.000	9.995	9.995
DR2	7.788	7.747	9.198	9.182	7.387	7.387	7.429	7.422	9.670	9.654	9.646	9.653
DR3	5.025	5.010	5.014	5.002	5.016	5.011	5.010	5.004	1.277	1.246	1.274	1.255
DR4	5.003	5.002	4.996	4.992	5.005	7.649	4.998	4.991	1.223	1.217	1.233	1.216
DR5	5.613	5.595	7.024	6.975	7.645	7.649	7.768	7.780	9.072	9.071	9.049	9.060
DR6	7.594	7.591	9.228	9.125	7.362	7.391	7.431	7.431	9.656	9.657	9.652	9.642
DR7	9.619	9.604	9.629	9.623	5.789	5.787	5.169	5.146	8.073	7.957	4.494	4.437
DR8	5.709	5.726	6.272	6.235	5.338	5.332	5.109	5.095	6.443	6.399	6.242	6.207
DR9	5.710	5.694	6.243	6.194	5.340	5.335	5.103	5.106	6.436	6.431	6.235	6.240
DR10	7.136	7.045	8.661	8.632	6.823	6.835	6.863	6.866	9.560	9.555	9.480	9.486
Panel 2. Average of (S/S_{max}) × 100% per period												
DR1	76.060	75.305	97.400	96.507	80.250	80.255	81.750	81.707	100.00	100.00	99.950	99.951
DR2	77.884	77.473	91.978	91.820	73.870	73.867	74.285	74.224	96.70	96.54	96.459	96.530
DR3	50.251	50.095	50.143	50.015	50.159	50.105	50.099	50.044	12.77	12.46	12.737	12.549
DR4	50.034	50.016	49.961	49.916	50.047	76.486	49.975	49.912	12.23	12.17	12.326	12.163
DR5	56.132	55.947	70.241	69.746	76.449	76.486	77.675	77.796	90.72	90.71	90.494	90.598
DR6	75.943	75.909	92.276	91.252	73.618	73.908	74.305	74.306	96.56	96.57	96.518	96.419
DR7	96.188	96.036	96.287	96.234	57.889	57.871	51.687	51.461	80.73	79.57	44.940	44.367
DR8	57.085	57.255	62.723	62.347	53.382	53.322	51.085	50.954	64.43	63.99	62.418	62.068
DR9	57.101	56.941	62.431	61.936	53.400	53.352	51.032	51.058	64.36	64.31	62.350	62.395
DR10	71.364	70.446	86.606	86.315	68.226	68.349	68.632	68.664	95.60	95.55	94.800	94.859
Panel 3. Standard deviation												
DR1	0.429	0.527	0.076	0.075	0.156	0.167	0.069	0.071	0.000	0.000	0.006	0.006
DR2	0.374	0.385	0.124	0.119	0.257	0.250	0.138	0.147	0.057	0.059	0.069	0.063
DR3	0.020	0.013	0.012	0.011	0.022	0.018	0.014	0.018	0.081	0.075	0.084	0.091
DR4	0.005	0.004	0.006	0.002	0.012	0.012	0.011	0.012	0.067	0.071	0.074	0.065
DR5	0.218	0.218	0.051	0.050	0.227	0.192	0.048	0.049	0.047	0.048	0.043	0.048
DR6	0.453	0.407	0.122	0.122	0.245	0.245	0.129	0.153	0.059	0.060	0.064	0.068
DR7	0.045	0.052	0.067	0.063	0.049	0.047	0.067	0.062	0.493	0.524	0.611	0.673
DR8	0.365	0.355	0.091	0.091	0.276	0.281	0.111	0.107	0.201	0.189	0.188	0.202
DR9	0.335	0.365	0.088	0.080	0.276	0.274	0.120	0.110	0.189	0.197	0.207	0.212
DR10	0.387	0.362	0.110	0.111	0.282	0.308	0.114	0.122	0.047	0.043	0.073	0.071

Note. "Good" is the good setting where each supply chain firm operations in a good state (2) at period 0. "Random" is the random setting where each firm's state is randomly assigned. Each result is an average of 200 runs of 365 period experiments.

Table 4 Base case results for the 25th, 5th, and 1st percentiles of supply chain performance per period and 1st percentile recovery performance ranking of the strategies.

	RC1		RC2		RC3		RC4		RC5		RC6	
	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random
Panel 1. The 25th percentile												
DR1	7.307	7.169	9.655	9.534	7.977	7.977	8.123	8.121	10.000	10.000	9.992	9.992
DR2	7.566	7.490	9.019	9.012	7.296	7.308	7.332	7.326	9.634	9.618	9.606	9.608
DR3	5.011	5.000	5.003	4.992	5.008	5.003	5.003	4.992	1.218	1.197	1.216	1.192
DR4	5.000	5.000	4.992	4.986	5.000	5.000	4.993	4.984	1.175	1.169	1.186	1.167
DR5	5.492	5.462	6.874	6.826	7.612	7.614	7.736	7.744	9.041	9.034	9.021	9.029
DR6	7.296	7.295	9.060	8.980	7.285	7.306	7.330	7.326	9.615	9.616	9.611	9.599
DR7	9.592	9.570	9.596	9.592	5.743	5.741	5.121	5.099	7.784	7.611	4.078	3.969
DR8	5.462	5.493	6.112	6.049	5.280	5.269	5.033	5.030	6.300	6.271	6.134	6.078
DR9	5.477	5.389	6.056	6.036	5.277	5.282	5.021	5.040	6.312	6.289	6.097	6.110
DR10	6.870	6.781	8.473	8.395	6.748	6.751	6.780	6.789	9.526	9.527	9.441	9.440
Panel 2. The 5th percentile												
DR1	7.003	6.684	9.408	9.353	7.901	7.904	8.067	8.058	10.000	10.000	9.981	9.984
DR2	7.155	7.114	8.738	8.762	7.175	7.203	7.193	7.166	9.575	9.555	9.532	9.540
DR3	5.003	4.997	4.980	4.973	5.000	5.000	4.988	4.980	1.143	1.135	1.153	1.115
DR4	5.000	5.000	4.973	4.969	5.000	5.000	4.978	4.970	1.110	1.101	1.121	1.118
DR5	5.256	5.214	6.648	6.685	7.570	7.563	7.685	7.703	8.995	8.997	8.980	8.982
DR6	6.880	6.945	8.753	8.699	7.155	7.173	7.243	7.174	9.552	9.552	9.536	9.533
DR7	9.544	9.507	9.559	9.543	5.688	5.699	5.056	5.047	7.184	7.040	3.564	3.416
DR8	5.110	5.067	5.789	5.775	5.180	5.189	4.941	4.918	6.125	6.099	5.944	5.859
DR9	5.149	5.164	5.747	5.681	5.208	5.190	4.908	4.927	6.147	6.141	5.907	5.864
DR10	6.529	6.455	8.162	8.092	6.647	6.666	6.675	6.675	9.477	9.480	9.345	9.358
Panel 3. The 1st percentile												
DR1	6.425	6.167	9.280	9.214	7.834	7.837	8.021	8.030	10.000	10.000	9.974	9.975
DR2	6.918	6.871	8.552	8.527	7.095	7.059	7.099	7.086	9.529	9.492	9.433	9.510
DR3	5.000	4.997	4.958	4.948	5.000	5.000	4.978	4.958	1.111	1.101	1.114	1.066
DR4	5.000	5.000	4.963	4.951	5.000	5.000	4.966	4.953	1.069	1.075	1.067	1.088
DR5	5.036	5.041	6.522	6.558	7.512	7.530	7.664	7.675	8.975	8.960	8.927	8.936
DR6	6.488	6.833	8.611	8.440	7.058	7.092	7.156	7.122	9.523	9.500	9.500	9.471
DR7	9.503	9.475	9.523	9.500	5.627	5.638	5.021	5.003	6.843	6.651	2.988	3.032
DR8	4.907	4.943	5.573	5.488	5.141	5.123	4.870	4.833	5.956	6.037	5.766	5.689
DR9	4.993	5.012	5.471	5.466	5.174	5.151	4.821	4.818	6.008	5.997	5.733	5.711
DR10	6.051	6.264	7.907	7.912	6.549	6.585	6.606	6.611	9.451	9.462	9.277	9.307
Panel 4. Ranking of recovery strategy												
DR1	4	5	2	2	1	1	1	1	1	1	1	1
DR2	2	2	4	3	3	4	4	4	2	3	3	2
DR3	7	9	10	10	9	9	7	7	9	9	9	10
DR4	7	8	9	9	9	9	8	8	10	10	10	9
DR5	6	6	6	6	2	2	2	2	5	5	5	5
DR6	3	3	3	4	4	3	3	3	3	2	2	3
DR7	1	1	1	1	6	6	6	6	6	6	8	8
DR8	10	10	7	7	8	8	9	9	8	7	6	7
DR9	9	7	8	8	7	7	10	10	7	8	7	6
DR10	5	4	5	5	5	5	5	5	4	4	4	4

