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# Supply chain risk and resilience: theory building through structured experiments and simulation

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The research literature of supply chain risk and resilience is at a critical developmental stage. Studies have established the importance of these topics both to researchers and practitioners. They also have identified factors contributing to risk, the impact of risk and disruptions on performance, and the strategies and tactics used to build the capacity for supply chain resilience. Although these efforts can provide support for constructing a theory of risk and resilience, researchers are currently restricted in their ability to build such a theory by the difficulty of collecting the necessary data. This paper contributes to this literature development effort by summarising prior research reviews and developing a three-component framework aimed at helping researchers to build better theories. This is accomplished through combining structured experimental design with discrete-event simulations of supply chains. The result is a methodology that allows researchers to develop better understanding of the factors that link a disruption to its impact on supply chain performance through both direct and interaction effects. Following the methodology development, the paper concludes with an example using the factors of shock interarrival time, supply chain connectivity and buffer stocks to illustrate the potential for contributing to the theory-building process.

**Keywords:** supply chain risk; supply chain disruption; resilience; theory-building; discrete-event simulation



## 1. Introduction

The supply chain shock that began on Friday, 17 March 2000 at the Philips plant in Albuquerque, New Mexico, impacted cell phone production for both Nokia and Ericsson (Latour 2001) and brought awareness to managers and researchers alike of the strategic and operational impacts of supply chain risks and disruptions. Lightning struck the facility and started a small fire. The resultant smoke damage to sensitive microchips and machines halted production. While Philips notified two of their key customers in Nokia and Ericsson, the former proactively reserved slack capacity in Philips plants worldwide, while the latter decided to wait and see when the microchips might become available. By the time the delay was specified, it was too late as Ericsson was not able to procure microchips for their phone production and was forced to merge with Sony.

In the nearly two decades since this event, researchers have come to recognise that supply chain shocks – a major element of supply chain risk – can significantly and adversely affect firms' performance operationally, financially and strategically (e.g. Blackhurst et al. 2005; Hendricks and Singhal 2005a, 2005b; Tang 2006; Craighead et al. 2007; Wagner and Bode 2008; Stecke and Kumar 2009; Ambulkar, Blackhurst, and Grawe 2015). Consequently, organisations and their supply chains need to develop resilience if they are to survive such events (e.g. Rice and Caniato 2003; Christopher and Peck 2004; Sheffi 2005; Pettit, Fiksel, and Croxton 2010; Blackhurst, Dunn, and Craighead 2011; Pettit, Croxton, and Fiksel 2013; Mari, Lee, and Memon 2014; Melnyk, Zobel et al. 2014; Matsuo 2015; Schmidt 2015).

With this in mind, researchers have identified a number of factors that influence the relationships between supply chain risk, disruptions, resilience and performance. Recent literature review articles (e.g. Tang 2006; Rao and Goldsby 2009; Tang and Musa 2011; Colicchia and Strozzi 2012; Sodhi, Son, and Tang 2012; Heckmann, Comes, and Nickel 2015; Ho et al. 2015; Rangel, de Oliveira, and Alexandre 2015) provide support for creating better classification schemes and thus, an improved understanding of the issues associated with the study of supply chain risk and resilience. From a theory-building perspective (Handfield and Melnyk 1998), the development of such classification schemes is consistent with the third stage in the theory-building process – mapping, which includes identifying and describing key

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attributes and variables associated with the concepts of interest. However, more work is required if this field is to further explore the subsequent stage in this process – characterising relationships, hypothesis testing and theory extension/refinement. We as researchers would benefit from some structure around the current state of research, which is one contribution of this paper.

Pursuing these latter stages of theory building is challenging for a couple of reasons. First, empirical analysis is typically restricted to what has been observed; unobserved combinations of factors cannot be evaluated. Second, the data generated by these empirical methods are often confounded by factors such as human intervention: not every incident involving risk and disruption is reported, and those that are reported may suffer from incomplete information. Consequently, a different approach to collecting and analysing data is needed. This paper proposes such an alternative approach.

Specifically, this paper employs structured experimentation to assess the integrated link between theoretical frameworks using computer simulation experiments. The experiment is structured such that the levels used in the experimental factors (needed to introduce variance in the independent variable) are anchored in the theoretical framework. By running experiments, we can draw conclusions that reflect on the theoretical frameworks and then enable us, as results, to refine the theoretical foundations and improve resilience for firms.

The approach starts with a framework developed in this paper that characterises supply chain risk, resilience and performance (and the relationship between these three concepts) into three major components: (1) supply chain shocks (and the factors contributing to these disruptions); (2) the supply chain ecosystem (the major elements of the supply chain that influence how the disruption passes from the source through the supply chain to the firm); and, (3) resilience-related investments (various policies and/or investments that the firm can make with the goal of reducing the onset of the disruption or increasing system resilience). The data to perform the analysis for this process of structured experimentation are generated by discrete-event computer simulation, a technique with a long history in operations management and supply chain management research (e.g. Lee et al. 2002; Venkateswaran and Son 2004; Van der Zee and van der Vorst 2005; Manuj, Mentzer, and Bowers 2009; Carvalho et al. 2012), and disruption research more recently (Yang, Pan, and Ballot 2017).

Data are analysed with the goal of understanding how the resultant outcomes impact system performance (resilience) either directly (through main effects) or indirectly (through interactions). The ability to study interactions in a disruption context has been identified as critical and the next research step that needs to take place, as Mizgier (2017) showed when his model output could not be attributed to just the main effect. The results and analysis can be then interpreted in terms of their implications for the theoretical framework and to develop better insights into how events occur – a shortcoming of previous research.

This approach is used because it integrates theory (and theory building), data collection, analysis and validation/refinement into a unified approach. The simulation model and the factors that drive its operation are motivated by theory, which allows the researcher to assess the theoretical framework and its operation. The analysis provides a mechanism for revising and extending the existing theoretical framework. Since the goal is theory building, this approach is consistent with the objective and effectively operationalises it. In particular, by joining a theoretical framework with simulation, researchers are no longer limited to studying actual supply chain disruptions. They may freely experiment with and explore alternative combinations of disruptions and resilience-inducing investments, without worrying about confounding factors.

In summary, the objectives and contributions of this research are to (1) clarify existing work through development of a three-component framework to facilitate the creation of a theory of supply chain risk, resilience and performance, (2) introduce an empirical approach for analysing the measure of resilience and (3) present and concisely demonstrate a simulation method that utilises the framework to encourage structured experimentation towards the goal of building theory. The paper begins by looking at existing characterisations of the study of supply chain risk and resilience. This is followed by a brief look at theory building and a presentation of the framework upon which the structured experimentation is built. Following a discussion of simulation and the operationalisation of the overall approach for theory building, the paper concludes by offering the reader an illustrative example of how the resulting framework and research methodology can be used to generate potentially useful insights.

## 2. Supply chain risk, resilience and performance: building the foundations

One indication of ongoing research interest in supply chain risk and resilience is the presence of literature reviews carried out by researchers such as Tang (2006), Rao and Goldsby (2009), Tang and Musa (2011), Colicchia and Strozzi (2012), Sodhi, Son, and Tang (2012), Ho et al. (2015), Rangel, de Oliveira, and Alexandre (2015) and Heckmann, Comes, and Nickel (2015). As noted by Seuring et al. (2005), such literature reviews are useful because they summarise the existing state of the literature, report the main theories and issues underlying that literature, and identify the current state, along with limitations, of theory-building activities.

