The Effect of Lead-time on Supply Chain Resilience Performance

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Abstract

Supply chain disruption resilience is receiving significant attention due to its role in increasingly complex and competitive economies. However, studies focusing on the factors that affect firms' resilience performance remain sparse. This study aims to gain new insights into the impact of suppliers' replenishment lead-time, an intrinsic characteristic of supply chain networks, on supply chain resilience following unexpected disruptive events, such as shipment failure. By modeling supply chain system dynamics with a multi-echelon design, this study provides an in-depth understanding of the system-wide impact based on four measurements, namely crisis readiness, response effectiveness, recovery speed, and impact propagation rate under different supply chains characterized by various lead-time durations. This study also examines the lead-time effect on resilience performances across different stratifications in a supply chain comprising a factory, a distributor, and a retailer. The results show that the major disruption impacts, such as impact propagation, deteriorate along with lead-time. Then, the effectiveness of two practices that can be used to mitigate the impacts is analyzed. The results show that constraining the order rate from the demand side perspective is effective only when lead-time is long while it is detrimental to firms' resilience when lead time is short. Additionally, a backup supply, from a supply side perspective, reduces disruption impacts.

Keywords: Supply chain management, Risk resilience performance, Replenishment lead-time, Bullwhip effect, Impact propagation

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1. Introduction

Firms in the modern economy adopt a variety of strategies, such as offshore outsourcing and complex alliance network, to stay competitive. The consequence of those strategic adoptions is that enterprises are exposed to a greater risk of supply chain disruptions (Trkman and McCormack, 2009). In global outsourcing, for example, firms face a higher uncertainty in transit due to a longer delivery time (Colicchia *et al.*, 2010). In addition, Bode and Wagner (2015) indicate that increasing supply chain complexity, whether in the form of horizontal or vertical cooperation, could enhance the likelihood of disruptions. The trend of risk diffusion and proliferation is an issue that calls for immediate attention and solution.

The risk of supply chain disruption could escalate as a consequence of two other industrial practices: lean manufacturing and just-in-time production. These methods aim to eliminate possible waste and improve flow within production and responsiveness from suppliers to customers. However, firms could become more vulnerable to supply chain disruptions while adopting those strategies (Pettit, 2008; Ghadge *et al.*, 2012; Schmitt and Singh, 2012). Furthermore, the close interconnection between associated parties in the supply chain makes the entire system susceptible to a single disruption if the disrupted party fails to handle the crisis (Basole and Bellamy, 2014). Facing the increasing challenge of intensive disruption risk, it will be necessary for firms to build a solid organizational resilience (Burnard and Bhamra, 2011).

An industrial example of these issues is the March 18, 2000 fire at a Philips plant in New Mexico, a microchip supplier to two cell phone giants at that time, Nokia and Ericsson. The 6-week supply disruption caused by a 10-minute fire at Philips plant had a significant after-effect that lasted more than a year for its clients, and spread to the entire cellphone industry. Ericsson alone claimed a $2.34 billion loss and eventually exited the cellphone market. This incident reflects the fragility of modern supply chains in many industries. The issue of risk dynamics and impact amplification and propagation should not be overlooked. With the increasing risk of exposure to both inbound logistics and an outbound supply chain and the escalating disruption susceptibility, the supply chain resilience capability is of importance for firms to sustain operation and stabilize output in a turbulent era (Pettit *et al.*, 2013).

Our research scheme is motivated by the relevant literature in the field of supply chain risk management. Risk management regarding supply chain resilience (SCRES) has gained considerable attention in recent years among both academics and practitioners. Risk management aims to minimize the impact of sudden disruptions and to resume operational normality in a timely and cost-effective manner (Tukamuhabwa *et al.*, 2015). Maintaining a good control over the operation and the overall performance during a disruptive period can be considered as one of the key success factors to thrive in today's business environment since a better reaction to disturbance than competitors can translate into a significant marketing advantage (Fridgen *et al.*, 2015).

Based on the resource-based theory, prior literature has shown that firms' internal resources, such as physical facilities, financial assets, human resources, technological development, (Brusset and Teller, 2017), as well as their external resources, such as supply connectivity (Braunscheidel and Suresh, 2009; Brandon-Jones et al., 2014; Dubey et al., 2017) are critical for SCRES performance. The more resources firms own, the better they would perform when disruptions occur. However, bolstering resources is costly, and may not be financially feasible for every enterprise. The cooperation between firms and their suppliers is very important (Dubey et al., 2017); however, achieving this can be a challenge. This is because trust is effective in enhancing SCRES (Papadopoulos et al., 2017), but difficult to foster and sustain (Hendricks and Singhal, 2005). Ambulkar et al. (2015) detail the effects of two practices—*resource reconfiguration* and *risk management infrastructure*—when firms are faced with two levels of disruptions; they show that *resource reconfiguration* is ineffective during low disruption but effective in high disruption, while the opposing effects are observed during the two levels of disruption in the case of *risk management infrastructure.* Economic efficiency would increase if firms know of the cost they have to incur to prepare for a certain level of disruption on top of firms' SCRES performance under a given supply chain structure. The research question then arises: does the performance of a firm vary according to the supply chain structure it adopts, if other conditions are held constant? Our objective is to characterize SCRES that is based on the fundamental supply chain structure before firms make any preparation. We examine supply lead-time as a cause of impact amplification and propagation under a stochastic turbulent supply chain environment. This supply chain attribute contains one of the elements of Brandon-Jones et al.'s (2014) visibility, which they define as the transparent flow of information regarding demand and inventory. In order to separate the effect of inventory on SCRES from that of demand, we are primarily interested in the influence of the time required to replenish inventory on the level of supply chain resilience when supply disruption occurs.

We argue that longer replenishment lead-time would increase task complexity in multiple aspects, such as inventory control (Zipkin, 2000; Agrawal *et al.*, 2009) and order decision (So and Zheng, 2003; Song *et al.*, 2010), and would ultimately affect firms' capability to react to unexpected disruptions. As such, firms may need to plan for more resources in order to combat the disruption in the case of longer lead-time. This paper contributes to the literature on supply chain risk management by isolating the impact of system characteristics from other alternative sources. As a result, one could choose proper strategies to deal with the impact of each source of supply chain risk.

2. Relevant Literature

Recently, risk management regarding disruption resilience has gained more attention in the literature (Hohenstein *et al.*, 2015), with a primary focus on three stages of SCRES. In the first stage, SCRES examines the ex-ante protection against unexpected disruption, so that firms and the supply system could reduce negative impacts and maintain operation during crises. Then, in the second stage, SCRES monitors the disruption and triggers the response to alleviate the disruptive impact when disruption occurs. In the final stage, SCRES engages in ex-post recovery, so that disrupted organizations and the supply network could quickly and efficiently resume normal performance or even move to a better, more favorable state to gain a competitive advantage (Sheffi and Rice Jr, 2005; Melnyk *et al.*, 2010; Jüttner and Maklan, 2011; Ishfaq, 2012; Tukamuhabwa *et al.*, 2015).

