Effectiveness of resilience capabilities in mitigating disruptions: leveraging on supply chain structural complexity

Seyoum Eshetu Birkie

Department of Sustainable Production Development, KTH Royal Institute of Technology, Stockholm, Sweden,

Paolo Trucco and Pablo Fernandez Campos

Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Milano, Italy

Abstract

Purpose – This study aims to investigate the influence of supply chain (SC) complexity on the effectiveness of resilience capabilities in mitigating supply chain disruptions. Hypotheses about direct and moderating influences of complexity on resilience capabilities and performance change after disruption are built and quantitatively tested.

Design/methodology/approach – Partial least square-based Structural Equation Modelling (SEM) with formative constructs was employed as an overall approach. Secondary data on SC disruptions, related performance change and resilience practices was collected from multiple sources through a systematic procedure. The data pertaining to independent, moderating and dependent variables was systematically encoded prior to performing regression analysis.

Findings – SC structural complexity is found to have a significant positive relation with performance improvement after disruption, along with resilience capability; it also positively moderates the resilience-performance link.

Research limitations/implications – The complexity factors we considered in this study do not include dynamic forms due to the nature of data collected. Future research may attempt to include and test if the results of this study could hold also when additional complexity parameters are taken into account.

Practical implications – Managers are often trying to reduce supply chain complexity. This study implies that some level of complexity is beneficial also for a better recovery of operational performance affected due to disruption. Resilience capabilities become more effective when leveraged on higher resources and complexity in the supply chain.

Originality/value – This is the first study to empirically investigate the influence of SC complexity on the resilience-performance link.

Keywords – Complexity, disruption, dynamic capabilities resilience, resource based view, structural equation model

Article classification – Research paper

Effectiveness of resilience capabilities in mitigating disruptions: leveraging on supply chain structural complexity

Introduction

Global businesses implement different operations management strategies to improve performance under turbulent business conditions. The performance benefit of such strategies and practices is argued to be dependent on the environmental context (e.g. Sousa and Voss, 2008). Thus, firms attempt to employ practices thought to help in achieving higher performance in a given business context, and change or adapt them as the context changes.

The increase in frequency and severity of unanticipated supply chain disruptions in recent years are indications of continued change in the global business context. A supply chain disruption can be thought of as a mismatch between supply and demand in an unexpected manner that can affect the short and long term operation as well as profitability of the firm (Hendricks and Singhal, 2003). Disruptions may occur due to different triggering events pertaining to supply, demand or internal processes. Melnyk et al. (2009) define a supply chain disruption as "the outcome of a process whereby one or more [triggering] events taking place at one point in the supply chain adversely affect the performance of one or more actors located elsewhere in the supply chain".

Several recent studies have argued that resilience capabilities help firms re-attain lost performance due to supply chain disruptions (e.g. Ambulkar et al., 2015; Grötsch et al., 2013; Knemeyer et al., 2009). Resilience can be conceptualised as an adaptive capability to prepare for unexpected events, and respond and recover from disruptions while sustaining operations (Ponomarov and Holcomb, 2009). It results from proactive and reactive capabilities (Kleindorfer and Saad, 2005; Knemeyer et al., 2009) that are formed from bundles of routine practices.

Managing supply chain disruptions in the current global business environment with resilience capabilities requires consideration of different forms of complexity. Complexity describes the number and heterogeneity of decision elements in a business environment and how these change over time (Duncan, 1972). In a supply chain, the firms' organisational design, SC network, product portfolio and other related factors are considered as sources of complexity (Bode and Wagner, 2015; Collinson and Jay, 2012; Manuj and Sahin, 2011). Different researchers have noted that complexity needs to be considered in dealing with supply disruptions (e.g. Bode and Wagner, 2015; Craighead et al., 2007). However, little has been investigated on how supply chain (SC) complexity as context factor might influence the relationship between resilience capabilities and performance. Moreover, prior research has focused on the role that complexity can play in triggering disruptions (Brandon-Jones, Squire and Van Rossenberg, 2014) and has not yet well investigated the potential influence of complexity on disruption management. This paper aims to systematically address this research gap.

The paper is organised as follows. The next section briefly reviews the adopted theoretical framework for discussing resilience, complexity and operations performance; it also highlights the interactions among these three concepts reported in earlier research. Based on this discussion, the research questions are introduced. A description of the research design and methodology is provided subsequent to that. Findings with regard to the research questions are presented, and a final section concludes summarising the main results obtained as well as highlighting their major implications and research limitations.

Theoretical framework

Theoretical background

Contingency theory posits that strategies and decisions in a business environment should take the context into account in order to create proper alignment at different levels and be effective in what they do (Duncan, 1972; Ketokivi, 2006). This makes it a suitable frame in discussing proactive supply chain management strategies for mitigating unanticipated disruptions (Grötsch et al., 2013). Likewise, contingent resource-based view (RBV) argues that sustained competitive advantage is created through building resources and creating (or regenerating) bundles of capabilities from existing ones (Ambrosini et al., 2009; Brandon-Jones, Squire, Autry, et al., 2014) based on prevailing conditions. Firms are facing disruptions in their supply chains that could have severe consequences on performance unless well prepared for and managed well on occurrence (e.g. Knemeyer et al., 2009). Practices that are routinely performed by a business firm can help them develop dynamic capabilities that are sources of resilience in supply chains (Ambulkar et al., 2015; Dabhilkar et al., 2016).

Empirical studies of supply chain disruption analysis discuss that proactive and reactive resilience capabilities enable better chance of surviving supply chain disruptions with relatively smaller extent of performance reduction (e.g. Dabhilkar et al., 2016). However, little is empirically investigated on how the supply chain context may affect the relationship between resilience and operational performance. This research attempts to re-evaluate the relationship between operational resilience capabilities and performance upon disruption by taking into account prevailing complexity issues.

Operational resilience

Resilience can be regarded as an adaptive capability to prepare for, respond and recover from disruptions while sustaining operations (Ponomarov and Holcomb, 2009). As such, it includes proactive and reactive strategies (Tukamuhabwa et al., 2015). To have better operational resilience, firms need to be prepared beforehand (Kleindorfer and Saad, 2005), and be able to reconfigure their assets, processes and resources according to prevailing disruption characteristics (Ambulkar et al., 2015).

Disruptions can be triggered by unanticipated and unplanned events that affect the normal flow of goods [and information] leading to severe unwanted consequences (Kleindorfer and Saad, 2005). A disruption can be an outcome of a chain of events. Natural disasters, supply shortages, demand shifts, quality problems, worker strikes are some popular triggering events for supply chain disruptions (Chopra and Sodhi, 2004). The primary triggering event and location could be close and direct or distant and indirect from where the final business consequence is observed. For example, the 2011 Japan triple disaster (a triggering event) has affected automotive and electronics supply chains across the globe as suppliers and manufacturing sites have been affected in terms of production discontinuity, shortage of parts, or delay of inventory on transit, etc. (e.g. Matsuo, 2015). The migration crisis in Europe in 2015 has severely affected cargo transportation across the continent; contamination, loss and delay have caused big damage especially to the food and pharmaceutical industries (e.g. BSI 2015). Deliveries for refugee aid were affected as well.

Several forms of conceptualising resilience exist in literature (Bhamra et al., 2011). For example, Johnson et al. (2013) and Jüttner and Maklan (2011) frame resilience in terms of formative elements of flexibility, velocity, visibility and collaboration. Dabhilkar et al. (2016) used temporal and locus dimensions to classify how dynamic resilience capabilities are formed from routine practices implemented within the firm or by interaction with external actors. These capabilities can be developed prior to or after occurrence of a disruptive incident, forming four bundles: proactive-internal, proactive-external, reactive-internal, and reactive-external. A list of practices identified to form resilience capability used in this study can be found in Appendix A. Resilience practices can also be seen in terms of the core functions of resilience they are supposed to accomplish: *sense, build, reconfigure, re-enhance, and sustain* (Birkie, 2016). While both are possible alternatives, we opted to proceed with that of Dabhilkar et al.'s (2016) as they provide some evidence of statistical analysis which makes it suitable to test with a different sample collected using a different methodology.