Table 1 provides a summary of various literature review/overview articles on supply chain risk. This table reveals that (1) the concepts of supply chain risk and resilience are complex and evolving, and can affect the supply chain both

Table 1. Literature reviews assessed for framework factors.

| Citation | Main framework factors | Levels | Comments |
|---|---|---|---|
| Tang (2006) | Supply management | Supply network design<br>Supplier relationship<br>Supplier selection process<br>Supplier order allocation<br>Supply contract | One of the first attempts to organise into a framework the literature dealing with supply chain risks |
| | Product management | Postponement (make to order without forecast updating)<br>Postponement (make to stock without forecast updating)<br>Postponement (make to stock with forecast updating)<br>Process sequencing | |
| | Information management | Managing products with short life cycles<br>Managing products with long life cycles<br>Managing product with long life cycles (information sharing)<br>Managing products with long life cycles (vendor managed inventory)<br>Managing products with long life cycles (collaborative forecasting) | |
| | Demand management | Shifting demand across time<br>Shifting demand across markets<br>Shifting demand across products | |
| | Supply chain risk | Strategic<br>Tactical | |
| Rao and Goldsby (2009) | Overall risk | Environmental factors<br>Industry factors<br>Organisational factors<br>Problem-specific factors<br>Decision-maker factors | Merged macro (organisational level issues) with behavioural issues<br><br>Focused primarily on risk, rather than also including how to manage supply chain risk |
| | Environmental risk | Political uncertainty<br>Policy uncertainty<br>Macroeconomic uncertainty<br>Social uncertainty<br>Natural uncertainty | |
| | Industry risk | Input market uncertainty<br>Product market uncertainty<br>Competitive uncertainty | |
| | Organisational risk | Operating uncertainty<br>Credit uncertainty<br>Liability uncertainty<br>Agency uncertainty | |
| | Problem specific risk | Risk interrelationship<br>Objectives and constraints<br>Task complexity | |
| | Decision-maker risk | Knowledge/Skill/Biases<br>Information seeking<br>Rules and procedures<br>Bounded rationality | |

(*Continued*)

Table 1. (*Continued*).

| Citation | Main framework factors | Levels | Comments |
|---|---|---|---|
| Tang and Musa (2011) | Material flow risk source | Single sourcing risk<br>Sourcing flexibility risk<br>Supply product monitoring/quality<br>Supply capacity<br>Supplier selection/outsourcing | Work strongly influenced by SCOR model |
| | Make | Product and process design risk<br>Production capacity risk<br>Operational disruption | |
| | Deliver | Demand volatility/seasonality<br>Balance of unmet demand and excess inventory. | |
| | Supply chain scope | Logistics<br>Price volatility of commodity/ alternative energy<br>Environment degradation and awareness<br>Cultural and ethics<br>Supply chain partners relationship | |
| | Financial flow risk | Exchange rate risk<br>Price and cost risk<br>Financial strength of supply chain partners<br>Financial handling and practice | |
| | Information flow risk | Information accuracy<br>Information system security and disruption | |
| | Intellectual property | Information outsourcing | |
| Sodhi et al. (2012) | Gaps | Closing the definition gap<br>Closing the process gap<br>Closing the methodology gap | Focus here on identifying research gaps<br>Data gathered from participants to the 2009 INFORMS Conference |
| Colicchia and Strozzi (2012) | Complexity and uncertainty | Uncertainty as a threat<br>Supply chain as a complex evolving system | Focus on distilling research to a limited number of key themes or directions for future research |
| | Process and tools for supply chain risk management | Disruption risk management | |
| | Organisation of supply chain risk management | Proactive approach<br>Focus on supply chain network | |
| | Increased supply chain resilience and robustness | Practitioner point of view<br>Focus on efficiency. | |
| Ho et al. (2015) | Demand risk factors<br>Manufacturing risk factors<br>Supply risk factors | | Focus on supply chain risk factors<br>Classification according to whether we are dealing with macro or micro level factors |
| | Infrastructural risk factors | Information risk factors<br>Transportation risk factors<br>Financial risk factors | |
| Heckmann et al. (2015) | Core characteristics of supply chain risk | Objective-driven risk<br>Risk exposition (Disruptive triggers, Affected supply chain, Time-based characteristics)<br>Risk attitude | Focuses on identifying core characteristics that can be used to define, quantify, model risk |
| | Risk measures | | |
| | Risk-aware supply chain optimization | Modelling approaches<br>Solution techniques | |

(*Continued*)

Table 1. (*Continued*).

| Citation | Main framework factors | Levels | Comments |
|---|---|---|---|
| Rangel et al. (2015) | Clusters of risks | Production flow problems<br>Relationship problems<br>Competitiveness problems<br>Global problems<br>Core competencies problems<br>Problems due to lack of control over the external environment<br>Regulatory. Legal and political problems<br>Financial market problems<br>Financial capacity problems<br>Demand forecast problems<br>Supply chain inbound problems<br>Transport system problems<br>Information system problems<br>Cultural problems<br>Strategic problems<br>Production capacity problems<br>Infrastructure problems<br>Customer services problems<br>Organisational problems<br>Other problems | Categorised research into clusters of risks and then mapped these risks against which of the six SCOR processes they affected |



upstream (supply) and downstream (demand); and (2) supply chain research in this area is also evolving – moving from a focus on risk and disruptions to a focus on the sources of these disruptions and how they affect performance. Managers desire more resilient systems (Melnyk, Closs et al. 2014; Fiksel et al. 2015) in response to such factors as the disruption itself, the supply chain ecosystem (Craighead et al. 2007) and the investments that are made to manage the effects of the disruption. Such investments may include those aimed at enhancing the supply chain's flexibility (Skipper and Hanna 2009), improving information acquisition and sharing (Wakolbinger and Cruz 2011), and enabling multi-sourcing (Yu, Zeng, and Zhao 2009).

There is a great deal of disagreement over what is meant by *supply chain risk* and *supply chain resilience*, as well as how to best categorise and organise the factors associated with these concepts. One of the objectives, and contributions, of our work is to help build on, and clarify, existing work by facilitating the creation of a theory of supply chain risk, resilience and performance.

## 3. Towards a theory

Supply chain risk and resilience research needs to continue transitioning from the stages of discovery and description to those of mapping and relationship building (Handfield and Melnyk 1998) – phases essential to theory development and evaluation. While some recent disruption research has furthered that transition, especially to mapping and the identification of key variables (see Table 1) (Ivanov et al. 2016; Yang, Pan, and Ballot 2017), the research is not yet in the final stage of building relationship linkages. To that end, this study proposes a three-component framework built on prior research. The intent of the framework is to help researchers explore how supply chain shocks affect the performance of a system and to investigate how various investments in resilience, or in the characteristics/structure of the supply chain, influence performance directly or indirectly.