While most research has focused on the resilience assessment methodology and the ways to improve resiliency to unforeseeable disruptions, little attention is drawn to the relationship between intrinsic networking characteristics, such as replenishment lead-time, and its SCRES performance. Nair and Vidal (2011) suggest that supply network vulnerability to risk would be affected by different network characteristics, such as the average path length, the maximum distance between nodes, etc., and find that long distance between supply nodes would jeopardize its robustness against disruptions under the adoption of an agent-based model. Basole and Bellamy (2014) study the relationship between various supply network topologies and risk propagation speed using the consequential system health level as measurement. They find that "small-world" networking structure, characterized by the shorter average distance between supply nodes and higher clustering coefficient, outperforms other supply network topologies in terms of slower risk propagation between supply entities and faster recovery rate. Prior studies seem to suggest that the impact of disruption may vary in different supply network structures and supply chain properties; some structures are more fragile to disturbance while others can maintain stable performance even in turbulent situations. The literature focusing on the interplay between the supply chain properties and SCRES remains scarce; thus, we feel the need to fill this gap. A crucial, yet unexplored supply chain property of SCRES is replenishment lead-time, which is considered a key parameter in operations planning (Song, 1994; Chopra *et al.*, 2004; Song *et al.*, 2010) and of strategic importance in improving supply chain performance (De Treville *et al.*, 2004; Kim *et al.*, 2006; Agrawal *et al.*, 2009). This study explores the effect of lead-time on firms' resilience by using a system dynamics simulation. By understanding the fragility inherited from different replenishment lead-time when facing disruptive events, firms can perform better in resource allocation and investment deployment. As such, firms will elevate its resiliency performance toward disruptions and eventually win itself competitive advantage more efficiently.

The Lead-Time Effect on Resilience

There has been ample evidence showing the effect of lead-time in the fields of operations research and inventory management. There are conflicting effects of lead-time in the closely related literature. First, the literature implies that lead-time has a positive relationship with firms' preparation to absorb the impact of a disruption. An empirical study conducted by Rumyantsev and Netessine (2007) using field data of U.S. public companies between 1992 and 2002 finds that inventory level is positively related to procurement lead-time in all eight of the industry segments investigated. In line with previous results, Chopra *et al.* (2004) claim that shortening the replenishment lead-time is a more efficient way to decrease base-stock level compared to reducing lead-time variances in the case of high variation customer demand. These studies all point to the same idea: the faster an order replenishment is, the lower the optimal safety stock required to hedge against demand uncertainty (Chopra *et al.*, 2004; Song *et al.*, 2010) since a shorter lead-time enables firms to dynamically respond to the shifting customer demand and provides less incentive for them to hold excessive inventory on-hand (Finke *et al.*, 2012). However, when facing supply disruptions that stem from delivery problems or supply shortage, firms would be severely affected by the disruptive impact, such as production halt, stockout frequency, and backorder rate, due to low buffering inventory (Simchi-Levi *et al.*, 2002). On the contrary, in a supply chain with longer delivery lead-time, supply chain members tend to increase stock levels (Song, 1994) to offset the forecast error of relative lead-time demand. This unintentionally increases the degree of abundance to mitigate the disruptive impact; therefore, the severity of the initial impact would be alleviated.

Second, a longer lead-time might not be beneficial in responding to the disruption. In the absence of real-time announcement of disruption events, the replenishment lead-time of upstream suppliers would cause a delay in responding to disruptions, which is crucial for downstream customers in alleviating the disruption impact (Schmitt and Singh, 2012). To be more specific, in supply chains with shorter order replenishment time, the downstream customer is more flexible in executing contingency strategies due to earlier awareness of the disruptive event, thus resulting in an increased agility, which is measured in this study by two indicators, responsiveness and recovery.

Furthermore, a longer lead-time could intensify inventory inefficiency (Agrawal *et al.* (2009) since firms with longer delivery lead-time could face a greater risk in terms of supply disruptions due to less accurate inventory management. Chen *et al.* (2000) show that longer replenishment lead-times cause inflated order variance at upper echelons by modeling a simple supply chain and manipulating different deterministic lead-times with autoregressive customer demand. Kim *et al.* (2006) show that wide lead-time variance enhances the magnitude of bullwhip effect[1] more than the mean lead-time does. Many studies also suggest that reducing lead-time is significantly beneficial for improving the phenomenon of upstream order oscillation (Geary *et al.*, 2006; Luong and Phien, 2007; Agrawal *et al.*, 2009; Hussain *et al.*, 2012), which could cause an imbalance between supply and demand, and thus leads to firms' inability to handle the disruption appropriately.

3. Assessing SCRES

Plenty of research has been conducted to enhance the understanding of formative capabilities of SCRES, such as velocity, flexibility, visibility, etc. For a comprehensive review, please refer to the work of Hohenstein *et al.*, (2015) and Tukamuhabwa *et al.* (2015). SCRES is rather subjective, and various measurements and definitions have been used for the purpose of making good comparisons to the resilience of firms in particular contexts. To quantify the resilience performance and make comparisons to various supply chains with specific system characteristics in our study, we redefine Tukamuhabwa *et al.'s* (2015) version of the resilience triangle to Ponomarov and Holcomb's (2009) three phases of SCRES performance, namely readiness, responsiveness, and recovery (3Rs). Readiness is the robustness of firms, such as slack capacity, on-hand inventory, or multiple sourcing, in the pre-disruption phase, which can help companies withhold the impact of an unexpected event without ceasing operation. Responsiveness is the interval from the disruption outburst until the time the impact stops spreading. The recovery phase of SCRES measures the restored capacity from the worst condition by calculating the time needed to resume to pre-disruption performance standard. The advantages of the resilience triangle measurement are that it not only presents the deviation from the desired state, but it also emphasizes the evolving performance dynamics over time. We consider it a useful and appropriate measurement for this research scheme since we intend to investigate the timed effect of order replenishment on the performance of SCRES.

In this paper, the resilience of a supply chain is measured in terms of the stability of the net inventory level. To be more specific, the performance of resilience in all phases affected by various order replenishment lead times is examined by comparing the timing in which the net inventory reaches critical points (e.g. dropping below zero, falling to the worse state, and resuming to the normal level). Figure 1 shows the measurement of the three phases of SCRES in terms of inventory level. T_s is the point when the disruption starts. T_c is the threshold at which a firm's customer service level will be impeded (we use zero of net inventory in this study). T_a is the time when a 100% recovery takes place after a disruption. T_r denotes the least acceptable performance post-disruption.

[1] The bullwhip effect is a well-known distribution channel phenomenon in which demand forecasts yield inventory inefficiencies. It refers to the amplification of orders in response to shifts in customer demand as one moves up the supply chain.