Supply chain complexity

Complex systems consist of a large number of different types of subsystems or underlying parts that interact with each other (Choi and Krause, 2006; Perona and Miragliotta, 2004; Simon, 1962). The complexity of a system may be examined adopting a structural (static) perspective or a dynamic one (Bozarth et al., 2009; Casti, 1979; Serdarasan, 2013; Sivadasan et al., 2002). Structural (static) complexity refers to the complexity of the systems structure, and thus accounts for the variety and dependencies within system components. Dynamic complexity refers to the dynamics that unveils or can arise over time due to uncertainties, randomness or changes within the system. While the relevance of dynamic complexity has been underlined theoretically and empirically in the SC complexity literature (Bozarth et al., 2009; Serdarasan, 2013), most empirical research accounted only for structural complexity. This work is no exception as, due to the nature of the methodology and data used, it must focus mostly on structural complexity.

SC Complexity is driven by several factors such as the range and characteristics of customers (Bozarth et al., 2009), supply base (e.g. Choi and Krause, 2006), product portfolio (e.g. Closs et al., 2010), aspects related to organisational (re)structuring and size (Ashkenas, 2007; Heywood et al., 2007). This paper relies on these SC complexity factors and their underlying indicators in the investigated relation between complexity, resilience and operations performance. As such, SC complexity is described in terms of product portfolio (number and variety of product lines, brands), supply base dispersion (number and geographical dispersion of production facilities and legal entities), size (turnover and number of employees) and restructuring (mergers, acquisition and sellouts).

Operations performance and the effects of complexity

Operations performance refers to the measurable aspects of the outcomes with regard to cost, quality, delivery (speed), flexibility, and dependability (Wong et al., 2011; Zhang et al., 2012). Multiple measures of each of the five objectives, indicated in Appendix B, are used in this study to capture change in values as described in the methodology section.

Complexity is recognised as both a source of competitive advantage and a hurdle for performance in the SC literature. A survey by researchers at MIT found that complexity was viewed as creating a competitive advantage by 30% of respondents while deemed of as a competitive liability by about 60% of managers (Mocker et al., 2016). Some researchers argue that complexity increases costs, lead times, inventories and variability of production processes (e.g. Bozarth et al., 2009; Mariotti, 2008; Perona and Miragliotta, 2004). Others underline that complexity is not always detrimental to performance (e.g. Manuj and Sahin, 2011; Mocker et al., 2014). Collinson and Jay (2012) found a negative quadratic relationship (i.e. inversed U-shape) between complexity and financial performance and argue that below a critical level firms may embrace complexity to improve their performance. This is in line with the claim that SC managers need not to reduce complexity to the lowest level possible (Bozarth et al., 2009; Manuj and Sahin, 2011). In the same vein, Perona and Miragliotta (2004) and Mocker et al. (2014) note that structural complexity can imply trade-offs between performance objectives and may be leveraged in pursuit of effectiveness.

Table 1. Summary of SC complexity drivers and impact on performance

Complexity factors	Impact on performance	References
Number of suppliers	Not significant but *positively directed influence on* competitive performance (consisting of measures of manufacturing cost, delivery flexibility, lead-time and timeliness, quality and dependability); Not significant but *negatively directed influence on* cost of manufacturing	Bozarth et al. (2009)
Number of suppliers	Conceptually propose *supply base complexity to be positively associated with the transactional cost* (with its supply base) that the focal company incurs	Choi and Krause (2006)
Supply-base complexity	Significant *positive impact on frequency of disruptions and plant performance* (cost, inventory turnover, quality, delivery performance and flexibility). The effect is mediated by frequency of disruptions in the model	Brandon-Jones, Squire and Van Rossenberg (2014)
Number of products and parts	*Not significant but positively directed influence on* both competitive performance and cost of manufacturing	Bozarth et al. (2009)
Product complexity	Significant *negative effect on unit and order fill rate service performance*	Closs et al. (2010)
Product and SC network complexity	Drawing from the empirical findings*: the level of complexity of an operative system was found connected to both its efficiency and effectiveness,* other things being equal	Perona and Miragliotta (2004)
Number of customers	Not significant but *positively directed influence on* competitive performance and cost of manufacturing	Bozarth et al. (2009)
SC complexity: size, structure, geographic dispersion, restructuring	Based on case studies proposed *positive impact on undesired outcomes* (i.e. lower performance: cost, quality, speed)	Manuj and Sahin (2011)
Inter-relationships among suppliers	Propose *negative quadratic relationship* between supply base complexity and supplier innovation	Choi and Krause (2006)

Complexity factors	Impact on performance	References
Level of differentiation between suppliers	Significant *positive impact* on the frequency of disruptions and on plant performance (cost, inventory turnover, quality, delivery performance and flexibility)	Brandon-Jones, Squire and Van Rossenberg (2014)
Differentiation of suppliers	Conceptually propose supply base complexity to be *negatively associated* with supplier responsiveness	Choi and Krause (2006)

While prior studies have looked at the effect of SC complexity on some aspects of supply chain disruptions (Bode and Wagner, 2015; Craighead et al., 2007), there is lack of empirical research examining the potential influence of complexity factors on the resilience-performance link. Nonetheless, there are several results which suggest that complexity and resilience may interact when influencing performance under disruption. For example, product portfolio and supply base dispersion complexity factors are argued to reduce the effectiveness of managers' decisions (Collinson and Jay, 2012; Mariotti, 2008). On the other hand, complexity has been argued to have a negative effect on integration and collaboration with suppliers (Sheffi, 2007), and to reduce agility and responsiveness (Ashkenas, 2007; Collinson and Jay, 2012). Manuj and Sahin (2011) argue that diverse supply and customer bases increase process outcome variability and drive workforce disengagement which may influence effectiveness of some resilience practices. Besides, the adoption of resilience practices can result in additional process complexity (Collinson and Jay, 2012). Table 1 provides summary of some relationships found in extant SC literature pertaining to structural and dynamic supply chain complexity items and operations performance measures.

Research question and hypotheses

Interrelationships among the concept of resilience and other organisational and infrastructure related phenomena have been among possible research directions suggested in extant literature (e.g. Bhamra et al., 2011). Drawing from the theoretical discussion in the preceding sub-sections, we argue that complexity could influence how resilience practices help restore performance upon disruption via two different mechanisms. On one hand, it is reasonable to argue that firms that suffer from a specific complexity outcome (e.g. increased frequency of supply disruptions) may respond by adopting practices which can mitigate these effects (e.g. setting redundancies such as dual sourcing or safety stocks). On the other hand, however, it is equally reasonable to argue that complexity may influence the outcomes of the firm's adopted practices; i.e., a firm with a more complex supply base achieves a lesser degree of collaboration than one implementing same practices but with a less complex supply base. Based on this consideration, we posit the following generic research question.

RQ: How does complexity influence resilience capability in mitigating supply chain disruptions?