### 3.1 *Building a framework*

#### 3.1.1 *Supply chain shocks*

The term 'shock' is adopted as a neutral term in order to emphasise that both 'negative' and 'positive' reasons can cause supply chain disruptions, which is the first framework component. It is generally understood that the term 'risk' refers to an event that has the potential to occur, but which has not yet done so (Manuj and Mentzer 2008). When an event occurs, it becomes a disruption and is often defined as an 'unplanned and unanticipated [event] that disrupt[s] the normal flow of goods and materials within a supply chain' (Craighead et al. 2007, 132). Similarly, Hendricks and Singhal (2003) use the term 'glitch' to describe disruptive events that cause delays in production or logistics processes, and mismatches in demand and supply (Hendricks and Singhal 2014). These are inherently negative events, often involving upstream supply causes, and resulting in network interruptions. A 'positive' reason for a shock is the example of a demand spike that, while welcome from a marketing perspective, represents a significant challenge for a supply chain. 'Positive' events can result in service failures and dissatisfied consumers just as easily as 'negative' disruptions.

Once a shock has taken place, its effects propagate through the supply chain in a ripple effect (Liberatore, Scaparra, and Daskin 2012; Ivanov 2017), eventually affecting operational performance. How and when the shock impacts the supply chain's actual performance is influenced by the next two components: the supply chain ecosystem and the investments that are made to improve resilience.

### 3.1.2 *Supply chain ecosystem*

The supply chain ecosystem is the network environment within which the system operates. Shocks happen within a network, and the ecosystem of that network (structure, centrality, and density) can amplify or dampen shocks passing through the system. Ignoring this ecosystem involves two assumptions that we reject: (1) the ecosystem has no significant impact on supply chain risk and resilience; and (2) the interactions between the ecosystem and the other supply chain network components are insignificant.

The ecosystem is made up of various factors, such as physical network density, network complexity, relative position in a network and relational influence:

3.1.2.1 *Network density.* This measures the physical proximity of locations within a supply chain. Denser networks result in increased supply chain disruption severity (Craighead et al. 2007).

3.1.2.2 *Network complexity.* Consistent with Choi and Krause (2006), Craighead et al. (2007) define complexity as the sum of the nodes within the system, where the forward, backward and within-tier flows of material affect the system's response to supply chain disruptions.

3.1.2.3 *Relative network position.* Demand amplification, first observed by Forrester (1961), and popularised as the bullwhip effect by Lee, Padmanabhan, and Whang (1997), is one form of stress within a supply chain and illustrates how the relative position of facilities within the flow of the supply chain plays a role in the effect of supply chain shocks.

3.1.2.4 *Relational influence.* Relationship factors such as the members' willingness to 'take one for the team' amid difficulties, the flow of information and the willingness to be flexible for others affect how shocks may propagate through a supply chain. A network with relationships that fully pass along all experienced shocks, like superconductors do with electricity, would lead a supply chain to perpetually work through each challenge experienced by any of its members. Conversely, if the members of the supply chain contain and fully dampen all shocks then the supply chain might never experience any supply chain-wide disruption at all.

### 3.1.3 *Investments in resilience*

Confronted with supply chain shocks, firms are not passive participants. They can make investments in capabilities or activities to improve their capacity to resist, or recover quickly from, a disruption. Such investments make up the third component in the framework. However, similar to the sentiment offered by Ivanov et al. (2016), there remains a research gap in identifying optimal recovery policies for investment.

Research has described numerous investments that can be examined for their impact on supply chain shocks. For example, Chiang, Kocabasoglu-Hillmer, and Suresh (2012) explored the impact of internal integration, information sharing with suppliers, supplier development, supply flexibility, product design-related flexibility, process-related flexibility and multiple sourcing on the ability of the supply chain to deal with disruptions. Costantino et al. (2012) focused upon the ability of a supply chain to be redesigned as a tool for effectively dealing with supply chain shocks.

Despite interest in the effectiveness of such investments, the complexity of a supply chain's resulting reaction is typically unexamined. Kim and Tomlin (2013) begin to unpack supply chain shocks by considering how investments aimed at either strategic failure prevention or improving recovery capacity affect overall outcomes.

Similarly, Melnyk, Closs et al. (2014) outline multiple categories of a priori investments that the firm can draw upon to improve its ability to deal with shocks.

As an example, the Japanese tsunami of 2011 wiped out billions of dollars' worth of assets in the Japanese automotive business, but all manufacturers were not equally impacted. Nissan in particular was less affected than some of its competitors (Punter 2013). Post-shock analysis has shown that investments made by Nissan may have helped reduce the severity of the tsunami on the balance sheet. Specifically, Nissan for years had staged disaster drills to build the company's ability to deal with disruptions (Greimel 2012).

### 3.2 *Performance measurement*

Performance measurement concerns the outcome of the framework and the three components. Operational performance generally can be measured in two ways: average performance assessed over time (such as average inventory in the year of a disruption), or, as noted by Melnyk, Zobel et al. (2014) and used in this paper, time series performance data generated as the system responds to the disruption. Critical to analysing time series are the points of inflexion representing shifts in behaviour, which are influenced by the first three components in the framework.

### 3.3 *Simulation for data generation and theory building and testing*

This research uses simulation to both generate the time series data and allow control over the experimental design. Simulation has been useful in studying supply chain risk and resilience in the literature (Carvalho et al. 2012), and is well established in the Operations Management field for description and exploration (Davis, Eisenhardt, and Bingham 2007). It has been advocated as a tool for theory development (Davis, Eisenhardt, and Bingham 2007; Harrison et al. 2007; Nair, Narasimhan, and Choi 2009) and is also used in theory testing (Sterman 1985; Mosler et al. 2001; Serrano and den Hengst 2005; Groff 2007; Neufeld et al. 2010).

As noted in particular by Davis, Eisenhardt, and Bingham (2007), simulation is extremely attractive when the theoretical focus is 'longitudinal, nonlinear, or processual, or when empirical data are challenging to obtain' (481), and can reveal the impacts of interactions among multiple organisational and supply chain processes as they unfold over time (Repenning 2002). These conditions are representative of the challenges of studying supply chain shocks and resilience. For theory building to be achieved, simulation must be linked to and driven by the existing literature. It is for this reason that there is bonding between the framework presented in the preceding section and the simulation. The framework identifies the factors to be evaluated by simulation; the simulation provides the data used to evaluate and refine the framework. This interaction between theory (framework) and data provides the basis for theory building, validation and refinement.

## 4. Operationalising the approach: deploying the framework to build and test theory

The supply chain risk and resilience framework are used as the basis for an experimental design that, in turn, defines the parameters by which data are generated via the simulation runs. From a theory-building perspective, an experimental design is an operational version of the theoretical taxonomy. As noted by Chrisman, Hofer, and Boulton (1988), a taxonomy includes 'not only the classification system itself but also (a) the theory on which the classification system is built and (b) the methods employed to construct it' (415). In other words, a taxonomy does more than link independent variables to dependent variables; it also shows how independent variables can be grouped into factors and levels based on their similarities, differences, and relationships to one another. Furthermore, it ensures that any data generation done using simulation is purposeful – building towards a better theory and understanding.

As discussed, these components interact with each other and impact supply chain performance. To show how these components act and interact with one another, we provide Figure 1. Using the controlled experimentation of simulation, we have the ability to assess various factors, levels and inputs and their dynamic impact upon the outcome. The figure also highlights the fact that the shock event is the impetus for then assessing the possible moderating effect of the other core components.