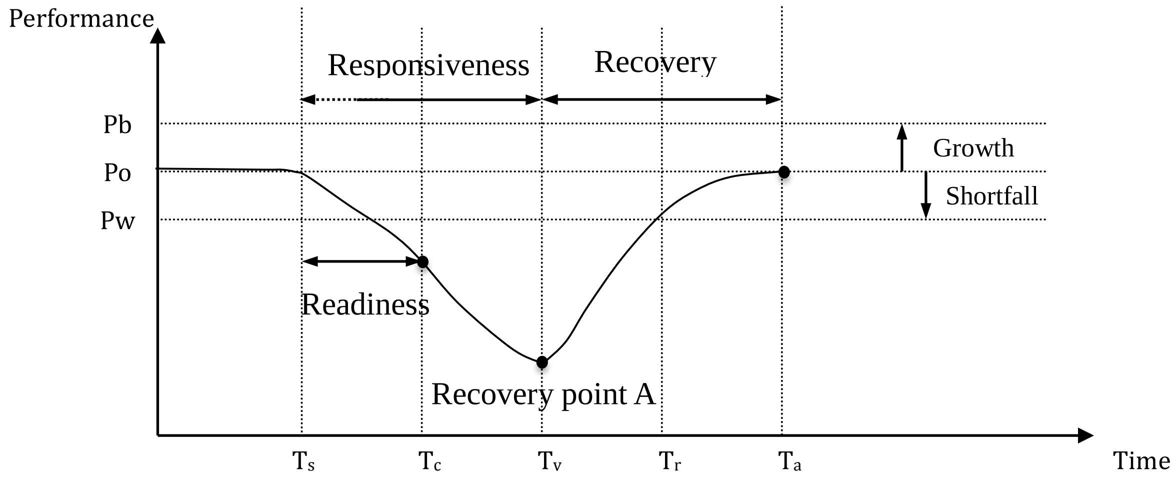

Figure 1. Visualizing resilience performance[2]

When the net inventory is negative, customer demand cannot be fulfilled. Readiness is then measured by the interval between the start of disruption and the time when stockout occurs, T_c-T_s. The later the stockout, the better the readiness to supply in case of disruption, and thus, firms would have more time to react to the crisis before the interruption of service to customers. The initial disruptive event, denoted as T_s, is designed in this study to occur at the lead supplier of the factory. The factory and its downstream partners would only learn the disruption crisis when they find their orders are not delivered on schedule. This implies that no advance alert of the disruption takes place, which is common in practice (Hendricks and Singhal, 2005; Schmidt and Raman, 2012). For the sake of comparison, we consider T_s as the time when the factory recognizes the presence of disruption. Then, the interval T_v-T_s measures the responsiveness capability of the factory, where T_v is the time when the inventory stops decreasing. For the lower tiers, the time at which these firms realize the occurrence of the supply disruption is when the shipment received at time t ($SHIPA_t$) is not equal to the quantity ordered at time t-LT ($ORATE_{t-LT}$), where LT is lead-time. Hence, the responsiveness of SCRES for the lower tiers is T_v- T($SHIPA_t \neq ORATE_{t-LT}$). The recovery phase of the resilience triangle reflects the time that the firm starts to have a persistently increasing marginal inventory at each time of stock-taking. The recovery ability of the firm is then measured as the time interval needed to return to the initial level from the bottom of the net inventory level, that is T_a-T_v.

Another indicator of SCRES performance is the impact propagation, defined as the ratio of stockout duration at an echelon to the duration of the initial disruptive event, which we set at three periods. When a stockout occurs, the firm is unable to serve its customers further; thus, we use this indicator to see how the interruption of operation propagates from upstream to

[2] Po refers to normal performance in the absence of disruption. The gap between Pb and Pw refers to the expected performance after recovery, which might be better or worse than the original performance.

downstream. Prior studies indicate that stockout at the retailer level can disturb order processing and lead to inaccurate demand forecasts that result in a cascade impact throughout the supply chain (Wu *et al.*, 2013). Furthermore, Chatfield *et al.* (2013) find that stockout propagation occurs upstream but not significantly in the downstream direction. It is not clear at this point whether an upstream disruption would pass downstream.

4. Simulation Framework

The system in our simulation model focuses on the SCRES of the retailer (k1), distributor (k2), and factory (k3). The supply chain also contains a lead supplier and faces a market in which customer demands are i.i.d from a normal distribution with a mean of 20 and a standard deviation of one. The lead supplier has "uptime" and "downtime." During the uptime, the lead supplier receives the order inquiry from the factory in time t and immediately dispatches the shipment as ordered. The shipment will be received by the factory at time t+LT. During the downtime, the lead supplier cannot fulfill any orders; thus, no shipment is able to be delivered. The downtime is the analog of real-time operation breakdown. As soon as the uptime resumes, accumulated demand from the downstream customer during downtime is fulfilled subject to the inventory level. There is no capacity constraint on the lead supplier. The lead-time (LT) of an order is fixed along a single supply chain. We assume no ordering information delay in an attempt to reflect modern information flows. During the uptime, a set of sequential activities takes place in every echelon within each time frame: (i) the replenishment order decision is made considering the demand forecast and inventory adjustment; (ii) shipment is placed LT periods before the current period t (t-LT); (iii) new demand from downstream customers arrives and is placed in the current period, t; (iv) customer demand is fulfilled from the inventory on-hand. Items are backordered in the case of a stockout.

Discrete Events System Dynamics Model

We adopt the system dynamics modeling approach, which originated from the model of industrial dynamics proposed by Forrester (Forrester, 1968) and is explicitly recommended by Tang and Musa (2011) to study the compound effects of risk disruption from the perspective of the entire system. We then follow the principle of Automatic Pipeline, Inventory, and Order Based Production Control System (APIOBPCS), which has been used to replicate many well-known production inventory systems, e.g., lean logistics (Stephen M Disney and Towill, 2003b), vendor-managed inventory (VMI) control system, and electronic data transmission (EDT) system (Stephen M Disney and Towill, 2003a; White and Censlive, 2015), and various inventory controlled policies (Dejonckheere *et al.*, 2003; Hoberg *et al.*, 2007; White and Censlive, 2015) or even closed-loop supply chains (Zhou *et al.*, 2016). Figure 2 depicts the causal relationship diagram of our modified APIOBPCS model, which is equipped with the setting of optimal target safety stock following the order-up-to (OUT) policy. Table 1 summarizes the relevant notations, equations, and parameter settings.