Contingent RBV generally views resilience as an outcome of assets built and capabilities created with an ultimate aim of mitigating the unwanted economic impact of disruptions (Brandon-Jones, Squire, Autry, et al., 2014). Consequently, resilience capabilities are broadly discussed by different researchers to have helped companies recuperate performance affected by supply chain disruption (e.g. Birkie, 2016; Dabhilkar et al., 2016; Rice and Caniato, 2003; Sheffi, 2007). Following this line of argument, we propose the first hypothesis as follows:

***H1**: Resilience positively affects recovery of operations performance after disruption.*

Based on qualitative observations, Manuj and Sahin (2011) propose that supply chain complexity is positively related to unexpected and unwanted outcomes, i.e., reduction of performance. In terms of performance under supply chain disruption, these unwanted outcomes could be viewed as reduction in different dimensions of performance. Bozarth et al. (2009) observe that some supply chain complexity factors negatively impact operational performance. While such studies investigated these relations presuming "normal" day-to-day functioning, relevant implications on how performance might be influenced by supply chain complexity and its antecedents can be perceived. Likewise, quantitative studies have examined the role that SC complexity may have in increasing the frequency of disruptions (e.g. Bode and Wagner, 2015).

Taking the focus of this study on SC disruptions into account, we state the second hypothesis:

***H2**: Supply chain complexity influences performance recovery after supply chain disruption.*

We could not immediately disregard the possibility of both negative and positive impacts of SC complexity on performance as both have been argued in earlier research.

A large literature base discusses that too much complexity destroys these benefits and has to be strategically managed, while many activities that can drive complexity can be sources of competitive edge (Bozarth et al., 2009; Collinson and Jay, 2012; Mocker et al., 2014; Serdarasan, 2013). In the same vein, Perona and Miragliotta (2004) and Mariotti (2008) argue that while complexity can drive competitiveness and financial performance (e.g. increasing the firm's product portfolio), they may do so at the expense of costlier coordination and management processes which may balance out the intended benefits. Together, these arguments suggest that firms should acknowledge the potentially opposite effects of complexity on different performance objectives and examine the extent to which they can benefit from reducing or enhancing complexity in their SCs. Acknowledging these results, we consider a linear (positive) and an opposing nonlinear (specifically quadratic) form of influence from complexity on performance.

H2a*: Supply chain complexity positively affects recovery of operations performance after supply chain disruption.*

H2b*: Supply chain complexity has negative quadratic effect on operations performance recovery after supply chain disruption.*

Morieux (2011) argues that complexity brings both opportunities as well as challenges. This means, for example, that firms have the opportunity to more flexibly handle disruptions leveraging on a wider supply base, or broader range of product offering. The positive and negative impacts, including non-linear ones, of some complexity drivers discussed in literature are indicated in Table 1. The moderating influence of complexity on the resilience-performance relationship has been investigated, for example, in Brandon-Jones, Squire, Autry, et al. (2014). Investigating if complexity provides sufficient opportunity for moderating the resilience-performance link is part of the aim of this study. As described in earlier sub-sections, supply chain complexity comprises of structural and dynamic factors. Given the design of this study (described in section 3) and treatment of complexity as formative construct, we limit the investigation of the moderation effect to the structural dimension only and propose the following hypothesis.

H3*: Supply chain complexity has a positive moderating effect on the relationship between resilience and performance upon supply chain disruption.*

Given the divergent opinions in literature regarding the influence of SC complexity, we consider that it is worth doing further exploration on the hypothesis through investigation of which underlying constructs of complexity provide the dominant or (possibly) divergent influences.

Research methodology

Overall approach

In this study we use the partial least square (PLS) approach-based Structural Equation Modelling (SEM). In fact, the application of the PLS approach in complexity analysis is not uncommon; several research papers have applied it in recent years (e.g. Braunscheidel and Suresh, 2009; Hanisch and Wald, 2014). The main reasons for choosing PLS over covariance-based SEM are that PLS: (1) is suitable for small sample size data analysis (e.g. Grötsch et al., 2013); (2) is relatively more effective to perform moderation effects analysis (Witzels et al., 2009); (3) enables to deal with formative multilevel constructs that are not easy to be dealt with in a single covariance-based SEM model (e.g. Peng and Lai, 2012); (4) does not require multivariate normal distribution of data. We employed the SmartPLS software package version 3 (Ringle et al., 2015) for our analysis. Bias corrected bootstrapping with 500 random samples is used to estimate the significance of path coefficients and item weights.

Earlier studies treated complexity as consisting of several dimensions or facets that can be aggregated into multiple sub-constructs, each of which consist of multiple measurement items, as described in the theoretical framework section. This clearly justifies that supply chain complexity can be viewed as a second order construct.

Methodologically, second-order constructs are argued to provide more theoretical parsimony and reduce model complexity (Witzels et al., 2009). Antecedents of a concept represent formative measures especially when judgement (retrospectively) is made based on actual actions rather than hypothetical action (Wilcox et al., 2008). For example, Wieland and Wallenburg (2013) used communication, cooperation and integration competencies as (formative) antecedents of agility and responsiveness that represent proactive and reactive resilience capabilities; Scholten and Schilder (2015) observe that visibility, flexibility, velocity and collaboration are formative antecedents of supply chain resilience, each of which can have more than one underlying constructs. The theoretical justification of formative measures is that the measures are the “cause” rather than being caused by the latent variable (e.g. Diamantopoulos and Winklhofer, 2001). The process of forming a composite latent variable using formative measures is called index construction (rather than scale formation as with reflective measures). Figure 1 shows the first-order and second-order constructs for resilience and complexity. The inner model (shaded region) represents the relationships among resilience, complexity and weighted performance described in the hypotheses.

--

Please insert Figure 1 about here

--

Due to the varying nature of index construction from scale development, the common procedures and tests for the latter cannot be directly applied for the former. We followed the suggested steps in supply chain complexity index development proposed by experts in the domain (Diamantopoulos and Winklhofer, 2001) throughout our analysis.

Weighting or summing is also another alternative way of formulating formative indices (Wilcox et al., 2008), as is done in this research for resilience and weighted performance variables. A similar approach could have been taken for complexity if we were not interested in understanding the contribution of each complexity sub-index to overall supply chain complexity.

Data collection

The study used secondary data from companies that have faced at least one SC disruption between the years 2002 and 2015. This approach has not been common in resilience studies in operations and supply chain domain as recent literature reviews outlined (e.g. Bhamra et al., 2011; Tukamuhabwa et al., 2015). Initial list of incidents has been developed based on news items on globally encountered supply chain disruptions. Using those initial descriptions of the disruptions, the research team has searched for and compiled data about the incident and its consequences from each of the companies that faced the incident. The secondary data collection methodology was inspired by the event study methodology (Hendricks and Singhal, 2003). However, subsequent steps were different in this study. Table 2 briefly describes the procedure followed.

Most of the companies that faced the disruptions were large firms with operations in multiple locations globally. There are also smaller firms operating in localised markets which faced disruptions; however the richness of details obtained from such firms was a challenge that the proportion of firms in our dataset becomes smaller. The operations of most of the companies represented in the dataset can be classified into electronics and electrical (36.4%), automotive (29.9%), or industrial goods (13%) sectors. Table 3 presents descriptive summary of the dataset. The risk categories in Table 3 represent the risk drivers according to the classification by Chopra and Sodhi (2004); for example, disruption risk includes drivers such natural disaster, labour disputes, war, and supplier bankruptcy; procurement includes drivers such as exchange rate risk and price of inputs. Logically resembling drivers which we encountered but did not appear in the original list have been included to the categories; fire accidents, and regulatory and sustainability related claims on suppliers have been classified as disruption and procurement risks respectively.