Note. Each result is based on 200 runs of 365 period experiments.

Table 5 Parameter instances used in our simulation experiments.

Parameter	Values
Δ for resource	1, 10
N for size	3, 5, 10
T for period	365 days (1 year), 3650 days (10 years)

Table 6 shows the impact of each experiment factor (parameter Δ, N, or T) on recovery dynamics among the ten recovery strategies. We highlight the parameters that lead to significant differences in the performance ranking of recovery strategies at $p < 0.05$. We find that chain size (N) has the greatest impact on the ranking of recovery strategies (seven p-values are less than 0.05; three are not: DR1, DR3, and DR4) over the other two factors, resource increment (Δ) and time (T). Chain size has both positive and negative effects on supply chain performance and the resulting ranking of recovery strategies; for instance, chain size has the strongest positive effect in DR7 and DR5 as it increases their ranking by 1.313 ($= 5.521 - 3.208$) and 0.771 ($= 5.625 - 4.854$), respectively. Chain size has the strongest negative effect in DR8, DR9, and DR6, as it decreases their ranking by 1.063 ($= 8.021 - 6.958$), 0.979 ($= 8.125 - 7.146$), and 0.791 ($= 3.812 - 3.021$), respectively. This suggests that when the chain size grows larger, DR5 and DR7 will generate better supply chain performance. In contrast, strategies that depend on the good state of adjacent neighbors (up- and down-stream) as a reference, such as DR6, DR8 and DR9, will lead to inferior supply chain performance.

Table 6 also shows that resource increment (Δ) is the second most influential moderating factor, where the effects are significant for DR1, DR5 and DR7 with $p < 0.05$. The resource increment appears to have a strong positive effect on DR7 with a 1.513 increase in ranking and on DR1 with a 0.5 increase. On the other hand, resource increment has a strong negative moderating effect on DR5 with a 1.472 decrease in ranking. Finally, the time period (T) has an insignificant impact ($p > 0.05$) on the ten recovery strategies' performance ranking. As a result, we omit parameter T in our discussion.

To illustrate the ranking of the ten recovery strategies, we provide a boxplot (Figure 2), where the robustness of each strategy is clearly expressed by its mean and variation in their performance ranking. For example, DR1 is the most robust recovery strategy for unanticipated

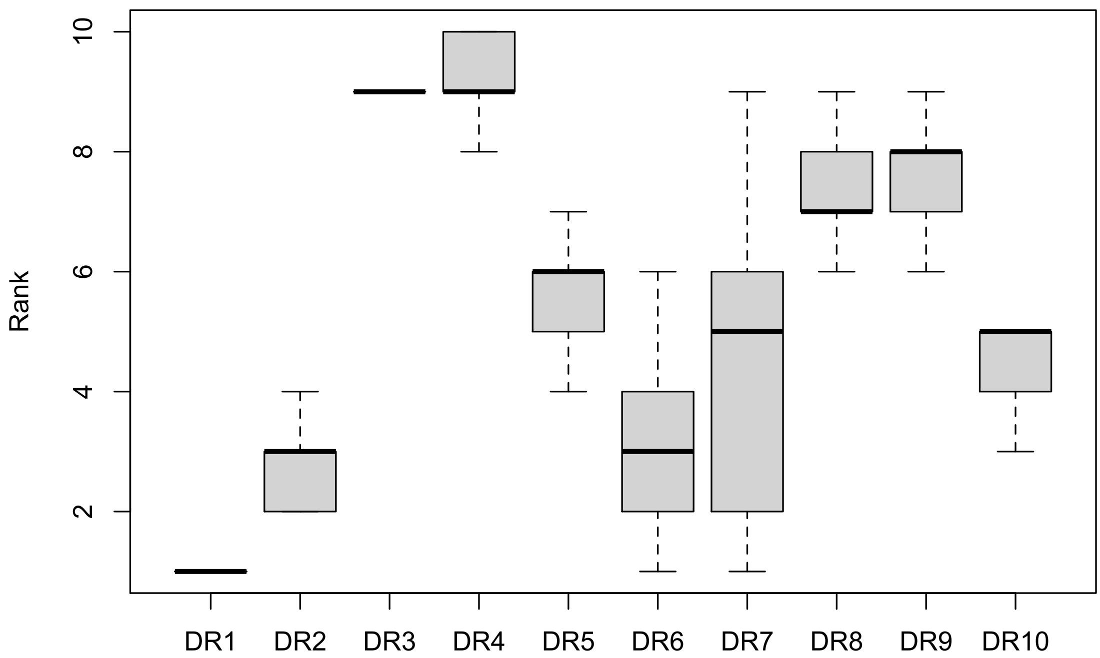
Table 6 Impact of experimental parameters on the recovery strategy ranking.