### 4.1 *Operationalising the framework: shocks, ecosystem, investments, performance*

The supply chain shock is used to initiate the entire sequence of cascading impacts. In the literature review section, we saw that there was a large-scale attempt to understand the source of such a shock; for example, whether it was considered to be financial, political or environmental. From the perspective of our proposed approach, however, such concerns,

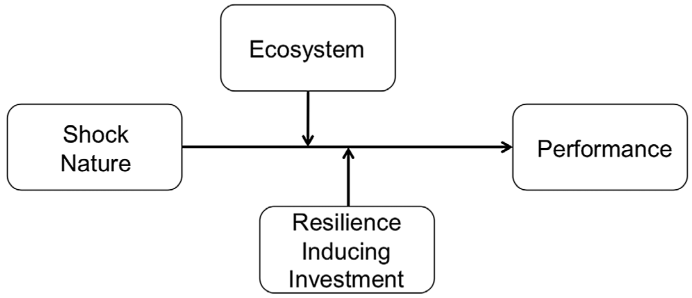


Figure 1. Supply chain shocks framework.

while important, are secondary to understanding the effect of the attributes that characterise the shock and influence its performance. These confounding factors are, therefore, controlled in the simulation. Examples of such attributes are:

- The length of the shock (number of time periods over which the shock manifests itself);
- The magnitude of the shock (size of the initial negative impact, and the extent to which the shock subsequently reduces supply chain performance over time);
- The shape of the shock (way in which the shock manifests itself – a step function, a ramp, etc.); and
- The number of shocks (number and frequency of shocks that occur during a given event)

A shock (as a collection of such attributes) is then implemented within the framework by effecting a disruption of the flow of goods within the supply chain according to the specified attribute values.

The supply chain ecosystem can be viewed as a filter that dampens (reduces) or amplifies (increases) the impact of such a shock. The best approach to operationalising this depends on the nature of the problem and on the questions being asked. Because, in this instance, we are focusing upon the ecosystem as a factor that impacts the supply chain response, we do not need to characterise it in detail. Instead, we assume a ripple effect of movement within the ecosystem, and model it as a simplified connective element between the shock and the outcome.

Supply chain connectivity, therefore, is used to describe how the ecosystem affects the impact of the shock. We define it as a normalised propagation value that ranges from 0 (the shock is completely dampened) to 1 (the full effect of the shock is experienced), continuously. Thus, a supply chain partner with a connectivity value of 0.50 would be expected to transmit half of the negative effects experienced in a shock event. This can be implemented as a simple multiplier that adjusts the throughput in the supply chain at the location where the shock occurs. So, for example, given a connectivity value of 0.50, a supplier that would provide 20 units of stock on a daily basis, in the absence of an upstream shock, would still provide 10 units per day for the shock's duration.

One could also use such a connectivity factor to represent a dampening of the time between the onset of a shock and the realisation of its impact, or it could be used to reflect various other issues related to an ecosystem's ability to endure shocks (duration of impact, scale of impact, etc.). In the interest of parsimony and ease of understanding the impact of these events, this paper simply considers it in the context of the transmission of shock impacts through the supply chain.

Finally, investments in resilience or the ability of the system to reduce the impact of a shock and/or reduce the time that it takes to return to acceptable performance levels, can be achieved by allocating resources within at least one of eight categories of possible investments (see Melnyk, Zobel et al. 2014). These different categories can be relatively easily operationalised within the simulation model.

### 4.2 *Simulation model*

While the use of discrete-event simulation as a tool for studying supply chain-related issues has been recognised and explored (e.g. Van der Zee and van der Vorst 2005; Manuj, Mentzer, and Bowers 2009; Carvalho et al. 2012), there currently exists no standard or widely accepted supply chain simulation model that can serve as a basis for experimentation. Most of the models currently encountered are situation or problem specific. At best, what we have are guidelines for how researchers can develop more effective simulation models (Manuj, Mentzer, and Bowers 2009). Consistent with past simulation work, the structure and complexity of the model reflects the problem(s) being studied and the focus of this research.

### 4.3 *Data management*

Analysis of the data generated by any study of shocks, resilience and performance presents challenges for the researcher. With empirical data, for example, the researcher faces the challenge of separating out the effects attributable to the shock, the ecosystem or the resilience investments from those effects due to other factors (e.g. randomness). This is one area where simulation offers an important advantage for the study of supply chain shocks and resilience.

In simulation, the most common procedure is to run the simulation for a certain period of time (non-terminating) or until some condition is reached (terminating) and then collect and analyse the distribution of the final outputs. The data that are produced can take one of two forms: data generated at the end of the run or time series data (i.e. performance data that is sampled and recorded at regular intervals over the simulation run). In either case, the data requires the researcher to identify and assess the effects attributable to the experimental factors that are present. It is possible, however, to simplify this analysis so that effects attributable to the experimental factors can be clearly and unambiguously identified, by adopting the technique of differencing.

Differenced data are generated by comparing each time series observation in a base-model against its corresponding observation in an alternative model. Where differences between the two models exist, the cause must be whichever factors were changed to create the alternative model from the base-model. In the context of generating data for an experimental design, we replicate a base-model time series for every cell (which does not include a shock), and then subtract that base-model from a replication that includes a shock. The differences between the base-model and each replication, which have the same common random numbers (CRN), will then be attributable only to the shock, the impact of the ecosystem and/or the effects of the resilience-inducing investments represented by that cell.

Differencing is not strictly necessary for studying supply chain shocks and resilience; however, it is a useful approach because it effectively 'cleans' the data by removing the effects of other extraneous factors. If CRNs (i.e. identical random seeds) are used to generate the base case and the disrupted case, then stochastic variability also disappears, leaving a constant difference (response) of zero. After the impact of a shock is applied to the disrupted time series, any deviations from zero in this differenced time series are directly attributable to the various experimental factors present. These deviations can then serve as the basis for calculating a measure of the area under the curve, as an indication of the relative amount of loss suffered by the supply chain because of the shock (Figure 2).

Measuring the area under the curve in order to compare system responses is an approach that has been adopted by a number of academic disciplines, including inventory control theory (Whitin 1955), psychology (Myerson, Green, and Warusawitharana 2001), physiology (Pruessner et al. 2003) and information security (Kumar, Park, and Subramaniam 2008). The work of Bruneau et al. (2003) was the first to apply such a technique to the issue of measuring system resilience to a disruptive event. This original work has since been extended to address issues such as uncertainty (Chang and Shinozuka 2004), multi-dimensionality (Bruneau and Reinhorn 2007), economic impacts of disruptions (Rose 2007), appropriate supply chain design (Falasca, Zobel, and Cook 2008), tradeoffs between loss and recovery time (Zobel 2011), and multiple-related disruptions (Zobel and Khansa 2012, 2014). Through the use of appropriate output measures (as discussed below), the characteristics of this loss in functionality over time can be evaluated using any conventional statistical procedure such as regression analysis or ANOVA.