Table 2. Procedure followed in data collection and analysis

Phase	*Description and activities*	*Criteria/reference*	*Milestone*
1. Surfing	• News items reporting supply chain disruption collected from media such as FT, Reuters, CNN Money, WSJ	• The incident should fit to one of the nine risk categories proposed by Chopra and Sodhi, (2004) • Table 3 shows categories covered	• More than a hundred incidents that affected business performance of firms were identified
2. Sorting	• Additional detail on the incidents with respect to the company in focus actively searched for • Secondary data sources include: annual reports, top management interviews, financial reports, press releases and cases written on the incident	• Discard if key details to characterise the incident are missing (i.e. at least some information on actions, circumstances and possible consequences of incident) • Adequate representation and balance of industries and risk categories in the sample • Table 3 shows risk categories and industries covered in this study	• 80+ potential incidents identified; further screening led to 77 usable cases.
3. Encoding	• The collected data was encoded according to pre-defined scheme	• Predefined systematic encoding procedure followed; multiple researchers encoded independently and discussed on differences to improve reliability	• Qualitative data from the different sources was converted to scale measure of constructs
4. Aggregation	• Item-values aggregated into constructs based on pre-set rules and second order formative PLS-SEM	• Likert scale categories shown in Appendix C; encoding procedure illustrated in Appendix D • Figure 1 depicts the PLS-SEM representation; Table 4 shows statistical results upon aggregation	• Correlation values and factor weights obtained.
5. Regression	• Regression models as per set hypotheses were run	• linear regression analysis done as shown in Table 6 with industry as control variable	• Statistics with which to assess formulated hypotheses were obtained

Table 3. Dataset description

Risk category	Frequency	Industry	Frequency
Disruptions	61	Automotive	23
Delays	11	Electronics & electrical items	28
Systems risk	4	Chemical/pharma	8
Procurement risk	1	Industrial goods	10
		Leisure and personal goods	6
		Utilities and services	2
Total	**77**	**Total**	**77**

Data encoding

The measurement items for resilience, complexity, and operations performance compiled from extant literature have been used to collect and encode relevant information.

In order to be consistent and account for extreme differences in collected data from secondary sources, we have implemented conversion of the absolute values for complexity measures into Likert-type scales. Therefore, we have effectively followed the common practice of survey methodology. For example, instead of taking annual sales figures directly, we classified the annual sales into seven intervals represented as Likert scale (see Appendix C for details).

Three variables out of the nine complexity measures have been encoded into two categories. Mergers and acquisitions (M&A) has been encoded into absent or present by combining presence of merger, acquisition, or sellout related to the organisation in the year the disruption incident happened. Because it was very difficult to extract exact information on the number of suppliers and customers from some companies, we decided to encode them as few or many only.

Regarding the resilience practices, we have adopted the item parcelling approach used by Birkie (2016) and each practice is encoded as binary (0 for absence, 1 for presence) in the face of that particular incident. The values are then aggregated into the respective four resilience bundles as weighted averages; essentially each bundle has a possible range of [0, 1].

In a similar manner, variations in performance measures are captured using three levels: -1 for reduction, 0 for no change, and +1 for increase in each measure. The values in measure belonging to the five performance objectives are summed and transformed to give aggregate values. Disruption scenario types are used as weighs to discriminate the performance changes in disruptions of different intensity. It is to be noted that for both resilience practices and performance measures, absence of data is the default with a value of zero. An example of the encoding procedure for performance changes and resilience practices is provided in Appendix D.

We applied a scheme for aggregating operations performance as used in Zhang et al. (2012) and Dabhilkar et al. (2016). We did not have a weighting mechanism for prioritized performance objectives; we treated all performance objectives as equally important across the dataset.

The aggregated performance is then weighted based on three categories of disruption scenario following the approach used in Birkie (2016) for specifying scenario types and encoding procedure. The justification for doing this weighting is that for extreme event disruptions, it is much more difficult to recover performances compared to “minor” disruption incidents. Therefore, we weighed the performance changes by a proportion of 3:2:1 for severe (type III): medium (type II): and minor (type I) disruptions respectively.

Index construction and validation

We used the detailed literature review to specify the different dimensions and measures of supply chain complexity. This is discussed in literature review, and summarised in the hypotheses formulation subsection (see Table 1). Accordingly, we have organised the measures of complexity into four sub-indices, one of them with just one measure, that in turn form the overall supply chain complexity indicator (see Table 4). In the same table specifications of the other constructs are also provided.

Formative measurement model is based on multiple regression. Therefore, collinearity is a major concern in such formulation. We have checked multicollinearity and all values were less than 2, which is much lower than the commonly agreed conservative threshold of 5.

Formative measures essentially bring complementary dimensions of the index under question. Therefore, more measures mean more dimensions of the index taken into account; but too much measures bear challenge of suitability for overall analysis especially for smaller sample sizes. While formal tests for external validity on formative measurement are still under discussion, we have used a common approach of checking the relevance of the measures forming each complexity (sub-)index by evaluating their level of significance ($p<0.05$). The measures indicated in our final model have all been found to be significant in forming the indices.

Table 4. Constructs and their specification

Constructs	Mean	SD	Weight on index	Weight on sub-index	Range
Complexity	**0.00**	**1.00**			**[-2.83, 2.11]**
Size	*0.00*	*0.99*	*0.487****		*[-2.73, 1.15]*
Employees	5.53	1.61		0.60***	
Annual turnover	4.81	1.64		0.448***	
Product portfolio	*0.02*	*1.00*	*0.302****		*[-2.16, 3.38]*
Product lines	3.03	1.06		0.694***	
Major brands	1.96	1.45		0.411***	
Major customers	1.65	0.48		0.3339*	
Supply base dispersion	*0.00*	*1.00*	*0.347****		*[-2.23, 2.46]*
Production facilities	3.23	1.37		0.695***	
Suppliers	1.61	0.49		0.544***	
Legal entities	2.08	0.81		0.185*	
Restructuring	*1.48*	*0.50*	*0.081*†		*[1, 2]*
M&A				1.00	
Resilience	**0.00**	**1.00**			**[-2.40, 2.03]**
Proactive-Internal	*0.46*	*0.41*	*0.377****		*[0, 1]*
Proactive-External	*0.44*	*0.27*	*0.344****		*[0, 1]*
Reactive-Internal	*0.52*	*0.26*	*0.443****		*[0, 1]*
Reactive-External	*0.54*	*0.24*	*0.289****		*[0, 1]*
Weighted performance	**26.26**	**9.24**			**[10, 54]**
Industry					**[1, 6]**

Note: *** p<0.005, ** p<0.01, * p<0.05; †p<0.1

Findings

Correlations among variables

Table 5 provides the correlations of relevant variables in this study. In the table, we do not observe exaggerated correlations (> 0.9) except in one case where complexity has with its size sub-index. Out of caution with this outcome, we have run the regression analyses (reported in the next subsection) with and without the size complexity sub-index, and results remained consistent. Therefore, we continued without the need to exclude size.

Regression results

The initial regression model, based on the research question and the stipulated hypotheses has been mathematically expressed as follows:

$$Weighted\_Performance = \beta_0 + \beta_1 * Resilience + \beta_2 * Complexity + \beta_3 * Complexity * Resilience + \beta_4 * Complexity^2 + \beta_5 * Industry + \varepsilon$$

We started by investigating the direct effects and controlling for industry; then we continued to interaction and quadratic effects. Important values for the models are presented in Table 6.

All the regression models estimated the coefficients of the independent variables after controlling for the effects of industry sector, even though this control variable did not appear to have significant effect in all models. The first model estimates variance explained by the industry control variable. The control variable barely explains any variation in performance.

Estimation of the second model reveals that both resilience and SC complexity bear significant direct influences on performance recovery, explaining sample adjusted variance of 16.3%; at this stage, hypotheses *H1* and *H2a* find support. In model 3 estimation, where the moderation effect is introduced, both direct and moderation effects remain significant (at p=0.05 or less). The moderation explains 3.5% additional variance on top of main effects in model 2. Model 4 introduced the quadratic effect of SC complexity but no significant observations have been made. The negative coefficient of the quadratic term does not appear significant; no additional variance compared to model 3 has been explained. Altogether models 2-4 reveal that all our hypotheses, except H2b that refers to the quadratic effect, were supported.