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
Δ	(1)	**1.500**	2.778	8.625	8.736	**4.514**	3.444	**5.069**	7.472	7.694	4.708
		(0.993)	(0.716)	(0.985)	(1.492)	**(2.169)**	(1.362)	**(2.661)**	(1.233)	(1.328)	(0.458)
	(10)	**1.000**	2.708	9.000	9.139	**5.986**	3.139	**3.556**	7.403	7.583	4.528
		(0.000)	(0.680)	(0.000)	(0.348)	**(0.118)**	(0.997)	**(1.288)**	(0.494)	(0.496)	(0.581)
N	(3)	1.188	**2.500**	8.938	8.729	**5.625**	**3.021**	**5.521**	**6.958**	**7.146**	**4.312**
		(0.571)	**(0.505)**	(0.522)	(1.498)	**(1.721)**	**(1.695)**	**(2.052)**	**(0.771)**	**(0.743)**	**(0.468)**
	(5)	1.271	2.625	8.979	9.146	5.271	3.042	**4.208**	**7.333**	**7.646**	**4.812**
		(0.792)	(0.761)	(0.526)	(0.545)	(1.594)	(0.713)	**(1.978)**	**(0.630)**	**(0.978)**	**(0.394)**
	(10)	1.292	**3.104**	8.521	8.938	**4.854**	**3.812**	**3.208**	**8.021**	**8.125**	4.729
		(0.849)	**(0.660)**	(0.945)	(1.019)	**(1.726)**	**(0.762)**	**(2.021)**	**(1.041)**	**(1.024)**	(0.574)
T	(365)	1.292	2.833	8.681	9.014	5.278	3.278	4.181	7.542	7.736	4.542
		(0.759)	(0.822)	(0.728)	(0.911)	(1.762)	(0.953)	(2.381)	(1.006)	(1.061)	(0.580)
	(3650)	1.208	2.653	8.944	8.861	5.222	3.306	4.444	7.333	7.542	4.694
		(0.730)	(0.535)	(0.690)	(1.259)	(1.646)	(1.411)	(2.048)	(0.856)	(0.934)	(0.464)

Note. The ranking of recovery strategies is based on the 1st percentile of supply chain performance per period on an average of the six resource consumption scenarios of the good and random initial state settings; each is based on 200 runs of 12 experiments. Standard deviations are in parentheses. Recovery strategies with smaller numbers rank higher in supply chain recovery performance, where 1 is the best possible ranking.

disasters because it has the lowest mean values and a very small variation in ranking, followed by DR2 and DR6. In contrast, DR3 and DR4 have poor supply chain performance. DR10, DR5 and DR7 have relatively moderate rankings (despite DR7's very large variations). Table 6 and Figure 2 illustrate some interesting findings at a more granular level, summarized as follows.

Fig. 2. Boxplot of the 1st percentile performance ranking of recovery strategies.



The firms using DR1 return to best supply chain performance following unanticipated disasters when they have greater resource increments per period. This is in line with the base-case result in that DR1 must consume a large amount of resources, and therefore ranks lower under RC1 and RC2 than under the other four resource consumption scenarios. Yet a small variance implies it has a consistently high recovery performance under the six RC scenarios. In contrast, the amount of resources does not play a significant role in DR2 and DR6. These two strategies are more effective in restoring supply chain performance following unanticipated disasters as the number of firms in a supply chain decreases from ten to five (or three).

The robustness of DR5 and DR7 is dependent on both the amount of resource increments and the supply chain size. In DR5, the supply chain's recovery performance increases as the chain size increases, yet decreases as the amount of resource increments increases. In contrast, a large supply chain using DR7 is likely to have better recovery performance when firms receive greater resource increments per period. While the resource impact of DR7 is similar to DR1, the supply chain's recovery performance is more sensitive to chain size when the firms in the supply chain incrementally return to a good state than rapidly and radically returning to a good state following a disaster.

DR8, DR9, and DR10 show consistent ranking patterns suggesting that the chain size is a significant factor of influencing supply chain recovery performance, which negatively affects the performance following unanticipated disasters. This pattern for these three strategies reinforces our findings observed in strategies DR2 and DR6 that when a supply chain grows larger, if firms use the state of their adjacent upstream and downstream neighbors as a benchmark, the overall recovery performance decreases.

Finally, DR3 and DR4 are not responsive to the resource increment and chain size parameters, and they are less robust than the other eight recovery strategies that rank 9 and 10 in average.

4 Robustness of Model and Insights

Thus far, we have examined supply chain performance in which all member firms implement an identical rule over time based on CA convention. In this section, we extend our model settings to incorporate plausible real-world situations to investigate the robustness of the findings in Section 3. First, we relax the identical rule assumption and allow member firms to make stochastic decision rules during the simulation period. Next, we employ a supply network structure where one member firm has several upstream and downstream neighbors, an extension to the supply chain structure. These two models further validate our understanding of the robustness of each proposed recovery strategy against disruptions caused by unanticipated disasters, obtained in Section 3.

4.1 Stochastic decision rule

This model extension specifies that member firms in a supply chain implement heterogeneous recovery strategies over time, which impacts the chain's overall performance. Specifically, we introduce a new decision rule, DR11, which is a function of the discrete probability distribution of the ten recovery strategies (Table 1). Supply chain firms that adopt DR11 can change a selected recovery strategy at each time period based on its recovery performance in the preceding

Table 7 Impact of experimental parameters on the ranking of the eleven recovery strategies.