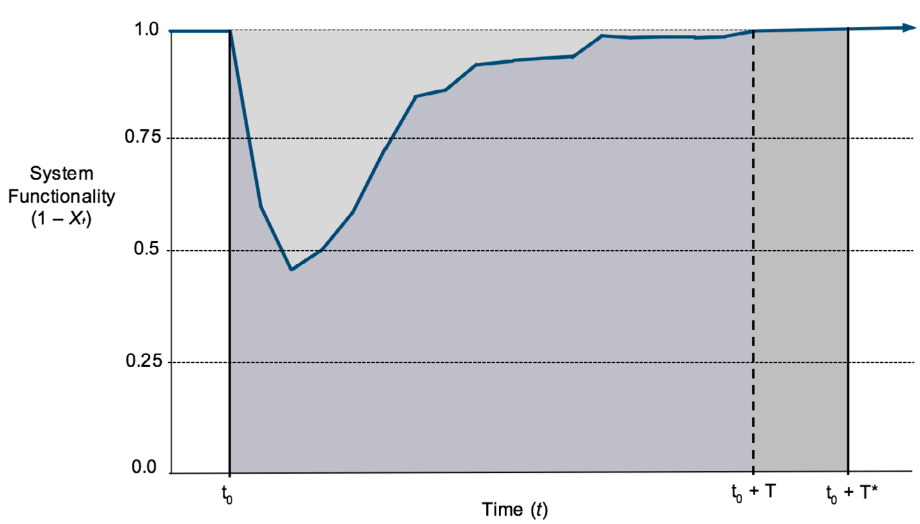


Figure 2. Resilience as the area under a differenced response curve.

## 5. Example of theory building using the approach

The preceding discussion laid out the structure of a procedure intended to facilitate theory building into issues involving supply chain shocks and resilience. In order to demonstrate the utility of this approach, we provide a simple, illustrative example.

The example focuses specifically on determining how the level of buffer stocks affects system performance when a supply chain is exposed to a series of upstream shocks. It also explores how these results are affected by supply chain partners whose actions influence some of the product flows. The supply chain simulation model that we use to generate the data are driven by an experimental design consisting of three factors that represent the first three components in the framework: (1) shock interarrival time (representing shock nature); (2) connectivity (representing the supply chain ecosystem); and, (3) buffer stocks (representing resilience-inducing investments). We focus on the behaviour of only a single factor for each of the three dimensions in order to illustrate the approach without unnecessary complexity. Other individual factors, such as the magnitude of the shock, are given fixed values in this case (i.e. 100% loss of output for the duration of the event). These factors could also easily be varied in the context of alternative experiments.

For each factor, multiple levels were studied (these factors and their associated levels are summarised in Figure 3). The resulting full factorial design consists of 27 cells – a design that, with sufficient replication, allows us to study both the main effects and the interactions. For each cell, 10 replications are carried out in order to illustrate the stochastic nature of the underlying supply chain model. Although the number of replications is limited to 10 in order to keep the current example relatively simple, this number easily can be expanded to support other, more in-depth analyses. As a means of reducing variance, the same 10 common random number streams are used for the runs in each cell, as well as for a base set of 10 runs of the underlying non-disrupted system.

The impact of these three factors on the system is captured using four different measures that are associated with the loss of system functionality over time. The first is the number of time periods in which a negative change in inventory is observed; the second is the total negative change in inventory over the course of these time periods; the third is the average negative change in inventory over this same interval; and the fourth is an overall measure of overall system resilience derived from these first three measures, as developed by Zobel and Khansa (2012).

Zobel and Khansa (2012) construct their quantitative measure of system resilience by calculating the actual area under the time series curve between shock onset and system recovery (representing the total remaining functionality in the system during the disruption) and dividing it by the total area under the curve that would have resulted if no loss had occurred (as captured in Equation (1)):

$$R(\bar{X}, T) = \frac{T^* - \bar{X}T}{T^*} = 1 - \frac{\bar{X}T}{T^*} \bar{X} \in [0, 1], T \in [0, T^*] \tag{1}$$

Resilience, $R$, thus, represents the relative percentage of functionality retained over time, where $\bar{X}$ (X_BAR) is the average amount of loss experienced by the system per unit of time, $T$ is the time until the system recovers and $T^*$ is the maximum recovery time for the system (Zobel and Khansa 2012). $R$ varies from a value of 0, which represents total

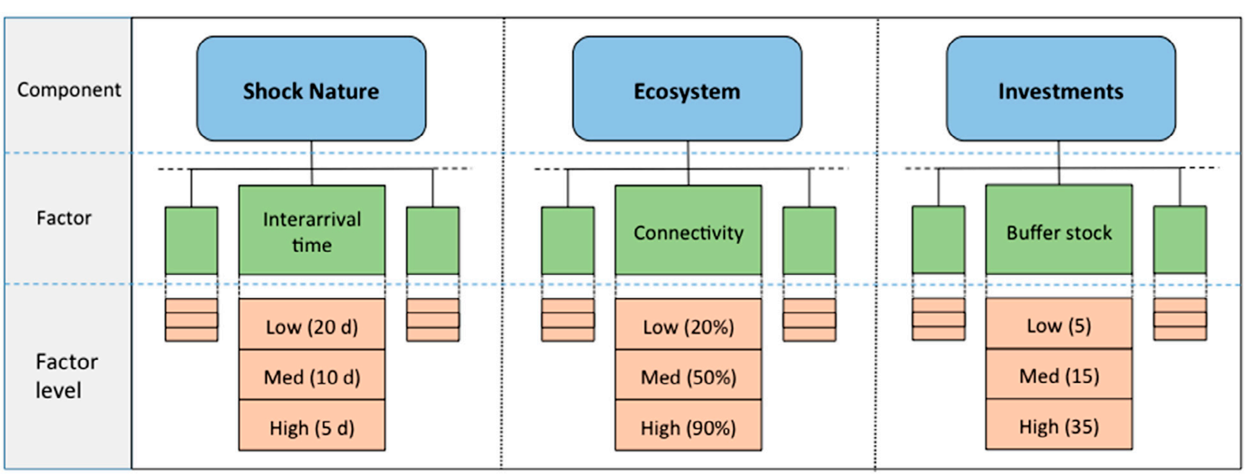


Figure 3. Theory-building approach: Example using three-component framework.

system loss, to 1, which represents no impact from the shock, and it allows for establishing a direct relationship between investments in resilience and improved system behaviour. The four output measures are summarised in Table 2.

### 5.1 *Simulation model*

The simulated supply chain consists of three echelons (supplier, manufacturer, customer) – the minimum number necessary to describe a supply chain. This simulation model is not meant to represent the details of a real supply chain, but is instead illustrative in the manner that the Beer Distribution Game (Sterman 1989) is illustrative and used to study dynamic decision-making behaviour within the supply chain. The first component in the supply chain is the supplier, the second the manufacturing plant and the third is the customer. Separating the three components is the logistics or delivery system. The shock is incorporated into the system by adding an additional component within the simulation, immediately after the supplier, which could be used to interrupt the flow of goods according to the shock attributes. The simulation model was implemented in Arena, and its baseline assumptions and parameter values are summarised in Table 3.