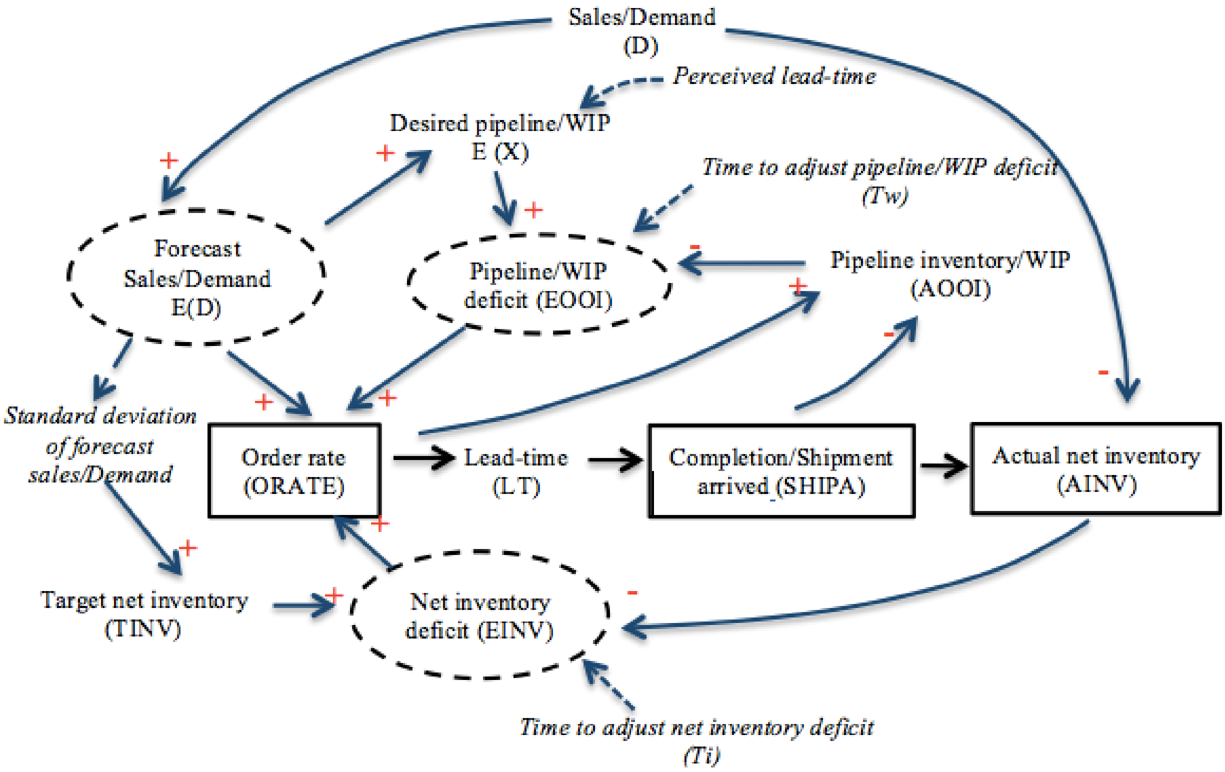

Figure 2. APIOBPCS model causal relationship

Source: Simon et al. (1994)

The decision rules within the system are as follows: the order quantity (ORATE) is computed as the sum of the three information flows including a fraction ($1/T_i$) of inventory error (EINV), a fraction ($1/T_w$) of on-order inventory error (EOOI), and the forecast demand with exponential weighted average (E(D)). The inventory error (EINV) represents the discrepancy between the target net inventory (TINV) and the actual net inventory (AINV). The on-order inventory error (EOOI) is the discrepancy between the mean demand during lead-time (E(X)) and the actual on-order inventory (AOOI). The portion of net inventory error and pipeline inventory information takes into consideration the ordering amount that can be leveraged by the multipliers $1/T_i$ and $1/T_w$ set to 0.3 in this research[3]. The target inventory (TINV) level is programmed to satisfy a desired customer service level of 98.5%.

[3] A test of this ratio shows stable system performance. For a comprehensive review, please refer to Disney, S. M. and Towill, D. R. (2005) 'Eliminating drift in inventory and order based production control systems', *International Journal of Production Economics*, 93, pp. 331-344.

Table 1. System dynamics simulation parameter settings

Symbol	Notation	Equation/Description
D	Customer consumption	$D \sim \mathcal{N}(\mu_D, \sigma_D^2)$ Initial setting: μ_D= 20, σ_D^2= 1
LT	Replenishment lead-time	Initial setting: 1, 2, 4, and 5 time units
E (D)	Demand forecast	$E(D_t) = (1 - \frac{1}{w_{t,\lambda}})\overline{D}_{t-1,\lambda} + (\frac{1}{w_{t,\lambda}})D_t$, where λ equals to 0.3
EINV	Error in inventory	$EINV_t = TINV_t - AINV_t$
TINV	Target net inventory position	$TINV_t^{k=1} = z \times \sqrt{LT+1} \times \left\lvert \sigma_{E(D)} \right\rvert$ $TINV_t^{k=2,3} = z \times \sqrt{LT+1} \times \left\lvert \sigma_{E(ORATE_t^{k-1})} \right\rvert$, where z value is 2.17 according to $\mathrm{F}(z) = 0.98.5$
AINV	Actual net inventory position	$AINV_t = AINV_{t-1} + SHIPA_t - D_t$
SHIPA	Shipment arrival	$SHIPA_t^{k=1,2} = MIN\left[ORATE_{t-LT}^{k=1,2}, A\right]$ $Let\ A = AINV_{t-LT-1}^{k+1} + SHIPA_{t-LT}^{k+1},$ $A = \begin{cases} AINV_{t-LT-1}^{k+1} + SHIPA_{t-LT}^{k+1} & if\ AINV_{t-LT-1}^{k+1} + SHIPA_{t-LT}^{k+1} > 0 \\ 0 & if\ AINV_{t-LT-1}^{k+1} + SHIPA_{t-LT}^{k+1} \leq 0 \end{cases}$ $SHIPA_t^{k=3} = \begin{cases} 0 & if\ 100 \leq t \leq 102\ (disruption\ period) \\ ORATE_{t-LT}^{k=3} & if\ t < 100\ or\ t > 102 \end{cases}$
CBS	Conditional backup supply	$CBS_{t+1}^{k=1,2} = \begin{cases} 10 & if\ SHIPA_t^{k=1,2} SHIPA_t = 0 \cap SHIPA_{t-1}^{k=1,2} SHIPA_{t-1} = 0 \\ 0 & else \end{cases}$
EOOI	Error in on-order inventory	$EOOI_t = E(X_t) - AOOI_t$
E(X)	Mean demand during lead-time	$E(X_t) = \mathrm{E}(D_t) \times \overline{LT}$
AOOI	Actual on-order inventory	$AOOI_t = \int (ORATE_t - SHIPA_t)dt$
ORATE	Replenishment ordering amount	$ORATE_t = \mathrm{E}(\mathrm{D}_t) + \frac{1}{T_i}(EINV_{t-1}) + \frac{1}{T_w}(EOOI_{t-1})$