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10	DR11
Δ	(1)	**1.528**	2.944	9.611	10.014	**5.347**	3.375	**5.708**	8.472	8.694	5.097	4.972
		(1.061)	(0.837)	(0.972)	(1.081)	**(2.579)**	(0.926)	**(3.208)**	(1.233)	(1.328)	(0.754)	(1.363)
	(10)	**1.000**	2.875	10.000	10.139	**6.806**	3.306	**3.889**	8.403	8.583	4.694	5.347
		(0.000)	(0.711)	(0.000)	(0.348)	**(0.432)**	(0.973)	**(1.588)**	(0.494)	(0.496)	(0.799)	(1.620)
N	(3)	1.479	2.750	9.521	9.917	**5.562**	3.104	**5.438**	**8.604**	**8.812**	4.771	5.542
		(1.010)	(0.786)	(0.850)	(1.069)	**(2.475)**	(0.857)	**(2.946)**	**(1.180)**	**(1.249)**	(0.831)	(0.743)
	(5)	1.188	2.979	10.104	10.292	**6.312**	3.521	**4.417**	**8.083**	**8.250**	4.875	**5.417**
		(0.673)	(0.887)	(0.371)	(0.544)	**(1.776)**	(1.031)	**(2.916)**	**(0.647)**	**(0.729)**	(0.761)	**(1.674)**
	(10)	1.125	3.000	9.792	10.021	6.354	3.396	4.542	**8.625**	**8.854**	5.042	**4.521**
		(0.606)	(0.619)	(0.713)	(0.668)	(1.509)	(0.917)	(2.021)	**(0.815)**	**(0.850)**	(0.798)	**(1.701)**
T	(365)	1.319	2.833	9.681	10.014	5.861	3.306	4.514	8.542	8.736	4.708	**5.861**
		(0.853)	(0.822)	(0.728)	(0.911)	(2.085)	(0.988)	(2.778)	(1.006)	(1.061)	(0.795)	**(0.810)**
	(3650)	1.208	2.986	9.931	10.139	6.292	3.375	5.083	8.333	8.542	5.083	**4.458**
		(0.730)	(0.722)	(0.678)	(0.678)	(1.865)	(0.911)	(2.572)	(0.856)	(0.934)	(0.765)	**(1.703)**

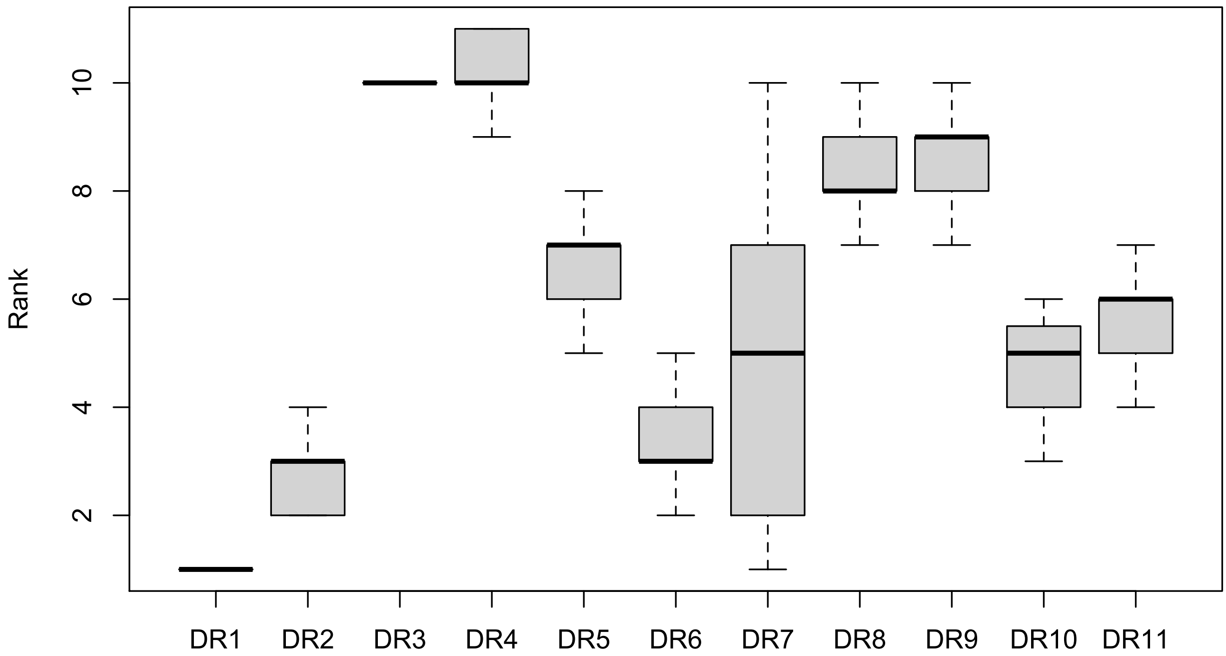
Note. The experimental settings are identical to those in Table 6.

period. The rationale for DR11 is that firms are inclined to choose a recovery strategy that has been proven effective to restore supply chain performance following a disaster.

DR11 begins with period 0, where member firms select one of the ten strategies, DR1 to DR10, each strategy with an equal probability 0.1 of being selected. If the chosen strategy improves supply chain performance from the previous period, then, at period 1 its probability increases to 0.109, taking 0.001 from each of the other nine (not chosen) strategies. That is, the probabilities are no longer equally distributed among the ten strategies: one has a probability of 0.109 and nine have the probability of 0.009. As a result, the proven robust recovery strategy (the one with probability 0.109) has a larger chance of being chosen again in the subsequent period. For instance, DR1 is robust in most scenarios (see Figure 2); therefore, DR1 is likely to become the dominant strategy once it is selected. In contrast, consider a scenario where a strategy is constantly passed by member firms or fails to generate positive supply chain performance. Its probability diminishes as time proceeds and will eventually become extinct.

We examine 12 ($= 2 \times 3 \times 2$) parameter instances consisting of every combination (see Table 5) and analyze the impact of parameters Δ, N and T on the eleven recovery strategies, as illustrated in Table 7. The patterns in DR1 to DR10 are predominantly consistent with those in Table 6, showing the reliability of our chief findings in Section 3. However, different from the results of those ten strategies, time is a significant factor of DR11. Specifically, member firms adopting DR11 return to a better recovery performance when the simulated period is 10 years. Specifically, we observe a large increase in DR11's performance ranking 1.403 (= 5.861 − 4.458) because it takes the robust strategies such as DR1 and DR2 some time to dominate the others (e.g., DR3 and DR4) and achieve a high supply chain recovery performance. As illustrated in Figure 3, DR1 ranks higher than DR11, yet DR11 can perform slightly better than DR5 and DR7. These observations support our main result (in Section 3) – that the radical recovery strategy (DR1) is most robust in resolving supply chain functioning following unanticipated disasters.

Fig. 3. Boxplot of the 1st percentile performance ranking of the eleven recovery strategies.



4.2 Network effect

We now consider a supply network structure including three interactive chains indexed by $k \in \{1, 2, 3\}$. Each supply chain has size N; so the entire supply network has size $3N$. For a firm i, in addition to its upstream and downstream neighbors $i-1$ and $i+1$ in the same chain, it has two cross-chain neighbors, one in each of the other two chains. For instance, member firm 3 in chain 2 has four neighbors: firm 2 in chain 2 (upstream neighbor), firm 4 in chain 2 (downstream neighbor), firm 3 in chain 1 (cross-chain neighbor), and firm 3 in chain 3 (cross-chain neighbor). We denote the state of firm i in supply chain k at time t as $s_{k,i}(t)$.