Table 5. Multivariate correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Industry	1										
(2) Complexity	-0.089	1									
(3) Size	-0.125	0.909**	1								
(4) Product portfolio	0.037	0.749**	0.519**	1							
(5) Supply base dispersion	-0.112	0.886**	0.729**	0.561**	1						
(6) Restructuring	-0.017	0.249*	0.204†	0.085	0.106	1					
(7) Resilience	-0.069	**-0.191**†	-0.221†	-0.069	-0.149	-0.010	1				
(8) Proactive-Internal	0.117	-0.224†	**-0.258***	**-0.008**	**-0.240***	**-0.042**	0.714**	1			
(9) Proactive-External	-0.224†	-0.191†	**-0.216**	**-0.165**	**-0.090**	**-0.057**	0.673**	0.266*	1		
(10) Reactive-Internal	0.051	-0.155	**-0.161**	**-0.043**	**-0.157**	**-0.013**	0.792**	0.446**	0.366**	1	
(11) Reactive-External	-0.203†	0.096	**0.077**	**0.033**	**0.145**	**0.108**	0.514**	0.163	0.230*	0.189†	1
(12) Weighted performance	0.006	0.261*	0.251*	0.189†	0.208†	0.097	0.296**	0.153	0.064	0.337**	0.232*

Note: Correlation significant at the respective levels (2-tailed) of :** $p<0.01$ level; * $p<0.05$; † $p< 0.1$

Table 6. Regression analysis on weighted performance

Model	Standardised coefficients for	β	Adj. R^2	Δ adj. R^2	SRMR	NFI	*p* of d_ULS
1	***Control variable***		-0.013		0.00	1.00	-
	Industry	0.006					
2	***Direct effects (H1, H2a)***		0.163	0.176	0.079	0.796	0.09
	Industry	0.061					
	Resilience	0.364***					
	SC complexity	0.336***					
3	***Moderation (H3)***		0.198	0.035	0.071	0.764	0.175
	Industry	0.035					
	Resilience	0.302***					
	SC complexity	0.257*					
	Resilience*SC complexity	0.260*					
4	***Quadratic effect (H2b)***		0.198	0.000	0.074	0.711	0.177
	Industry	0.035					
	Resilience	0.308**					
	SC complexity	0.196					
	Resilience*SC complexity	0.267*					
	Quadratic of SC complexity	-0.077					

*** *p<0.005;* ** *p*< .01; * *p*< 0.05; † *p*< 0.1; (all 2-tailed)

In SmartPLS, four indicative models of fit statistics are provided: standardised root mean residual (SRMR), Normalized fit index (NFI), squared Euclidean distance (d_ULS) and geodesic distance (d_G). The last two, d_ULS and d_G, are exact measures (bootstrap-based) of discrepancy between the empirical covariance matrix and the results of the composite factor model. We want the discrepancy to be small for a better fit. This minimal discrepancy is tested by non-significant (p>0.05) value corresponding to d_G and d_ULS. We also expect NFI as close to 1.0 and SRMR to be as close to zero as possible. Rule of thumb suggests an acceptable model fit with these values: NFI>=0.9, SRMR<0.08. Even though second order formative PLS models are neither required nor expected to fit any better than their single order counterparts (Wilcox et al., 2008), and model fit tests in SmartTPLS are only indicative, the inner model seems to have quite acceptable fit with NFI close to 0.8, SRMR less than 0.08, and p value of the Euclidean distance being higher than 0.5; this is particularly true for models 3 and 4.

Our endogenous variable, the weighted performance, is calculated as a product of the aggregated performance and the disruption scenario type. To show how well the model holds when the weighting scheme is released, we used the aggregated performance without weighting**.** While the adjusted r-squared value dropped to 5%, moderation effect became insignificant at p=0.1 level; model fit stats showed little reduction: SRMS=0.074; NFI=0.662; p of d_ULS=0.159.

Indirect effect of sub-indices

Going a step further in the direction of the supported hypothesis of interaction (*H3*), we have tried to understand which of the underlying sub-indicators for both complexity and resilience would have dominant influences. To do this, we computed the indirect effects of sub-indices (first order constructs) on the weighted performance variable.

The indirect effects are obtained by multiplying the weights in respective paths from the sub-index to performance. For example, the moderating effect of size is calculated as the product of loading of size on complexity (0.487) by the moderation standardised coefficient in model 3 (0.26), giving 0.127 as contribution of size in the moderation effect. Likewise, the moderating indirect effects of product portfolio, supply-base dispersion, and restructuring are 0.079, 0.090, and 0.021 respectively. The path weights from these four sub-factors to weighted performance are 0.125, 0.078, 0.089 and 0.021; this indicates the dominance of size and supply-base dispersion as SC complexity factors among the structural category.

Proactive-internal, proactive-external, reactive-internal, and reactive-external bundles of resilience have indirect effects on weighted performance of 0.114, 0.104, 0.134, and 0.087 respectively.

The results in this study generally imply that firms which operate under higher level of operational complexity tend to employ resilience capabilities to a higher extent when responding to disruptions. This result provides empirical evidence to extant resilience theory which discusses the relevance of SC network complexity issues, such as the number of suppliers, in dealing with SC disruptions (e.g. Bode and Wagner, 2015; Sheffi, 2007).

Discussion

This research has empirically examined the influence of supply chain complexity on how firms mitigate performance losses under operational disruptions using resilience capabilities. Accordingly, we have formulated three main hypotheses to be empirically tested. The hypotheses represent direct effects of complexity and resilience upon performance following a disruption (*H1*, *H2a*), quadratic influence of complexity (*H2b*), and moderation influence of complexity (*H3*).

This study included incidents affecting several industry sectors. Therefore, before proceeding with the testing of the hypotheses set forth, we have controlled for possible variance due to industry differences. We noted that the industry control variable does not seem to have any significant effect in all estimation models.

Use of weights for different disruption scenarios provides indication that the resilience capabilities are far more important in avoiding much worse performance consequences of severe disruptions compared to, say, normal accidents. This strengthens the argument that resilience capabilities are much worth for unanticipated (and likely low probability) events that can have high impact on performance (Knemeyer et al., 2009).

The first hypothesis intended to observe direct influence of resilience on performance. The analysis shows that resilience has significantly positive ($p<0.01$) relation with improvement of performance from an affected lower level due to disruption. This in support of the recent studies that found significant positive correlation between resilience capabilities and performance recovery after disruption (Ambulkar et al., 2015; Dabhilkar et al., 2016; Wieland and Wallenburg, 2013). Our analysis adds confirmation and deeper understanding to those studies through relatively larger sample size and additional measurement items for both resilience (5 additional items) and operations performance (at least 2 items for each of the 5 objectives). For example, the relative strength of the different capability bundles forming resilience was estimated (Table 4). We can observe that internal resilience capabilities (both proactive and reactive) are stronger than external-focused capabilities in affecting performance. This suggests that assets and capabilities embedded elsewhere in the supply chain can be leveraged when the efforts within the firm boundary drive them well enough. Reactive-external seems to be relatively weaker leading to a possible interpretation that reactive efforts to solicit resources are better achieved only when proactive relations have been in place beforehand. In general, these results are coherent with formation of resilience capabilities from routine practices (e.g. Dabhilkar et al., 2016); for example, utilising multiple competences of large work force, or leveraging from pre-established supplier relationships to switch among possible supply bases during disruption.

According to the findings in this study, increased SC complexity seems to positively affect performance loss reductions (*H2a*). Based on contingent resource based view, this implies that more resources and interconnections could provide opportunities to keep (up) performances. Our results strongly support this argument. Considering that we mainly focused on structural drivers of SC complexity, the weak contribution of restructuring to SC complexity (Table 4) is a possible indication that it is more of a dynamic SC complexity issue rather than structural, which needs to be explored further in future research.

Literature suggests that some level of complexity is required to bring about economically viable performance levels; this also appears to explain the finding that the moderating effect of complexity on the resilience-performance link was significantly positive with some additional variance explained (*H3*).