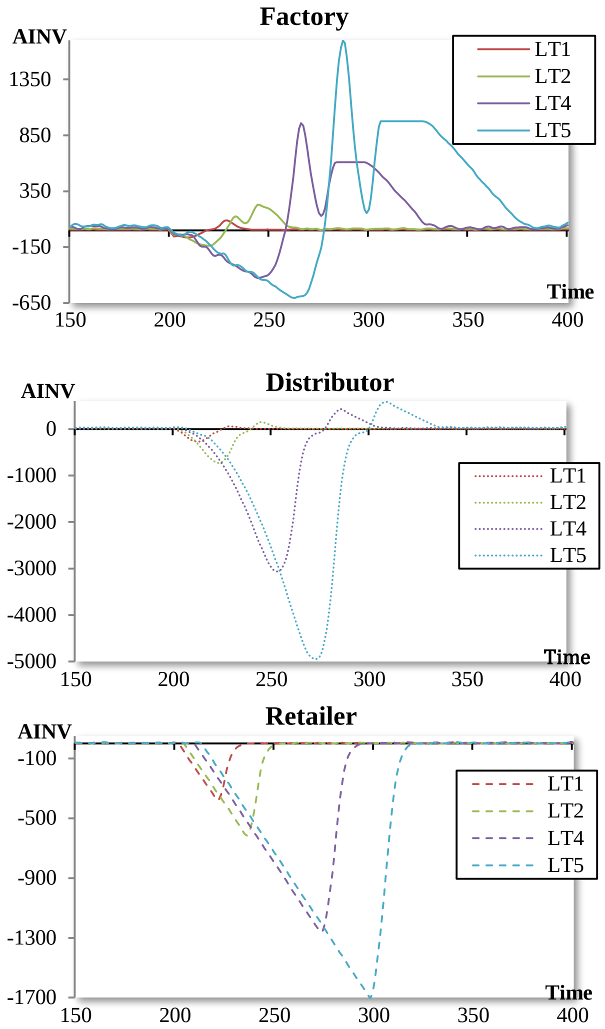

Figure 3. The AINV movement of different suppliers with various lead-times

Table 2. SCRES performance regarding 3Rs with various lead-times

	LT1	LT2	LT4	LT5
Readiness				
k1	2	5	10	13
k2	1	3	6	8
k3	0	0	1	2
Responsiveness				
k1	19	31	63	84
k2	11	21	48	68
k3	9	20	44	68
Recovery				
k1	22	25	34	36
k2	34	43	59	70
k3	33	46	91	114

k1:retailer; k2:distributor; k3:factory

The structures of the three supply echelons share the same configuration, except for the SHIPA at the factory, and distributor and retailer level. The consumption demand of the distributor and factory is assumed to be equivalent to the order quantity (ORATE) at of the retailer and distributor, respectively. The total simulation time is 500 periods and the disruption is scheduled to take place between time 200 and time 202.

We first analyze the resilience performance of the three echelons in various lead-time supply chains without an ORATE capacity constraint and contingency backup supply as the basic model using four lead-times with two short (1 and 2 periods) and two long (4 and 5 periods) periods. We then simulate the model with the ORATE constraint and the embedded backup supply and compare it to the baseline model.

Table 3. SCRES performance in terms of impact propagation with various lead-times

		Factory	Distributor	Retailer
LT1	Stockout duration	19	24	35
	Impact propagation rate	6.33	8.00	11.67
LT2	Stockout duration	29	37	54
	Impact propagation rate	9.67	12.33	18.00
LT4	Stockout duration	58	71	84
	Impact propagation rate	19.33	23.67	28.00
LT5	Stockout duration	77	93	107
	Impact propagation rate	25.67	31.00	35.67

5. Results and Discussion

Evaluating SCRES Performance on 3Rs

Figure 3 shows the AINV of each supply echelon over time given a variety of lead-times. Please note that the simulation model is designed as a purely discrete system, but appears continuous due to the scaling of the figures. Before the start of the disruption at period 200, the firms' AINV is stable. Changes afterward are noticeable. First, the net inventory fluctuates over a long period, much longer than the initial downtime periods. It drops soon below zero as the disruption occurs, then rises and becomes positive before resuming the normal level for all echelons. Second, the fluctuation over the positive inventory level reduces as we move down the supply chain. Third, the effect aggravates in the cases of longer lead-time.

We further examine the detailed SCRES performance in terms of readiness, responsiveness, and recovery (3Rs) in Table 2. We observe a positive relationship of replenishment lead-time and readiness to an unanticipated event in all echelons, in particular for distributor and retailer. The larger forecast error and variance resulting from the extension of lead-time leads suppliers to raise their safety stock level (Song, 1994; Song *et al.*, 2010). Consequently, the abundant inventory then serves as a buffer and enables the firm to improve readiness to manage a supply disruption. One could see that improved readiness in lower echelons stems from the accumulated buffering effect from all stocks in prior echelons.