To recover from disasters, firm i applies a recovery strategy both within and cross chains so as to determine its possible state at period t by considering all four neighbors. For example, with DR2, first within firm i's supply chain 2, i derives a possible future state by examining $\max\{\xi_{2,i-1}(t), \xi_{2,i}(t), \xi_{2,i+1}(t)\}$ (see Table 1), denoted as $x_{2,i}(t)$. Next, across the other two supply chains, firm i derives a second possible future state, denoted as $y_{2,i}(t)$, by examining $\max\{\xi_{1,i}(t), \xi_{2,i}(t), \xi_{3,i}(t)\}$. $x_{2,i}(t)$ ($y_{2,i}(t)$) will return to state 2 if firm i had a good-state neighbor in the same chain (across the chains); otherwise, firm i will return to state 1, the normal state. In general, firm i's state in period t is easily determined if $x_{k,i}(t)$ and $y_{k,i}(t)$ return the same value. Otherwise, firm i must choose between these two possible future states. Specifically, it can either act aggressively by striving to attain the best possible recovery performance, that is, $s_{k,i}(t) = \max\{x_{k,i}(t), y_{k,i}(t)\}$, or act conservatively by settling on a modest recovery performance, that is, $s_{k,i}(t) = \min\{x_{k,i}(t), y_{k,i}(t)\}$. We now examine the robustness of the ten recovery strategies under these two scenarios, namely network-maximum and network-minimum.

Table 8 shows the main effects of the experimental factors under the network-maximum scenario. Similar to the results in the supply chain model (see Table 6), the resource increment (Δ) generates significant impacts on DR1 and DR5, whereas time (T) does not generate significant impacts. The impacts of supply chain size (N), contrary to our early findings in the supply chain model, are less significant to eight out of the ten recovery strategies in a supply network model. For instance, in the presence of a supply network, the robustness of DR2, DR6 and DR7 becomes insignificant to chain size. Further, as the resource increment increases, we observe a positive effect on the supply network performance in DR2. Nonetheless, the overall patterns in the rankings of recovery strategies are quite similar to that of the supply chain model (see Figure 2). As illustrated in Figure 4, DR1 remains the most robust recovery strategy, followed by DR2 and DR6. On the other hand, DR3 and DR4 are again less robust than the other eight strategies in the supply network model.

Under the network-minimum scenario, results (see Table 9 and Figure 5) show that DR1 is consistently the best recovery strategy to restore supply network functioning following disas-

Table 8 Impact of experimental parameters on the ranking of the ten recovery strategies under the network-maximum scenario.

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
Δ	(1)	**1.653**	**2.875**	9.083	9.597	**4.361**	3.014	5.792	6.736	**7.264**	4.486
		(1.224)	**(0.711)**	(0.599)	(0.548)	**(1.802)**	(0.813)	(2.950)	(0.787)	**(0.919)**	(0.605)
	(10)	**1.000**	**2.375**	9.000	9.583	**5.194**	2.556	5.833	6.972	**7.972**	3.986
		(0.000)	**(0.516)**	(0.000)	(0.496)	**(0.399)**	(0.500)	(0.411)	(0.236)	**(0.165)**	(0.118)
N	(3)	1.354	2.625	9.104	9.312	**5.021**	2.688	5.750	6.792	**7.417**	4.208
		(1.000)	(0.640)	(0.371)	(0.468)	**(1.495)**	(0.803)	(2.198)	(0.504)	**(0.794)**	(0.459)
	(5)	1.333	2.604	9.104	9.646	**4.646**	2.896	6.021	6.792	7.500	4.208
		(0.930)	(0.707)	(0.371)	(0.483)	**(1.329)**	(0.692)	(2.168)	(0.544)	(0.652)	(0.582)
	(10)	1.292	2.646	8.917	9.812	4.667	2.771	5.667	6.979	**7.938**	4.292
		(0.849)	(0.668)	(0.498)	(0.491)	(1.260)	(0.627)	(1.950)	(0.699)	**(0.697)**	(0.459)
T	(365)	1.403	2.667	8.986	9.639	4.722	2.861	5.736	6.889	7.556	4.222
		(1.002)	(0.712)	(0.459)	(0.539)	(1.386)	(0.775)	(2.320)	(0.683)	(0.785)	(0.562)
	(3650)	1.250	2.583	9.097	9.542	4.833	2.708	5.889	6.819	7.681	4.250
		(0.835)	(0.622)	(0.381)	(0.502)	(1.353)	(0.638)	(1.866)	(0.484)	(0.709)	(0.436)

Note. The experimental settings are identical to those in Table 6.

Fig. 4. Boxplot of the 1st percentile performance ranking of the ten recovery strategies under the network-maximum scenario.

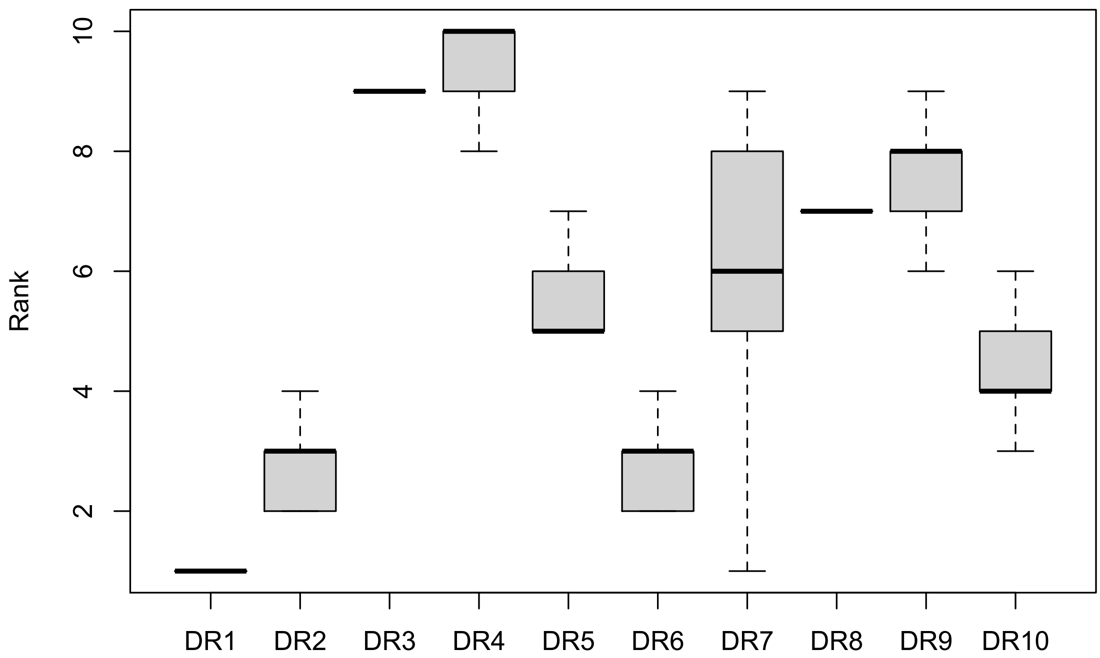


Table 9 Impact of experimental parameters on the ranking of the ten recovery strategies under the network-minimum scenario.