As discussed in the theoretical background section, extant research has provided with some empirical quantitative evidence which suggest that the relation between complexity and performance may be represented by an inverted U-shape (e.g. Collinson and Jay, 2012). Following this line of argument, our model has considered the possibility that complexity, as an aggregate variable in a quadratic form, may influence performance linearly (*H2b*). However, the hypothesis is not supported by our empirical analysis as the quadratic link between complexity and performance resulted not significant (at $p<0.1$). The direction of the coefficient for the quadratic influence (negative β value) is in line with the previous argument, but the statistical evidence was not significant enough. This is possibly due to the presence of dominant linear effects from resilience and complexity.

Table 7 provides summary of this study in supporting or rejecting the proposed hypotheses. The use of different data collection (encoding from secondary data) and data analysis (formative PLS-SEM) methodology are unique values which further strengthen the robustness of the validation in this study.

We have tried to perform an in depth exploration on the moderation mechanisms contributed by the first order constructs (sub-indices) as described in the findings section. The size of the business organisation, followed by supply base dispersion, dominantly contributes to the majority of the moderation on the resilience-performance link. Big size could mean, for example, that the firm would have higher financial and human capital to be employed in building and (re)generating capabilities (Ambrosini et al., 2009) to mitigate disruptions, and thus that it could be more effective in sustaining performance upon disruption with the same resilience capabilities (i.e. functional and resource redundancies) supported by proper decision models. In the same manner, a more diversified supply base and wider network of SC facilities may provide the firm with additional opportunities in leveraging resilience capabilities to manage unexpected disruptions if sufficiently capable processes and infrastructure are in place.

There are several instances in which we can practically observe how firms leveraged larger size and supply base dispersion complexity for improving effectiveness of resilience capabilities. For example, ON Semiconductors explains this in the annual report as follows:

“Our large global scale and international manufacturing network proved invaluable in mitigating the impact from these two significant natural disasters [Japan earthquake and Thailand flooding in 2011]. We were able to minimize the resulting supply disruptions to our customers by leveraging our 20 worldwide internal front-end and back-end manufacturing facilities, and working closely with our extensive network of external manufacturing partners and suppliers”.

The organisational restructuring sub-index seems to provide the weakest contribution of all complexity sub-indices. A possible explanation is that coincidence of merger or sellout with disruption hampers focus of effort on disruption mitigation. For example, workers who have good experience and are trained to perform coordinated tasks during disruptions might not work as expected because restructuring and job redesign may, for example, lead to confusion and ambiguity.

Companies often strive to manage and limit complexities in their supply chains and internal operations in search of economies of scale and better efficiency. However, some level of complexity is required in dealing with supply chain disruptions and recovering operations performance. The firm may have invested in these complexity drivers somehow, and utilising them for sustaining competitive advantages upon disruption should be a logical consideration. In this vein, resilience capabilities can be seen as those practices that exploit structural complexity factors as desirable resources to recover operations performance after exceptional disruptions.

Table 7. Discussion on hypotheses

Direct effects	**H1** (*supported*): resilience capabilities do significantly help in better recovering performance after disruptions. Result has been claimed in earlier studies. We provide validation through extended sample and different data collection method.
	H2a (*supported*): supply chain complexity does significantly improve performance recovery after disruptions.

Moderating effect	**H3** (*supported*): the positive resilience-performance link is significantly positively moderated by supply chain complexity. At higher complexity, resilience capabilities lead to more effective performance benefits compared to situations with lower complexity. The moderation is partial as both H3 and H2a are supported.
Quadratic effect	**H2b** (*rejected*): quadratic effect of complexity on performance does not appear to be significant; the direct and moderating effects seem to dominate the negative influence.

Even though we did not find strong evidence to support hypothesis H2b, we cannot disregard the possibility of a negative quadratic relation between SC complexity and performance (e.g. Collinson and Jay, 2012) or performance recovery. Indeed, it stands to reason that even if firms may benefit from increased diversity and variety of resources in responding to disruptions (as the findings of the present study strongly suggest), excessive complexity can impair decision making and SC coordination (Manuj and Sahin, 2011) and may no longer positively contribute to operations performance recovery in the event of a supply chain disruption.

Seeing the findings under the lenses of contingent RBV and CT, once can easily gather that the outcome of capabilities is contingent on the existing context. Furthermore, the creation of resilience capabilities is also contingent on what is available embedded somewhere in the supply chain, not just the rare resources that the specific firm owned and controlled as traditionally thought before. Moreover, the presented findings call to consider how resilience practices and complexity management actions under routine operating conditions can be reconciled with each other.

This study relied on secondary data and by design could not consider the dynamic complexity factors. However, earlier studies indicated or implied that dynamic complexity has significant influence on performance (e.g. Azadegan et al., 2013; Brandon-Jones, Squire and Van Rossenberg, 2014; Choi and Krause, 2006); hence, the combined interplay of structural-dynamic complexity factors in supply chain disruption setting would be an interesting issue for future investigation.

Conclusion

Following the theoretical lenses of CT and contingent RBV, this study investigated how contingent complexity factors influence firms' capabilities in recovering performance when affected by SC disruption events. Based on encoded secondary data and PLS-SEM approach with formative second order constructs, the findings indicate that resilience capabilities help reduce performance-degrading possibilities of supply chain disruptions. Complexity seems to positively affect performance recovery and also positively moderate the resilience-performance link.

Our study provides with additional support and insights on the discussion of resilience performance theory with the inclusion of context factors.

Theoretical implications

In light of contingent RBV, the findings of this study indicate that resources embedded along the supply chain network, out and beyond the control of a single firm, contribute to developing resilience capabilities. Therefore, contingent RBV and CT help us understand how supply chain complexity drivers may lead better performance recovery. In the context of this study, increasing supply base complexity means additional resources that have potential not only for improving competitiveness during ordinary business conditions, but also for addressing the challenge of fast and better performance recovery after disruptions. It appears that complexity has the tendency to increase the effectiveness of resources utilised to cope with disruptions. This means that the diversity of resources and number of possible configurations (due to complexity) seem to enable better and faster bounce back from disruptions.

In addition, our results contribute to the growing body of research which claims that SC complexity might play a dual role (i.e. positive and negative) with regards to performance; the study's empirical findings suggest that the benefits of having additional resources can offset the detrimental effects of complexity in dealing with SC disruptions.

Practical implications

Business decision makers are often cited to have tried simplification of their supply chain elements. Researchers in the field recognise that supply chains are becoming more and more complex. It is only logical to think of how such complexity in supply chains can be used for betterment of operational performance at times of high uncertainty.

An implication of this study is that some level of supply chain complexity is beneficial for having competitive performance and also for a better recovery of operational performance affected due to disruption. As shown in this study, resilience capabilities are likely to become more effective when leveraged on higher resources and flexibility that come with more complexity in the supply chain. It could be of relevance for supply chain managers how the impact of disruptions can be offset through leveraging SC complexity drivers such as custom configurations from existing product and supply base diversities.

Limitations and future research

The proposed quadratic relationship between complexity and performance (*H2b*) has not been supported. However, there are possible avenues for future research including investigation of possible negative mediation influence of SC complexity on the resilience-performance relationship. The contribution of complexity at sub-factors level has been briefly explored in this study. However, a more rigorous investigation is called for to establish a much clearer understanding of the underlying mechanisms. Investigation of the structural and dynamic forms of SC complexity separately and jointly on the resilience-performance link is an interesting future research direction, and one that could shed further light onto the weak contribution/effect of restructuring encountered in this study. It is also of future research interest to understand how performance improvement can be achieved and managed by firms operating in industries with high supply chain complexity, even in circumstances where unanticipated disruptions are not faced.