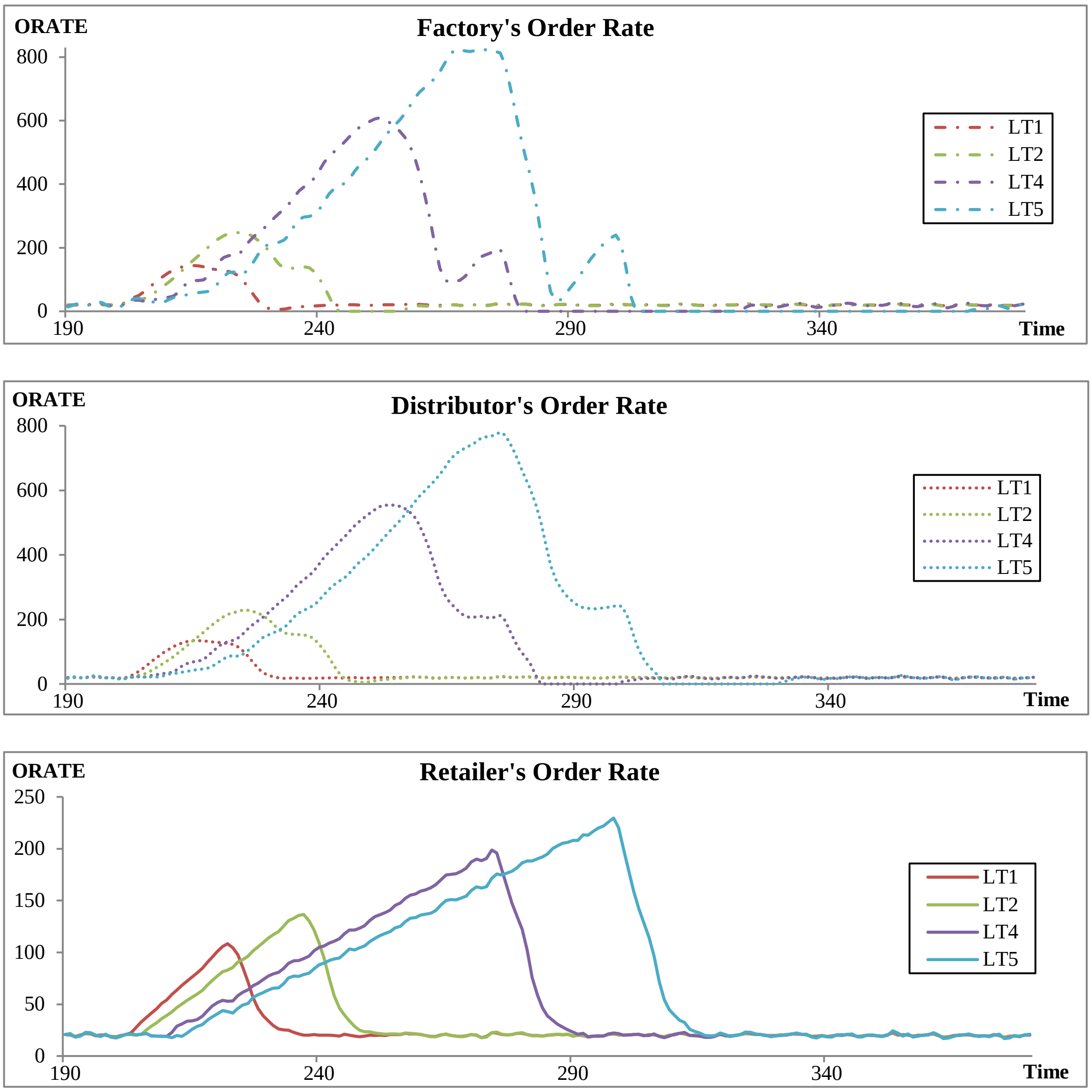

Figure 4. The ORATE movements of a 3-tier supply chain with various lead-times

Regarding firms' performance in responsiveness and SCRES recovery, the results show completely opposing patterns across stratifications. It takes shorter periods to stop plunging, but a longer time to resume the normal state when one moves upstream. This trend is persistent and amplified when lead-time gets longer. This phenomenon is likely due to the bullwhip effect, as the disruption causes an imbalance between supply and demand due to the variations in demand fluctuations across echelons. The upstream supply disruption triggers order changes downstream, as such the demand fluctuations may build up the supply chain. In the early stage in which there is insufficient supply, upstream firms benefit from the inflated demand forecast so a higher ordering quantity allows them to close the gap between supply and demand more quickly. However, the inflated demand hurts the firms in the later stage as they begin to hold excessive inventory. Since the demand oscillation is higher when moving up the supply chain, upstream firms require a longer time to reach the stable and normal state. The information that firms receive becomes a pitfall; therefore, overall analysis and planning become critical to the firms' SCRES performance. The issue we observe here provides support to Braunscheidel and Suresh's (2009) and Brusset and Teller's (2017) findings about the effect of inter-organizational integration on resilience. If firms do not cooperate closely with suppliers and customers, the imbalance between supply and demand becomes a serious issue when disruption occurs.

Table 4. The peak value and variance of ORATE under supply disruption

	Supply Echelon	LT1	LT2	LT4	LT5
ORATE Peak Value	k1	108	137	199	229
	k2	135	230	555	780
	k3	144	248	608	826
Order Variance	k1	880	1565	3518	4771
	k2	2213	6104	33599	62874
	k3	2737	7455	38465	69450

Moving on to impact propagation, the stock out duration expands as we move downstream, regardless the length of the lead-time, as shown in Table 3, which is likely due to the fact that operations in the lower echelons hinges on their prior echelons' supply. Furthermore, the impact propagation (rate) is positively correlated with the replenishment lead-time length. This is contrary to the result in Chatfield *et al.* (2013). This has great implications on the supply chain, particularly for lower echelons with longer lead times because they are not able to serve the customers for a longer time. This phenomenon reflects the importance of the information sharing between echelons (Brandon-Jones et al., 2014; Dubey et al., 2017). This is because the visibility of inventory and demand could be greater for downstream firms who suffer from insufficient supply; this, in turn, compels them to take actions sooner to deal with the disruption.

Changes in the Order Rate after Supply Disruption

To verify the potential bullwhip effect triggered by the disruption, we examine the ordering, as Figure 4 represents visually, after a supply disruption. We construct the peak values and order variance to address dynamic orders across time, as in Table 4. We find that (1) the order rate peaks are not only positively related to the increment of lead-time, but also to the increment of supply chain stratification; (2) both the replenishment lead-time and the supply chain stratification are positively and highly associated with order variance in the presence of a supply disruption. These results are quite similar to findings for the bullwhip effect across tiers such as (Chen *et al.*, 2000). Longer lead-times could prevent firms from determining accurate demand information earlier (De Treville *et al.*, 2004; Finke *et al.*, 2012), thus amplifying the bullwhip effect stemming from the disruption.