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
Δ	(1)	1.264	**4.444**	**5.222**	5.417	2.972	10.000	2.431	**8.417**	**8.542**	**5.861**
		(0.475)	**(0.785)**	**(0.736)**	(0.915)	(1.736)	(0.000)	(0.885)	**(0.496)**	**(0.502)**	**(1.763)**
	(10)	1.000	**5.000**	**5.778**	5.875	3.167	10.000	2.000	**9.000**	**8.000**	**3.833**
		(0.000)	**(0.000)**	**(0.419)**	(0.555)	(0.375)	(0.000)	(0.000)	**(0.000)**	**(0.000)**	**(0.375)**
N	(3)	1.188	4.729	5.479	5.417	3.042	10.000	2.188	8.708	8.250	4.812
		(0.445)	(0.644)	(0.714)	(0.846)	(1.320)	(0.000)	(0.734)	(0.459)	(0.438)	(1.553)
	(5)	1.125	4.729	5.458	5.708	3.292	10.000	2.208	8.688	8.312	4.750
		(0.334)	(0.610)	(0.651)	(0.713)	(1.383)	(0.000)	(0.651)	(0.468)	(0.468)	(1.804)
	(10)	1.083	4.708	5.562	5.812	2.875	10.000	2.250	8.729	8.250	4.979
		(0.279)	(0.617)	(0.616)	(0.762)	(1.024)	(0.000)	(0.601)	(0.449)	(0.438)	(1.537)
T	(365)	1.181	4.694	5.486	5.556	3.028	10.000	2.181	8.708	8.264	4.931
		(0.422)	(0.620)	(0.671)	(0.803)	(1.311)	(0.000)	(0.718)	(0.458)	(0.444)	(1.568)
	(3650)	1.083	4.750	5.514	5.736	3.111	10.000	2.250	8.708	8.278	4.764
		(0.278)	(0.622)	(0.650)	(0.769)	(1.205)	(0.000)	(0.599)	(0.458)	(0.451)	(1.691)

Note. The experimental settings are identical to those in Table 6.

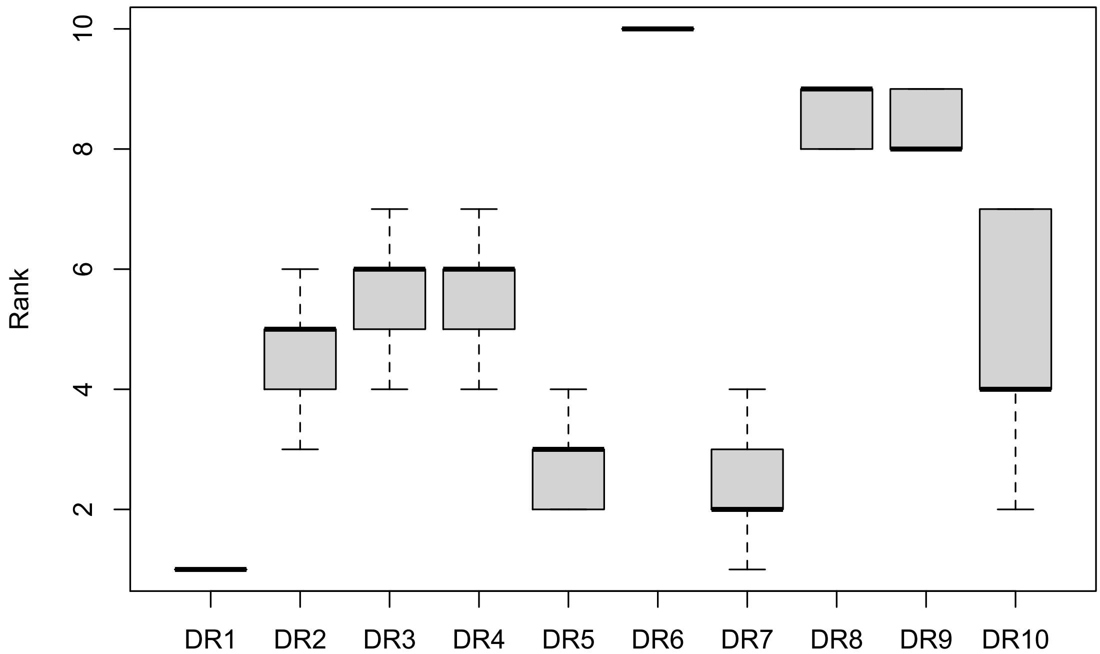
ters. DR7 is the second best recovery strategy to address unanticipated disasters. Despite the insignificant impact of chain size, the general patterns in the recovery strategy ranking in the supply network model are similar to those in the supply chain model; a notable difference is the dramatic decrease of DR6's ranking (Figure 5). Under the network-minimum scenario, the additional immediate neighbors in the supply network increase the likelihood of the focal firm matching a neighbor with a bad state (0), which is responsible for DR6's poor performance and low ranking. This finding is consistent with the insights identified in Section 3: as the number of member firms in the system increases, if firms use the state of their adjacent neighbors as a benchmark, then the system's overall recovery performance decreases.

In summary, the chief insights we derived from Section 3 are generally consistent with the extensions of the stochastic decision rule and the supply network structure.

5 Case study and model validation

In this section, we use the case of Taiwan's 2011 food contamination scandal to validate our findings on the robustness of supply chain recovery strategies in a real-world setting. This food

Fig. 5. Boxplot of the 1st percentile performance ranking of the ten recovery strategies under the network-minimum scenario.



safety scandal arose when Taiwan's health department discovered that upstream firms had used an industrial plasticizer, DEHP, rather than the customary palm oil in food and drinks as a clouding agent and to reduce costs (Economist, 11/06/2011). Evidence shows that repeated exposure to DEHP among children could lead to cancer and developmental problems as it affects hormones. The customers, both locally and globally, stopped buying those contaminated products and were in shock and panic about the fact that these two firms' immoral conduct had gone unnoticed for two decades. The discovery and ensuing embargo on the contaminated foods severely damaged major food and drink supply chains in Taiwan; the food contaminated an estimated 780 products including beverages, soda fruit juices, sports drinks, tea, jam, syrups, health supplements, pastries, and yoghurt powder (Taipei Times, 05/06/2011).