### 5.2 *Specification of the example experimental design*

The simulation incorporates the three framework components of shock interarrival time, connectivity and buffer stocks. Each model component is set at three different levels. The first, interarrival time (IAT), is set at 5, 10 and 20 days between shocks. The second component, supply chain connectivity (CON), is set at the levels of 0.2, 0.5 and 0.9, representing the percentage of the shock's impact that is transmitted through the supply chain. This component captures the impact of actions taken by supply chain partners to reduce the shock's impact. The final component is the buffer size (BUF), or the number of units of safety stock used by the manufacturing firm to protect itself from shocks. This component is set at the three levels of 5, 15 and 35 units. In each case, the chosen levels are intended to provide a range of different behaviours, in order to illustrate the potential of the approach most effectively.

### 5.3 *Data analysis*

For each of the 270 total runs across the 27 cells in the experiment, a daily time series of 1500 observations was generated to capture fluctuations in inventory levels. After dropping the first 500 observations in each case, in order to remove any start-up bias, every time series was then differenced from its corresponding non-disrupted base replication. The resulting set of differenced time series, in each case, was subsequently analysed statistically with respect to each of the chosen dependent variables, capturing system loss and resilience. We recognise that equivalent-dependent variables could be captured that quantify *positive* changes in inventory with respect to the baseline conditions; such situations could occur, for example, when the ordering process overcompensates for reduced supply levels by ordering more in subsequent periods. For the sake of our current discussion, however, we focus only on negative changes in inventory and leave consideration of such broader system behaviours to future work.

### 5.4 *Results and implications*

Regression analysis was used to analyse both the magnitude and the direction of the impacts of the three independent factors: IAT, CON and BUF, and the impact of the common random numbers (CRN) was controlled for by including a set of nine dummy variables (with the first random number being the base or control). Because the three independent factors were operationalised as interval variables, we treated them as such for the purposes of the regression analysis.

Table 2. Dependent variables for assessing shocks and resilience.

| Dependent variable | Orientation ($T$–time; $Q$–quantity) | Definition |
|---|---|---|
| $T$ | $T$ | Number of time periods where a negative change in inventory is observed |
| SUM_X | $Q$ | Cumulative negative change in inventory (summed over $T$ periods) |
| X_BAR | $T$, $Q$ | Average negative inventory per period (i.e. SUM_X/T) |
| $R$ | $T$, $Q$ Aggregate measure | Overall measure of system dynamic resilience (as calculated in Equation (1)) |

Table 3. Simulated supply chain: Operating and simulation assumptions.

| Traits | Operating assumptions |
|---|---|
| Operating time horizon | 1500 days |
| Initialisation time horizon | 500 days (dropped from analysis) |
| Data analysed | Day 501–1500 |
| Random number generation | Common random number streams used ($n$ = 10) |
| Dependent variable | Inventory levels (measured at the end of each day) |
| Production rates | Constant production of 10 units/day at the supplier<br>Shipping time: 3 days (constant)<br>Assembly time at manufacturing = 1 day (constant)<br>Enters into inventory at the manufacturing plant at day 5 |
| Demand | Daily demand (integer units) – drawn from a triangular distribution (9, 10, 11). P(demand = 9) = .15; P(demand = 10) = .70; P(demand = 11) = .15 |
| Stock outs | If not enough items in inventory, all remaining orders for that day are lost |
| Available safety stock | Determined by the buffer size (BUF) within the experimental design |
| First-order generated | Day 5 |
| Reordering system logic at manufacturing facility | Min/max system |
| Timing of first shock | Day 525 |
| Shock traits (common to all disruptions) | Occurs at the supplier's side<br>Duration of 5 days<br>Stepwise shape<br>100% loss of output for the duration |
| Number of shocks | 3 (fixed) |
| Time between shocks | Determined by the interarrival time (IAT) within the experimental design |
| Propagation of shocks | Determined by the supply chain connectivity (CON) within the experimental design |



All regressions were executed using a zero intercept (consistent with the use of differenced data), and in each case, only the main effects and the first-order interactions were modelled due to the problems of interpreting second and higher order interactions. Four regression models in total were run on the simulated data – one for each dependent variable: *recovery time* ($T$), *cumulative loss* (SUM_X), *average loss per unit of time* (X_BAR) and *dynamic resilience* ($R$). The results of the regression analyses are summarised in Table 4. These results show that the main effects are significant in each of the regression models, except in the case of the effect of buffer size on recovery time. Furthermore, the interaction effects are also significant in all four models.

### 5.4.1 *Main effects*

The results for the IAT between shocks in the recovery time and loss models are relatively straightforward: IAT has a positive coefficient for recovery time. Essentially, as the time between shocks increases, the overall amount of time spent in a state of loss also increases. If shocks are far apart, the system is not able to leverage the resources (inventory ordering in the model) allocated to recover from a previous shock to help recover from the next one. In this case, each shock is a separate event and the operational efficiencies traditionally offered by investments such as safety stock are not available because they have recently been consumed by a previous shock. IAT has a negative coefficient for cumulative loss and average loss per unit time. As the time between shocks increases, the system experiences more negative loss as the effective time when the system is impacted becomes extended.

The results also indicate that CON, the percentage of the shock transmitted through the supply chain, has an impact on recovery time, $T$. Systems where the suppliers pass on more of the shock, as might be expected, experience longer recovery times. The coefficient for CON is negative for cumulative loss, average loss and resilience. This also matches expectations, because loss of inventory is measured as a negative change in inventory. A greater shock transmission results in more negative outcomes.

The results further show that BUF has a positive coefficient for the latter three dependent variables: total loss, average loss per time unit and resilience, even though it was not significant for recovery time. As buffer size increases, losses will not be as severe (i.e. a less negative value for both cumulative and average loss) and resilience is increased. Though operationalised differently, this result is consistent with the dampening effect of buffer stocks on supply chain shock impact observed by Croson et al. (2014) in their experiment using the Beer Distribution Game.

Table 4. Regression results.

*Panel A: dependent variable is T*

| Source | SS | df | MS | |
|---|---|---|---|---|
| Model | 659886377 | 15 | 43992425.1 | Number of obs = 270 |
| Residual | 67491906.1 | 255 | 264,674.141 | *F* (15,255) = 166.21 |
| Total | 727378283 | 270 | 2693993.64 | Prof. > *F* = 0.00 |
| | | | | R-squared = 0.91 |
| | | | | Adj R-squared = 0.90 |
| | | | | Root MSE = 514.46 |

| *T* | Coef. | Std. err | *t* | *P* > \|*t*\| | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| IAT | 114.73 | 9.13 | 12.57 | 0.00 | 96.76 | 132.71 |
| CON | 2606.53 | 199.65 | 13.06 | 0.00 | 2213.35 | 2999.7 |
| BUF | −6.79 | 5.61 | −1.21 | 0.23 | −17.84 | 4.27 |
| *IAT x CON* | −113.46 | 15.04 | −7.54 | 0.00 | −143.09 | −83.84 |
| *IAT x BUF* | −1.91 | 0.37 | −5.19 | 0.00 | −2.64 | −1.19 |
| *CON x BUF* | −53.61 | 8.02 | −6.69 | 0.00 | −69.40 | −37.83 |
| c_crn2 | 436.14 | 132.24 | 3.30 | 0.00 | 175.72 | 696.55 |
| c_crn3 | 383.47 | 132.24 | 2.90 | 0.00 | 123.05 | 643.89 |
| c_crn4 | 390.32 | 132.24 | 2.95 | 0.00 | 129.91 | 650.74 |
| c_crn5 | 390.47 | 132.24 | 2.95 | 0.00 | 130.05 | 650.89 |
| c_crn6 | 480.43 | 132.24 | 3.63 | 0.00 | 220.02 | 740.85 |
| c_crn7 | 374.51 | 132.24 | 2.83 | 0.01 | 114.09 | 634.92 |
| c_crn8 | 410.88 | 132.24 | 3.11 | 0.00 | 150.46 | 671.29 |
| c_crn9 | 383.58 | 132.24 | 2.90 | 0.00 | 123.16 | 644 |
| c_crn10 | 470.77 | 132.24 | 3.56 | 0.00 | 210.35 | 731.18 |