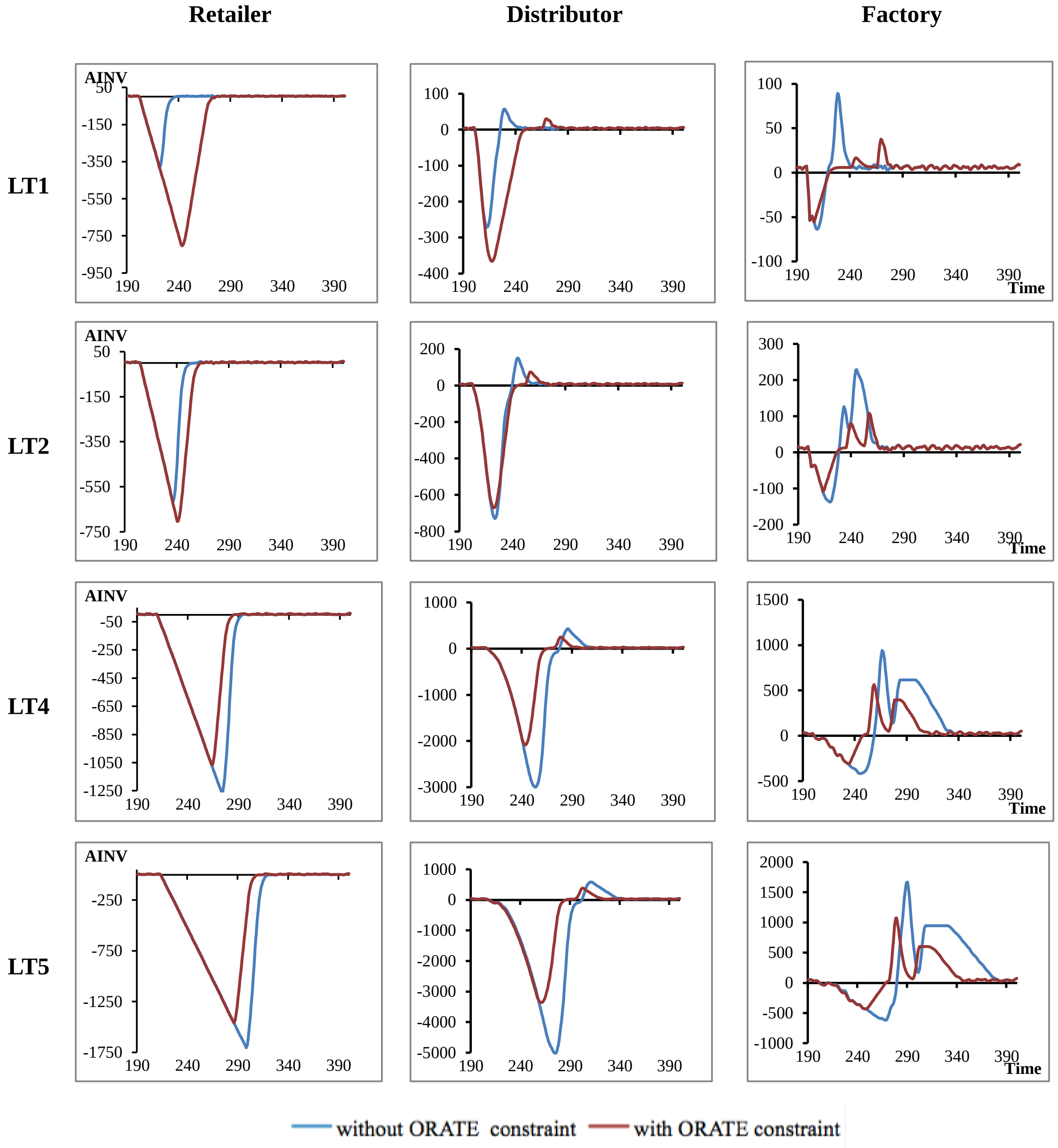

Figure 5. Comparison of constrained and unconstrained ORATE

Table 5. Change rate of various indices after constraining ORATE

	Change Rate	LT1	LT2	LT4	LT5
on Readiness	Retailer	100%	100%	100%	100%
	Distributor	100%	100%	100%	100%
	Factory	100%	100%	100%	100%
on Responsiveness	Retailer	221.05%	112.90%	85.71%	86.90%
	Distributor	145.45%	95.24%	79.17%	79.41%
	Factory	66.67%	65.00%	77.27%	69.12%
on Recovery	Retailer	172.73%	108.00%	82.35%	83.33%
	Distributor	205.88%	123.26%	94.92%	90.00%
	Factory	224.24%	123.91%	85.71%	85.96%
on Impact Propagation	Retailer	211.43%	107.41%	89.29%	95.33%
	Distributor	200.00%	113.51%	83.10%	83.87%
	Factory	110.53%	93.10%	81.03%	87.01%

Note: 3R compared with the baseline in Table 2; propagation is compared with its counterpart in Table 3.

Effect of Order Amplification on SCRES Performance

In the prior section, we showed that an unexpected supply disruption would boost the order rate and order variance at a rate increasing with replenishment lead-time. An immediate question arises: would the order amplification caused by lead-times be the mediator that drives SCRES performance? To answer this question, we limit ORATE to 50% of ORATE peaks in Table 4, and compare the results with the no-limit baseline model Tables 2 and 3. We consider this setting as closer to reality since there is a high probability that suppliers cannot meet the suddenly increased order requirements. Figure 5 and Table 5 show that after constraining ORATE, the net inventory takes more time to resume stability for all supply partners in LT1 and LT2, mostly due to the slow pace of recovery. In a low lead-time environment, firms can handle the disruption quickly when ORATE is not constrained because the demand information does not differ too much across echelons (see the ORATE peak in Table 4), so the supply and demand at each echelon are more likely to maintain a balance. In contrast, when the ORATE is constrained, the delayed demand later turns into demand uncertainty, which reduces the accuracy of demand predictions and aggravates the inventory shortage. As the lead-time increases to 4 and 5 time periods (LT4 and LT5), the ORATE across echelons starts to deviate, which breaks the supply-demand balance. The constrained ORATE helps to stabilize inventory performance, while the SCRES performance in terms of responsiveness and recovery improve for all supply partners since constraining ORATE reduces the off-balance supply and demand, and thus the inventory instability level. A moderate constraint on ORATE when under a relatively long lead-time suppresses both the amplification and fluctuation of ORATE, resulting in improved resilience performance in terms of response effectiveness and recovery speed, while a constraint on ORATE might be detrimental to firms' resilience under short lead-times. The simulation results implicitly demonstrate the importance of demand-side stability on building SCRES, while other relevant works such as Colicchia *et al.* (2010) focus more on exploring supply-side stability in forming SCRES.