5.1 Background and parameter settings for the case study

The food scandal was exposed on May 23, 2011, affecting five echelons of member firms, the DEHP supplier, emulsifier supplier who substituted palm oil with the toxic plasticizer (Yu Shen Chemical Co.), food ingredient supplier (Seicheng Biotechnology Group), manufacturer (Triko Foods Co.), and retailer (7-Eleven), i.e., $N = 5$. As the downstream firms claimed innocence, their investment in mitigating food safety risk was small or $\Delta = 1$. Taiwan's health department had carried out a large-scale domestic food inspection for approximately one month from May 23 until June 18, 2011 ($T = 27$), up to 465,638 bottles of DEHP-tained beverages had been taken off from shelves, after which the department declared that food products should be relatively safe.

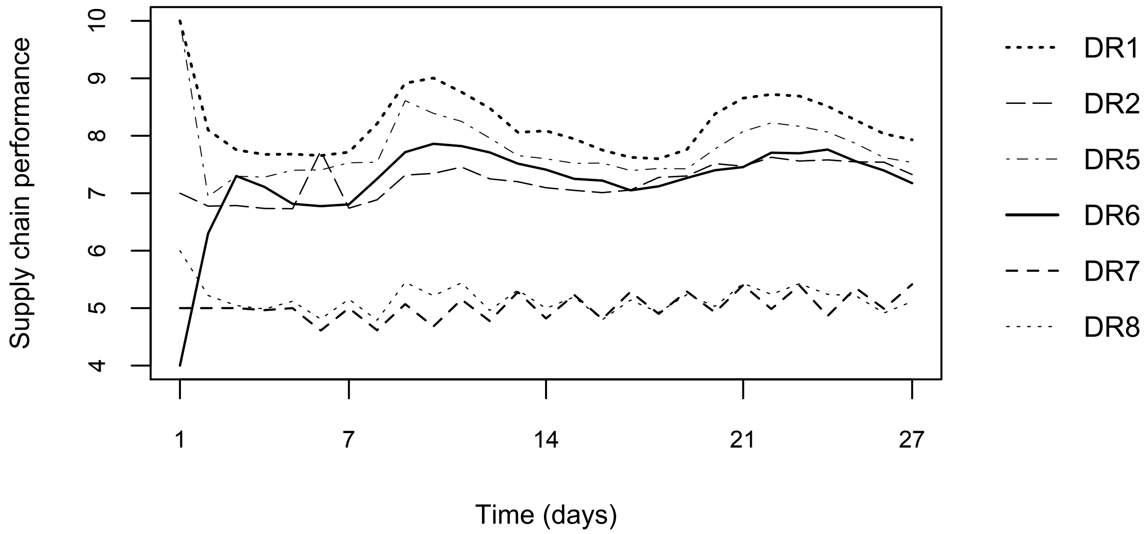
In order to amid the food safety scares, the supply chain firms took a radical strategy (i.e., DR1) to restore customer confidence. Specifically, the manufacturer immediately stopped production and sales of all of its manufacturing processes, recalled the tailed products and voluntarily submitted their products to government inspectors for DEHP test; the retailer pulled the tailed products from its shelves without sending the foods through DEHP tests. The manufacturer and retailer's rapid, radical, yet costly recovery actions of pulling off the food enabled them to maintain day-to-day operations. However, this hazardous event had dented Taiwan's once good reputation as a reliable and safe exporter of food. Several countries banned Taiwanese food imports, such as Malaysia (which lifted its import restriction in March 2012) and Singapore (which dropped its restrictions in March 2012). So, reinstating the supply chain's reputations worldwide cost even more than the actions of pulling off the food, i.e., $c_1 < c_2$. A fundamental and cheap solution was available when the government enforced new food safety regulations – The manufacturer and retailer knocked out the unscrupulous emulsifier supplier and replaced it with other reliable firms. This case study's resource consumption scenario is similar to RC4 so we adopt it in the section. Based on the above information, we use this case to verify our findings, obtained by our formal modeling, on the robustness of recovery strategies for restoring supply chain performance following this specific disaster.

5.2 Model validation

Figure 6 illustrates the supply chain recovery performance based on the parameter settings considered in the Taiwan food disaster case study. In addition to the adopted radical recovery strategy (DR1), we also include the recovery performance resulting from the five next best strategies, including DR2, DR5, DR6, DR7, and DR8.

It is clear that DR1 is more effective and robust than the other five strategies in the Taiwan food disaster case in terms of restoring supply chain's performance following the disaster. In other words, a supply chain is more likely to return to its pre-disrupted condition when using DR1. This result is in line with the findings in Figure 2: the radical recovery strategy, in general, dominates other strategies (e.g., DR2, DR5, and DR6) in which firms use their neigh-

Fig. 6. Simulating 1st percentile supply chain performance under the six top recovery strategies for the case study of Taiwan's 2011 food scandal.



Note. The parameters used in the Taiwan food disaster case study are $N = 5$, $\Delta = 1$, $T = 27$, $f = 17/365$. A small Δ can also mean that when food supply chains encounter a safety disaster, they rarely receive government or humanitarian support for recovery. $s_i(0) = 0$ and RC4 is applied.

bors' state as a reference. In fact, the Taiwan's food supply chain recovered well from this disaster by containing the devastated impact to the emulsifier supplier by quickly excluding them from the supply chain. We can predict that an incremental strategy, DR7, which carries out recovery activities in a gradual manner, does not reinstate consumers' confidence as well as other strategies, as evidenced by the low ranking in Figure 6. Likewise, strategies such as DR8, in which firms adjust only to the state of one upstream firm (in the Taiwan case, that would be the dishonest supplier), would halt the entire supply chain. In summary, as the main insight generated in our formal analysis, the radical recovery strategy, DR1, is most effective in preventing a crisis from escalating and in recovering the supply chain to a good state.