*Panel B: dependent variable is SUM_X*

| Source | SS | df | MS | |
|---|---|---|---|---|
| Model | 4.32E + 11 | 15 | 2.88E + 10 | Number of obs = 270 |
| Residual | 3.23E + 10 | 255 | 1.27E + 08 | *F* (15,255) = 226.91 |
| Total | 4.64E + 11 | 270 | 1.72E + 09 | Prof. > *F* = 0.00 |
| | | | | R-squared = 0.93 |
| | | | | Adj R-squared = 0.93 |
| | | | | Root MSE = 11262.00 |

| SUM_X | Coef. | Std. Err | *t* | *P* > \|*t*\| | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| IAT | −3153.33 | 199.80 | −15.78 | 0.00 | −3546.79 | −2759.87 |
| CON | −65433.19 | 4370.55 | −14.97 | 0.00 | −74040.15 | −56826.23 |
| BUF | 512.33 | 122.89 | 4.17 | 0.00 | 270.32 | 754.33 |
| *IAT x CON* | 3149.48 | 329.34 | 9.56 | 0.00 | 2500.90 | 3798.05 |
| *IAT x BUF* | 54.92 | 8.06 | 6.81 | 0.00 | 39.05 | 70.79 |
| *CON x BUF* | 1131.10 | 175.48 | 6.45 | 0.00 | 785.52 | 1476.68 |
| c_crn2 | −14326.26 | 2894.80 | −4.95 | 0.00 | −20027.01 | −8625.5 |
| c_crn3 | −12941.51 | 2894.80 | −4.47 | 0.00 | −18642.27 | −7240.76 |
| c_crn4 | −13167.85 | 2894.80 | −4.55 | 0.00 | −18868.60 | −7467.09 |
| c_crn5 | −12883.81 | 2894.80 | −4.45 | 0.00 | −18584.57 | −7183.06 |
| c_crn6 | −14487.00 | 2894.80 | −5.00 | 0.00 | −20187.75 | −8786.24 |
| c_crn7 | −13122.81 | 2894.80 | −4.53 | 0.00 | −18823.57 | −7422.06 |
| c_crn8 | −12624.51 | 2894.80 | −4.36 | 0.00 | −18325.27 | −6923.76 |
| c_crn9 | −13006.07 | 2894.80 | −4.49 | 0.00 | −18706.83 | −7305.31 |
| c_crn10 | −14285.74 | 2894.80 | −4.93 | 0.00 | −19986.49 | −8584.98 |

*Panel C: dependent variable is X_BAR*

| Source | SS | df | MS | |
|---|---|---|---|---|
| Model | 129809.21 | 15 | 8653.95 | Number of obs = 270 |
| Residual | 10832.19 | 255 | 42.48 | *F* (15,255) = 203.72 |
| Total | 140641.40 | 270 | 520.89 | Prof. > *F* = 0.00 |
| | | | | R-squared = 0.92 |
| | | | | Adj R-squared = 0.92 |
| | | | | Root MSE = 6.52 |

(*Continued*)

Table 4. (*Continued*).

| *Panel A: dependent variable is T* | | | | | | |
|---|---|---|---|---|---|---|
| X_BAR | Coef. | Std. Err | *t* | *P* > \|*t*\| | 95% Conf. interval | |
| IAT | −1.72 | 0.12 | −14.84 | 0.00 | −1.94 | −1.49 |
| CON | −23.81 | 2.53 | −9.41 | 0.00 | −28.79 | −18.83 |
| BUF | 0.29 | 0.07 | 4.07 | 0.00 | 0.15 | 0.43 |
| *IAT x CON* | 1.77 | 0.19 | 9.29 | 0.00 | 1.39 | 2.15 |
| *IAT x BUF* | 0.04 | 0.00 | 8.18 | 0.00 | 0.03 | 0.05 |
| *CON x BUF* | −0.53 | 0.10 | −5.23 | 0.00 | −0.73 | −0.33 |
| c_crn2 | −6.82 | 1.68 | −4.07 | 0.00 | −10.12 | −3.53 |
| c_crn3 | −7.42 | 1.68 | −4.43 | 0.00 | −10.72 | −4.12 |
| c_crn4 | −8.21 | 1.68 | −4.90 | 0.00 | −11.51 | −4.92 |
| c_crn5 | −7.29 | 1.68 | −4.35 | 0.00 | −10.59 | −3.99 |
| c_crn6 | −7.39 | 1.68 | −4.41 | 0.00 | −10.69 | −4.09 |
| c_crn7 | −8.28 | 1.68 | −4.94 | 0.00 | −11.58 | −4.98 |
| c_crn8 | −7.10 | 1.68 | −4.24 | 0.00 | −10.40 | −3.8 |
| c_crn9 | −7.69 | 1.68 | −4.59 | 0.00 | −10.99 | −4.39 |
| c_crn10 | −7.39 | 1.68 | −4.41 | 0.00 | −10.69 | −4.09 |
| *Panel D: dependent variable is R* | | | | | | |
| Source | SS | df | MS | | Number of obs = 270 | |
| Model | 253.72 | 15 | 16.91 | | *F* (15,255) = 886.79 | |
| Residual | 4.86 | 255 | 0.02 | | Prof. > *F* = 0.00 | |
| Total | 258.58 | 270 | 0.96 | | R-squared = 0.98 | |
| | | | | | Adj R-squared = 0.98 | |
| | | | | | Root MSE = 0.14 | |
| *R* | Coef. | Std. err | *t* | *P* > \|*t*\| | 95% Conf. interval | |
| IAT | 0.04 | 0.00 | 15.97 | 0.00 | 0.03 | 0.04 |
| CON | −0.90 | 0.05 | 16.71 | 0.00 | −0.79 | −1 |
| BUF | 0.02 | 0.00 | 12.88 | 0.00 | 0.02 | 0.02 |
| *IAT x CON* | −0.04 | 0.00 | −9.40 | 0.00 | −0.05 | −0.03 |
| *IAT x BUF* | 0.00 | 0.00 | −7.16 | 0.00 | 0.00 | 0 |
| *CON x BUF* | −0.16 | 0.00 | −7.52 | 0.00 | −0.02 | −0.01 |
| c_crn2 | 0.23 | 0.04 | 6.58 | 0.00 | 0.16 | 0.3 |
| c_crn3 | 0.25 | 0.04 | 6.93 | 0.00 | 0.18 | 0.32 |
| c_crn4 | 0.24 | 0.04 | 6.79 | 0.00 | 0.17 | 0.31 |
| c_crn5 | 0.24 | 0.04 | 6.83 | 0.00 | 0.17 | 0.31 |
| c_crn6 | 0.22 | 0.04 | 6.14 | 0.00 | 0.15 | 0.29 |
| c_crn7 | 0.25 | 0.04 | 6.97 | 0.00 | 0.18 | 0.32 |
| c_crn8 | 0.25 | 0.04 | 6.90 | 0.00 | 0.18 | 0.32 |
| c_crn9 | 0.24 | 0.04 | 6.90 | 0.00 | 0.17 | 0.31 |
| c_crn10 | 0.23 | 0.04 | 6.44 | 0.00 | 0.16 | 0.3 |

Notes: *T* = time, SUM_X = total loss , X_BAR = average loss , *R* = resilience, IAT = interarrival time, CON = connectivity, BUF = buffer stocks, crn = common random number.