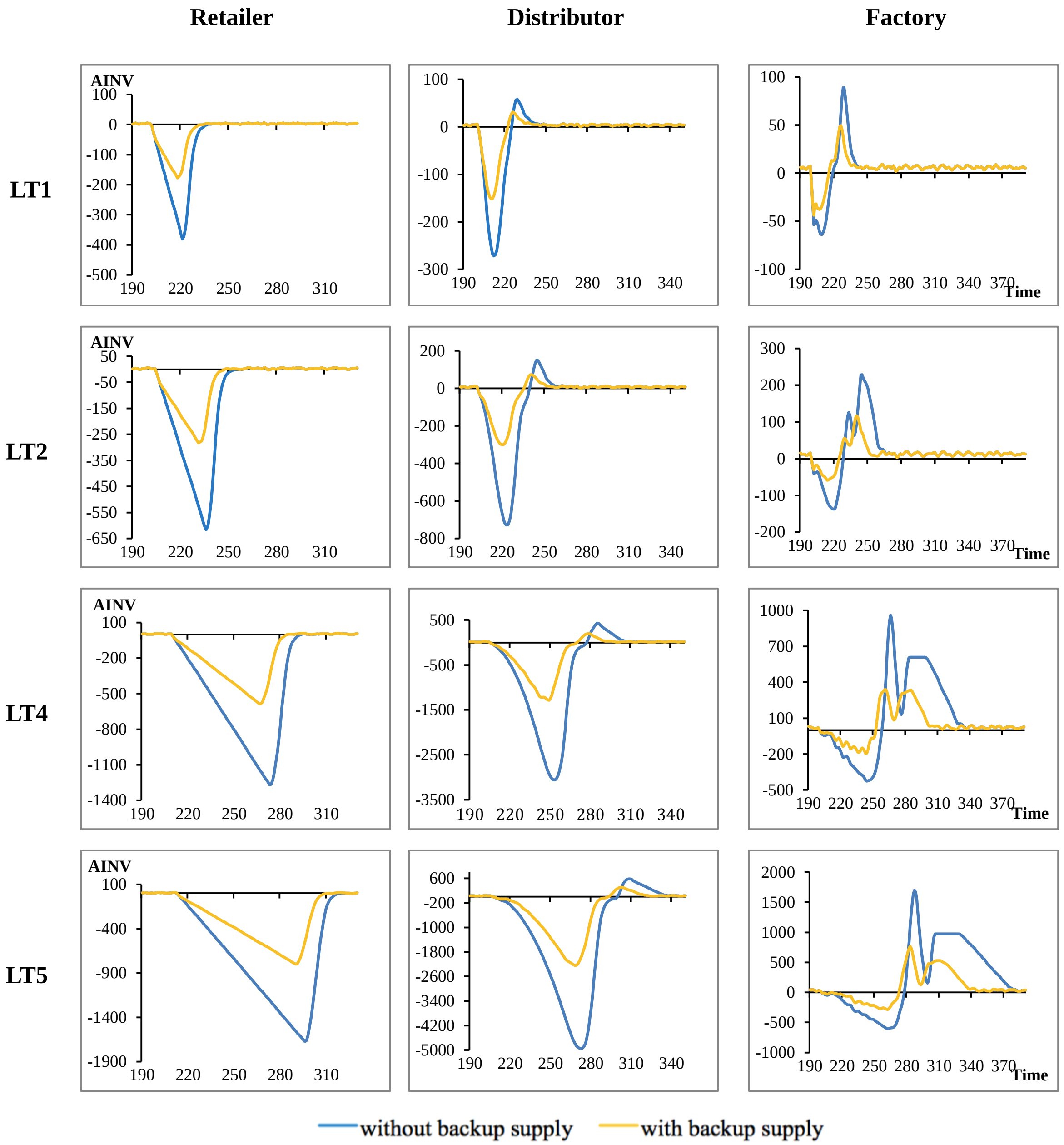

Figure 6. Comparison of performance between having and not having a backup supply

Table 6. Change rate of various indices after adding a backup supply

	Change Rate	LT1	LT2	LT4	LT5
on Readiness	Retailer	100.0%	100.0%	100.0%	100.0%
	Distributor	100.0%	150.0%	100.0%	114.3%
	Factory	100.0%	100.0%	100.0%	100.0%
on Responsiveness	Retailer	84.2%	83.9%	90.5%	92.8%
	Distributor	81.8%	85.7%	91.7%	93.8%
	Factory	22.2%	70.0%	97.7%	100.0%
on Recovery	Retailer	81.8%	72.0%	74.2%	76.5%
	Distributor	92.1%	85.7%	84.7%	76.7%
	Factory	100.0%	82.6%	75.8%	69.2%
on Impact Propagation	Retailer	94.3%	79.6%	89.3%	96.2%
	Distributor	91.7%	89.2%	90.3%	92.4%
	Factory	84.2%	86.2%	89.7%	93.5%

Note: 3R is compared with the baseline in Table 2; propagation is compared with its counterpart in Table 3.

Influence of Replenishment Lead-time on Contingency Plan Effectiveness

A backup supply can mitigate a supply disruption. To learn more about how replenishment lead-time affects SCRES performance, we examine the influence of lead-time on the effectiveness of the backup supply; that is, we compare the SCRES performance for a supply chain with a fixed 10 units of backup supply available after two consecutive periods without receiving any shipment as a contingency plan for all suppliers, thus immediately reacting to a sudden short supply, with the baseline supply chain. The simulation result in Figure 6 and Table 6 clearly shows the inventory movements with backup supply fluctuate less and recover to the initial states sooner than those without a backup supply. Our systematic simulations are consistent with the proposition derived from resource-based theory that more resources prove more beneficial in ensuring firms' recovery from the impact of disruption (Braunscheidel and Suresh, 2009; Brandon-Jones et al., 2014; Dubey et al., 2017). More importantly, Ambulkar et al.'s (2015) *resource reconfiguration* may work better in the case of longer lead time because the disruption spreads faster in such an environment and causes damage; in contrast, their *risk management infrastructure* would prove adequate in the case of shorter lead time because the disruption causes less damage to firms.

6. Conclusions

In this paper, we attempt to analyze the impact of the order replenishment lead-time on firms' supply chain resilience in terms of disruption readiness, response effectiveness, and recovery speed. We investigate the dynamic performance of inventory control system by adopting an APIOBPCS model in a three-echelon supply chain under the scenario of a disruptive event that causes a three-period shipping failure to the factory. The study yields some valuable results: (1) The supply lead-time length affects the severity of the supply disruption impact in multiple aspects, that is, a longer supply lead-time creates more time before the full interruption of customer service and requires more time to stop the deterioration and resume the pre-disruption state; (2) Lead-time could be one of the drivers of impact propagation since demand uncertainty is amplified, which disrupts the balance between supply and demand; (3) Under a supply disruption, the order rate peak and order variance increase as one moves up the supply chain, and lead-time amplifies the effect; (4) Order amplification aggravates supply chain recovery performance; thus, constraining the order rate limit reduces the disruption impact under long lead-times, while it is detrimental to firms' resilience under relatively short lead-times; and (5) Backup supply is effective in all lead-time conditions.

Our findings show that firms need to pay attention to the systematic characteristics of the supply chain, for example, lead-time, since they play a role in determining firms' resilience performance. Two useful practices that firms could adopt to reduce the negative impact on firms' resilience due to lead-time variance are moderate ordering constraint and holding a backup supply. However, when firms are able to balance supply and demand such as in the case of low lead-times, constraining orders has an adverse effect.

Our results provide support for Colicchia *et al.'s* (2010) statement that supply lead-time is a vulnerabilities for resilient supply chains. The research findings are also congruent with results of Basole and Bellamy (2014) showing that shorter average distances between supply nodes and higher clustering worsen the risk diffusion rate and bring about a faster recovery speed. This study makes two contributions to the SCRES literature. First, it offers a major contribution to our understanding of the temporal effect of order replenishment on resilience performance in a multi-echelon supply chain. Second, it sheds light on how firms should prepare for the impact of unexpected disruptions in industries with different replenishment lead-times. The bullwhip effect seems to deteriorate when lead time increases; from the point of view of resource-based theory, firms would need to build up internal and external resources to deal with the disruption. Moreover, a closer relationship and greater cooperation might be necessary, along with higher network distance that prior literature has suggested.

This study attempts to show how firms' resilience performance in event readiness, response speed, recovery rate, and impact propagation would vary by structural supply attributes, where we primarily discuss lead-time in this paper. However, we do not specify the optimal length of the supply lead-time in confronting disruptions. Our research is limited to simulated control systems adopting an order-up-to inventory policy. Considering human behavioral factors in SCRM research may improve the robustness of the results since the decision maker can be seen as a risk source that affects the outcome of risk management (Rao and Goldsby, 2009). Overlooking this issue may prevent a full understanding of effective approaches to create resiliency in the event of unforeseen disruptions (Ghadge *et al.*, 2012; Tukamuhabwa *et al.*, 2015). Hence, future research can include a decision maker risk perspective and behavioral experiments to describe the real supply chain ecosystem under supply uncertainty and demand risk further. Another potential research direction could extend the linear supply chain context to a complex supply chain network with more players in each tier in the supply chain.

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