6 Discussion and conclusion

The simulation outcomes, illustrated in Figures 2 to 5, suggest that DR1 is the most effective strategy for recovering from unanticipated disasters (since we consider only the 1st percentile results as our performance measure). Results also suggest a rather small variation in DR1's performance ranking in comparison to the other nine strategies. Consistent with Chopra and Sodhi's (2014) strategy on regionalizing the supply chain, the radical recovery strategy DR1 will mitigate the negative impact of disruptions caused by unanticipated disasters within the affected region so that one bad-state firm will not drag the entire supply chain down. In other words, the supply chain becomes less fragile as the devastating impact of a disruption will be halted quickly, and will not spread to all member firms. Table 6 shows that the robustness of DR1 increases in resource increments per period (parameter Δ). Table 4 reports no clear relationship between the initial states of firms (i.e., either good or randomly assigned) and supply chain performance following the disasters. From this, we can infer that recovery strategies have a greater impact on supply chain performance than do resource consumption scenarios and the firms' initial states. Drawing on these findings, we propose the following observations:

Observation 1a. *A supply chain is robust against disruptions from unanticipated disasters if each supply chain member employs a radical recovery strategy aimed to return to a good state following a disruption.*

Observation 1b. *The robustness of the radical recovery strategy increases with resource increment.*

Our analysis statistically demonstrates that the radical strategy (DR1) is the most effective among the nine others for supply chains striving to recover from an unanticipated disaster, no matter how serious the disaster is. However, using the radical strategy may be unrealistic in practice due to the high level of resource consumption (high costs) that a firm must invest in order to return to a good state after a disruption (i.e., in RC1 and RC2). Therefore, we search for alternative recovery strategies under scenarios RC1 and RC2. We first consider DR7 that firms take recovery activities incrementally. We find that it generates the best recovery performance among the ten strategies (see panel 4 of Table 4). In other words, DR7 is quite effective in recovering from extreme disasters when the recovery process that involves changing a firm's state from bad (0) to good (2) requires plenty of resources. If this resource consumption condition does not hold, the performance of the incremental recovery strategy is not as good as most other recovery strategies. Also, we find that the robustness of DR7 increases as the chain size (N) increases, as shown in Table 6. Formally,

Observation 2a. *Supply chain performance following unanticipated disasters is sensitive to resource consumption requirements for recovery when an incremental recovery strategy is em-*

ployed by each supply chain member.

Observation 2b. *The robustness of an incremental recovery strategy increases as the size of the supply chain increases.*

We now consider DR2, the benchmarking recovery strategy. Similar to DR7, we find that DR2 can perform well under RC1 or RC2 (for details, see panels 3 and 4 of Table 4 and Figure 2). We should note that the strategic intent of DR2 is quite different from that of DR7. When facing a disruption, a good-state firm using DR2 will remain good (2); a normal- or bad-state firm will regain its good state if either of its adjacent neighbors – the upstream or downstream firm – has a good state (2). As reported in Table 6, benchmarking recovery strategy leads to better performance following unanticipated disasters when the chain size is small. This leads to the next observation,

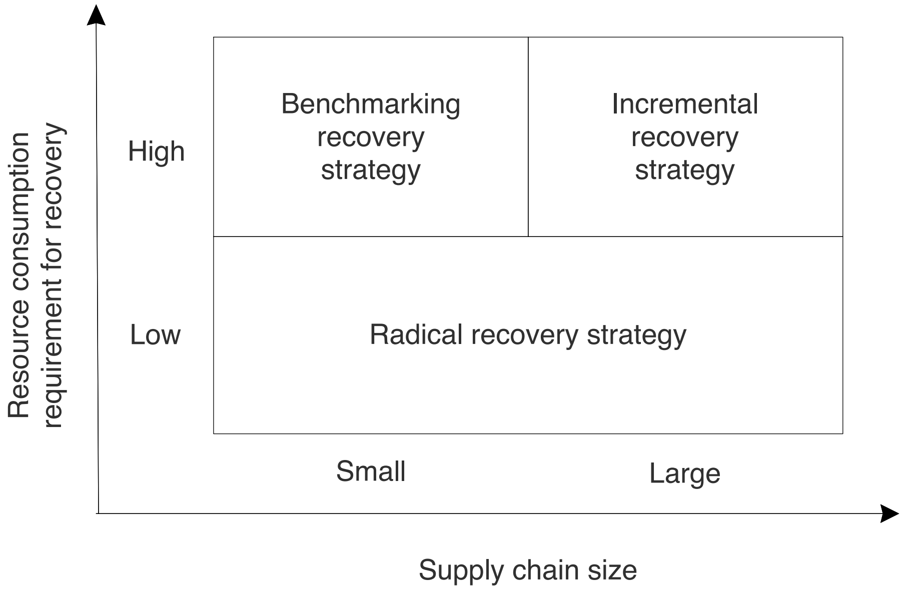
Observation 3a. *A supply chain is robust against disruptions caused by unanticipated disasters if firms employ a recovery strategy using the strategy of at most one neighboring firm with good performance as a benchmark to improve their operational performance following a disruption.*

Observation 3b. *The robustness of the benchmarking recovery strategy in a supply chain decreases as the chain size increases.*

The insights from the analysis and discussion are distilled into a conceptual framework in Figure 7, which provides managerial insights in the demarcating regions of robustness of a supply chain's various recovery strategy options. Specifically, the radical strategy is the best recovery option for scenarios in which the resource consumption requirements are relatively low for recovery activities from a bad state (0) to a good state (2). A benchmarking strategy is a good option for a small supply chain with high recovery resource needs. When the supply chain size is large and the recovery resource consumption requirements are high, the use of incremental recovery strategy among member firms in a supply chain is expected to outperform all the nine other strategies.

This paper contributes to the literature by examining the robustness of practical supply chain strategies for recovering from unanticipated disasters in a dynamic setting. We develop a supply chain model of unanticipated disasters using cellular automata (CA), a complex adaptive system found in nature (Miller and Page, 2007). The proposed CA model incorporates

Fig. 7. Robust supply chain recovery strategies.



the spirit of behavioral game theory as do past studies (e.g., Xiao and Yu, 2006; Ginits, 2009) and the key features extracted from real-world supply chain recovery activities (e.g., Kunz and Reiner, 2012; Transportation Report Board, 2012). Our stylized, behavioral model depicts the dynamic evolution of supply chain performance under the disruptive threat of unpredictable disasters. Through carefully chosen computational analysis, we uncover the weaknesses of popular incremental strategies for supply chain recovery when the chain size is relatively small. We further find that supply chain member firms using a radical recovery strategy can help maintain a positive supply chain performance over time. Counterintuitively, playing strategically for recovery by looking at what one's neighbors do in a large supply chain may hurt the entire supply chain's performance in the long run.

As for future research, this study can be extended in several directions. First, our formal model can be extended to consider the supply chain as an evolving system so that member firms can restore supply chain operations following unanticipated disasters by adding and/or removing a member (i.e., flexible chain size) over time. Second, further empirical research could test our observations in different industries (i.e., logistic, semiconductor, service) with real disaster dataset (e.g., www.emdat.be; www.airdisaster.com) and analyze whether other novel recovery strategies could effectively improve supply chain performance. We believe that the analytical observations and managerial framework derived from our results provide rich insights into supply chain emergency management facing unanticipated disasters and lay the groundwork for future analytical and empirical studies in this increasingly important field.

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