We are aware of the limitations and criticisms of using second-order formative constructs in SEM estimates. However, the compelling findings, and the outweighing benefits of PLS-SEM make a strong case for our approach given the study design characteristics. Earlier studies implied that dynamic complexity might have significant influence on performance during unpredictable circumstances (e.g. Azadegan et al., 2013; Brandon-Jones, Squire and Van Rossenberg, 2014); inclusion of dynamic complexity issues might have allowed for richer detail and discussion. However, the study design is limited in scope from the outset only on structural complexity. And the generalisability of our findings may not apply for dynamic supply chain complexity factors. Consequently, we see room for relevant quantitative and qualitative research to further investigate these issues.

References

Ambrosini, V., Bowman, C. and Collier, N. (2009), “Dynamic capabilities: an exploration of how firms renew their resource base”, *British Journal of Management*, Vol. 20 No. S1, pp. S9–S24.

Ambulkar, S., Blackhurst, J. and Grawe, S. (2015), “Firm’s resilience to supply chain disruptions: scale development and empirical examination”, *Journal of Operations Management*, Vol. 33–34, pp. 111–122.

Ashkenas, R. (2007), “Simplicity-minded management”, *Harvard Business Review*, Vol. 85 No. 12, pp. 101–109.

Azadegan, A., Patel, P.C., Zangoueinezhad, A. and Linderman, K. (2013), “The effect of environmental complexity and environmental dynamism on lean practices”, *Journal of Operations Management*, Vol. 31 No. 4, pp. 193–212.

Bhamra, R., Dani, S. and Burnard, K. (2011), “Resilience: the concept, a literature review and future directions”, *International Journal of Production Research*, Vol. 49 No. 18, pp. 5375–5393.

Birkie, S.E. (2016), “Operational resilience and lean: in search of synergies and trade-offs”, *Journal of Manufacturing Technology Management*, Vol. 27 No. 2, pp. 185–207.

Bode, C. and Wagner, S.M. (2015), “Structural drivers of supply chain complexity and the frequency of supply chain disruptions”, *Journal of Operations Management*, Vol. 36, pp. 215–228.

Bozarth, C., Warsing, D.P., Flynn, B.B. and Flynn, E.J. (2009), “The impact of supply chain complexity on manufacturing plant performance”, *Journal of Operations Management*, Vol. 27, pp. 78–93.

Brandon-Jones, E., Squire, B., Autry, C.W. and Petersen, K.J. (2014), “A Contingent Resource-Based perspective of supply chain resilience and robustness”, *Journal of Supply Chain Management*, Vol. 50 No. 3, pp. 55–73.

Brandon-Jones, E., Squire, B. and Van Rossenberg, Y.G.T. (2014), “The impact of supply base complexity on disruptions and performance : the moderating effects of slack and visibility”, *International Journal of Production Research*.

Braunscheidel, M.J. and Suresh, N.C. (2009), “The organizational antecedents of a firm’s supply chain agility for risk mitigation and response”, *Journal of Operations Management*, Vol. 27 No. 2, pp. 119–140.

BSI (British Standards Institute). (2015), *2015 Security Risk Index*, BSI Supply Chain Solutions, London.

Casti, J.L. (1979), *Connectivity, Complexity and Catastrophe in Large-Scale Systems*, John Wiley & Sons, New York.

Choi, T.Y. and Krause, D.R. (2006), “The supply base and its complexity: implications for transaction costs, risks, responsiveness, and innovation”, *Journal of Operations Management*, Vol. 24 No. 5, pp. 637–652.

Chopra, S. and Sodhi, M.S. (2004), “Managing risk to avoid supply-chain breakdown”, *MIT Sloan Management Review*, Vol. 46 No. 1, pp. 52–61.

Closs, D.J., Nyaga, G.N. and Voss, M.D. (2010), “The differential impact of product complexity, inventory level, and configuration capacity on unit and order fill rate performance”, *Journal of Operations Management*, Vol. 28, pp. 47–57.

Collinson, S. and Jay, M. (2012), *From Complexity to Simplicity: Unleash Your Organization’s Potential*, Palgrave McMillan, London.

Craighead, C.W., Blackhurst, J., Rungtusanatham, M.J. and Handfield, R. (2007), “The severity of supply chain disruptions: design characteristics and mitigation capabilities”, *Decision Sciences*, Vol. 38 No. 1, pp. 131–156.

Dabhilkar, M., Birkie, S.E. and Kaulio, M. (2016), “Supply-side resilience as practice bundles: a critical incident study”, *International Journal of Operations & Production Management*, Vol. 36 No. 8, pp. 948–970.

Diamantopoulos, A. and Winklhofer, H.M. (2001), “Index construction with formative indicators: an alternative to scale development", *Journal of Marketing Research*, Vol. 38 No. 2, pp. 269–277.

Duncan, R.B. (1972), "Characteristics of organizational environments and perceived environmental uncertainty", *Administrative Science Quarterly*, Vol. 17 No. 3, pp. 313–327.

Grötsch, V.M., Blome, C. and Schleper, M.C. (2013), "Antecedents of proactive supply chain risk management - a contingency theory perspective", *International Journal of Production Research*, Vol. 51 No. 10, pp. 2842–2867.

Hanisch, B. and Wald, A. (2014), "Effects of complexity on the success of temporary organizations: relationship quality and transparency as substitutes for formal coordination mechanisms", *Scandinavian Journal of Management*, Vol. 30, pp. 197–213.

Hendricks, K.B. and Singhal, V.R. (2003), "The effect of supply chain glitches on shareholder wealth", *Journal of Operations Management*, Vol. 21 No. 5, pp. 501–522.

Heywood, S., Spungin, J. and Turnbull, D. (2007), "Cracking the complexity code", *McKinsey Quarterly*, Vol. 83 No. 2, pp. 85–95.

Johnson, N., Elliott, D. and Drake, P. (2013), "Exploring the role of social capital in facilitating supply chain resilience", *Supply Chain Management: An International Journal*, Vol. 18 No. 3, pp. 324–336.

Jüttner, U. and Maklan, S. (2011), "Supply chain resilience in the global financial crisis: an empirical study", *Supply Chain Management: An International Journal*, Vol. 16 No. 4, pp. 246–259.

Ketokivi, M. (2006), "Elaborating the contingency theory of organizations: the case of manufacturing flexibility strategies", *Production and Operations Management*, Vol. 15 No. 2, pp. 215–228.

Kleindorfer, P.R. and Saad, G.H. (2005), "Managing disruption risks in supply chain", *Production and Operations Management*, Vol. 14 No. 1, pp. 53–68.

Knemeyer, A.M., Zinn, W. and Eroglu, C. (2009), "Proactive planning for catastrophic events in supply chains", *Journal of Operations Management*, Vol. 27 No. 2, pp. 141–153.

Manuj, I. and Sahin, F. (2011), "A model of supply chain and supply chain decision-making complexity", *International Journal of Physical Distribution & Logistics Management*, Vol. 41 No. 5, pp. 511–549.

Mariotti, J.L. (2008), *The Complexity Crisis*, Adams Media, MA.

Matsuo, H. (2015), "Implications of the Tohoku earthquake for Toyota's coordination mechanism: Supply chain disruption of automotive semiconductors", *International Journal of Production Economics*, Vol. 161, pp. 217–227.

Melnyk, S.A., Rodrigues, A. and Ragatz, G.L. (2009), "Using simulation to investigate supply chain disruptions", in Zsidisin, G.A. and Ritchie, B. (Eds.), *Supply Chain Risk: A Handbook of Assessment, Management, and Performance (Vol. 124)*, pp. 103–122.

Mocker, M., Ross, J.W. and Kosgi, K. (2016), *Mastering Business Complexity: MIT CISR Survey Results*.