Each of these responses conforms to expectations. It is interesting to note that, in each model, the effects of IAT and CON are larger than the effects of BUF. With regard to interpreting the results, the analysis indicates that a one-unit increase in BUF reduces the cumulative negative inventory by 512 units (in the case of the upper limit of 35, this would translate into a 17,920-unit offset). This offset would still have difficulties dealing with the massive impact of CON, in which case, for CON = 0.9, we still have an effect of −58,890 on SUM_X.

### 5.4.2 *Interaction effects*

While most of these individual effects might have been expected, the value of the framework and the simulation example lies in the ability of researchers to also examine and explore interaction effects between factors. In assessing these interactions, we note that the main effect result for IAT and resilience doesn't initially appear to match the other results. That is, if a longer IAT time between shocks leads to a longer recovery time and a larger average loss per unit time, then according to Equation (1), we should expect less resilience to result. However, the opposite appears to be true: a larger IAT actually leads to more resilience. The first-order relationship between IAT and CON may help to explain this, however. In all four models, the size of the coefficient for this first-order interaction is similar to that of IAT, but it has the opposite sign. In Panels A, B and C from Table 4, the interaction also has the opposite sign from CON, but in the model for resilience, the sign for the interaction coefficient is the same as that for CON. Thus, instead of acting against each other, the contributions of CON and the interaction term appear to lead to reductions in resilience, even given the positive impact that the IAT coefficient has on resilience. This illustrates the complexity of the situation, and highlights the need for carefully considering the combined impacts of different factors on system performance.

In addition to helping illustrate the potential impacts of the interactions on model behaviour, the resilience model (Panel D from Table 4) also demonstrates greater overall predictive power. Whereas the $R^2$ values for Panels A, B and C are all 0.93 or below, the $R^2$ value for the resilience model exceeds 0.98. Although resilience is a simple non-linear combination of T and X_BAR, the independent variables are able to explain its behaviour much more precisely than that of either of the other two variables. This is a strong indicator that resilience is the more effective measure for capturing the complexity of system behaviour.

#### 5.4.3 *Potential managerial implications*

For risk managers, there are several insights relevant to the decisions they need to make. First, one of the key elements in the framework is that of investments. These are (the accumulation of) choices that supply chain managers must make in terms of inventory, communication technology, supplier relationships and others. The framework helps illustrate this in a manner readily understandable for managers. Second, this framework is designed for use by both researchers and risk managers to guide their analysis of their own supply chains. While our simulation is illustrative, risk managers can build a model that better represents the specific supply chain they manage and then include the factors from each framework element of greatest interest to them. Third, even the short, simple supply chain simulated in this paper allows one to observe that building resistance to connectivity of disruptions of supply chain partners will enhance the resilience of the focal firm.

#### 5.4.4 *Observations*

Even from a simple, illustrative example such as the one offered by this paper, we can see the advantages offered by the proposed approach. Researchers can now explore how shocks and their characteristics influence performance. They can begin to address questions such as:

- How far apart do the supply chains shocks have to be before they can be considered as distinct (i.e. the prior shock and its effects have worked themselves out before the onset of the next shock)?
- What aspects of the supply chain shocks (e.g. magnitude, duration) have the greatest impact on performance?
- Do the attributes of a supply chain influence the selection and deployment of specific investments made in resilience (can we identify a fit between the shock and the investment)?

They can also explore similar questions involving the other dimensions of the framework. For the supply chain ecosystem, we can begin to understand what attributes of the ecosystem have the greatest impact on performance. For the investments in resilience, we can begin to explore whether there are positive interactions between the variance investments – leading to potential situations where we can significantly enhance system resilience by making relatively small investments in a number of different areas (thus, taking advantage of these interactions).

The framework also lends itself to a variety of follow-on research methodologies. For example, we can explore the same issues raised in this illustrative example by focusing on how the factors influence the turning points in the underlying time series using outlier detection as proposed by Melnyk, Closs et al. (2014). Furthermore, although this research employs a simulation-based experimental design, there is also potential for empirical work assessing supply chains' responses to shocks based upon this same framework. This would allow researchers to systematically explore issues involving shocks, resilience and performance from a different perspective.

## 6. Conclusion

There is a relationship between supply chain shocks (and their attributes) and the resulting performance of the system, as shown in the literature review presented earlier. This relationship is also influenced by the supply chain ecosystem and by the investments that a firm makes either directly or indirectly in building dynamic resilience. What has been missing is a better understanding of how these various elements interact with each other, as highlighted by Mizgier (2017) – an issue that gets to the heart of this research's contribution.

The contributions of this research are threefold. First, this paper develops and then presents key elements of a three-component framework to provide a base for resilience- and shocks-based theory building. The three items are the shock nature, supply chain ecosystem and resilience investments, and together they will provide needed insight into resilience. Developing such an understanding is critical if theory related to shocks and resilience is eventually to be built. Second, this study has introduced an empirical approach for analysing the aggregated measure of resilience presented in Equation (1). The use of this overall resilience measure avoids the challenges of dealing with both time and quantity dimensions by addressing them in aggregate. Although previous research has shown the value of this aggregated measure in examining the tradeoffs between the loss and the recovery time (Zobel 2011), this current work strengthens resilience as a valuable measure of system performance by demonstrating its ability to capture subtleties of system interactions with a high degree of explanatory power. Third, a simulation method is presented that, when paired with the framework, is intended to encourage structured experimentation toward this the goal of building theory. A simple example is used to concisely illustrate its application.

The example shown demonstrates how this approach can be used to begin to understand *how* potential resilience factors affect supply chain performance. As seen in this research, and best seen in the results presented in Table 4, there are varying main effects and interaction effects at play when considering supply chain resilience. In this research, we have considered three such factors' impact upon how a supply chain disruption ultimately affects performance. To examine these same factors with a real-world empirical example would necessitate researchers finding a company with this exact experience, and a willingness to share data that likely was not gathered mid-disruption, while they sought to maintain operations. In this way, the experimentation approach using simulation allows discovery otherwise unlikely.

The opportunity exists for researchers and companies alike to use this research and better understand how the types of shocks that affect a company, the supply chain ecosystem that exists for the given company, and the investments managers have chosen to make, all interact and affect resilience performance.

## Disclosure statement

No potential conflict of interest was reported by the authors.

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