Mocker, M., Weill, P. and Woerner, S.L. (2014), *Revisiting Complexity in the Digital Age*, MITSloan Management Review.

Morieux, Y. (2011), "Smart rules: Six ways to get people to solve problems without you", *Harvard Business Review*, Vol. 89 No. 9, pp. 78–86.

Peng, D.X. and Lai, F. (2012), "Using partial least squares in operations management research: a practical guideline and summary of past research", *Journal of Operations Management*, Vol. 30 No. 6, pp. 467–480.

Perona, M. and Miragliotta, G. (2004), “Complexity management and supply chain performance assessment: a field study and a conceptual framework”, *International Journal of Production Economics*, Vol. 90, pp. 103–115.

Ponomarov, S.Y. and Holcomb, M.C. (2009), “Understanding the concept of supply chain resilience”, *The International Journal of Logistics Management*, Vol. 20 No. 1, pp. 124–143.

Rice, J.B. and Caniato, F. (2003), “Building a secure and resilient supply network”, *Supply Chain Management Review*, Vol. 7 No. 5, pp. 22–30.

Ringle, C.M., Wende, S. and J.-M., B. (2015), “SmartPLS 3.0”, available at: www.smartpls.de (Accessed 15 September 2016).

Scholten, K. and Schilder, S. (2015), “The role of collaboration in supply chain resilience”, *Supply Chain Management: An International Journal*, Vol. 20 No. 4, pp. 471–484.

Serdarasan, S. (2013), “A review of supply chain complexity drivers”, *Computers & Industrial Engineering*, Vol. 66, pp. 533–540.

Sheffi, Y. (2007), *The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage*, MIT Press, Cambridge, MA.

Sivadasan, S., Efstathiou, J., Frizelle, G., Shirazi, R. and Calinescu, A. (2002), “An information-theoretic methodology for measuring the operational complexity of supplier-customer systems”, *International Journal of Operations & Production Management*, Vol. 22 No. 1, pp. 80–102.

Sousa, R. and Voss, C.A. (2008), “Contingency research in operations management practices”, *Journal of Operations Management*, Vol. 26 No. 6, pp. 697–713.

Tukamuhabwa, B.R., Stevenson, M., Busby, J. and Zorzini, M. (2015), “Supply chain resilience: definition, review and theoretical foundations for further study”, *International Journal of Production Research*, Vol. 53 No. 18, pp. 5592–523.

Wieland, A. and Wallenburg, C.M. (2013), “The influence of relational competencies on supply chain resilience: a relational view”, *International Journal of Physical Distribution & Logistics Management*, Vol. 43 No. 4, pp. 300–320.

Wilcox, J.B., Howell, R.D. and Breivik, E. (2008), “Questions about formative measurement”, *Journal of Business Research*, Vol. 61 No. 12, pp. 1219–1228.

Witzels, M., Odekerken-Schroder, G. and van Oppen, C. (2009), “Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration”, *MIS Quarterly*, Vol. 33 No. 1, pp. 177–195.

Wong, C.Y., Boon-itt, S. and Wong, C.W.Y. (2011), “The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance”, *Journal of Operations Management*, Vol. 29 No. 6, pp. 604–615.

Zhang, D., Linderman, K. and Schroeder, R. (2012), “The moderating role of contextual factors on quality management practices”, *Journal of Operations Management*, Vol. 30 No. 1–2, pp. 12–23.

Appendices

Appendix A: Resilience sub-indices and practices (based on Dabhilkar et al., 2016)

Proactive-internal

- A plan for communication of incidents is established
- Crisis management exercises are regularly undertaken
- A systematic process for handling unforeseen supply disruptions is established
- People with earlier experience of handling supply disruptions are assigned
- Multi-competence teams are established

Proactive-external

- The business environment is regularly scanned for signals of possible disruption
- Alternative supply bases are identified in the event of a possible disruption
- Long-term supplier relationships are developed
- The firm has long-term relation with customers

Reactive-internal

- Responsibility for different parts of the recovery process is distributed clearly and appropriately
- Task forces make use of a systematic recovery process
- Managers are actively involved and support the recovery process through allocation of resources
- People in the organisation cooperate
- Production/delivery adjusted by balancing availed resources

Reactive-external

- The firm promptly collects information from the incident site
- Relevant functions of the firm and key actors are informed fast
- The firm effectively collaborates with external actors
- Demand is shifted across time, market or product
- Enhanced value propositions are offered to customers

Appendix B: Performance measures (adopted from Birkie, 2016)

Performance objectives	Metrics
Quality	Defect (scrap and rework) rate (reverse coded)
	Customer complaints (reverse coded)
Cost	Increase in revenue
	Increase in manufacturing unit cost (reverse coded)
	Increase in cost of extra work force, activity, or restructuring (reverse coded)
	Return on assets
	Total scrape & rework /sales (reverse coded)
Speed	On-time delivery
	Reduction in delivery lead time
	Improvement in order processing speed
	Throughput time efficiency (time worked on product/manufacturing lead time)
Flexibility	Delivery volume flexibility
	Delivery time flexibility
Dependability	Accuracy of delivered quality
	Accuracy and reliability of delivered quantity

Appendix C: Scheme for encoding collected data into Likert scale

Measure	Employees (FTE)	Turnover (million USD)	Product lines (count)	Production facilities (count)	Legal entities (count)	Major brands (count)	Number of suppliers	Number of customers	M&A
Scale and corresponding range									
1	<100	<50	1	<3	1	1	Few	Few	No
2	100-500	50-100	2-4	3-10	2-5	2-5	Many*	Many†	Yes‡
3	500-1,500	100-500	4-7	10-25	5-10	5-10			
4	1,500-5,000	500-5,000	7-10	25-60	10-15	10-15			
5	5,000-25,000	5,000-25,000	10-15	60-100	15-25	15-25			
6	25,000-100,000	25,000-100,000	15-20	100-250	25-50	25-50			
7	>100,000	>100,000	>20	>250	>50	>50			

* More than 100

† More than 3000

‡ M&A is considered yes if company had at least a merger, acquisition, or sell out in the year of the incident

Major industry is classified as follows: (1) Automotive; (2) Electronics & electrical items; (3) Chemical/pharmaceutical; (4) Industrial goods; (5) Leisure, personal goods; (6) Utilities and industrial services

Appendix D: Example of encoding procedure

The following excerpt from an annual report of Nissan after suffering the Thailand flooding in 2011 is used to exemplify the coding process. Note that the codes in the square bracket [ ] represent the code of resilience (proactive-internal, PI; proactive-external, PE; reactive-internal, RI; reactive-external, RE) bundle or performance measure (X) and a corresponding value. For resilience capabilities we aggregate at capability bundles level by calculating average of all indicators in that bundle. No evidence in the secondary data means zero for that practice. The resilience bundles PI, PE, RI, and RE have 5, 4, 5 and 5 indicators respectively.

"*…The power comes from inside….Our guiding principle for all employees, the Nissan Way has been fostered through our business operations [PI2, 1; RI4, 1]. It proved its worth again in addressing such challenges as the strengthening yen and flooding in Thailand and helping to lessen their impacts on us. Despite a number of difficulties beyond our control, Nissan's sales hit an all-time high in fiscal 2011 [X21, +1], while profit grew year-on-year...*

"*…We are increasing our competitive edge to adapt to the changes [PE1, 1]. In October 2011, when major flooding occurred in Thailand, Nissan's local plant was forced to halt operations in that area for four weeks due to the impact on the supply chain [X31, -1]. However, using the* *experience we had gained after the Great East Japan Earthquake in March that year [PI4, 1], we were able to minimize the operation suspension period and avoid undue impact on other factories. Nissan treats these events as valuable lessons and have shared the subsequent review with the entire Company [PI2, 1].*

"…New scenarios have been incorporated into the drills implemented …We have made our drills more challenging and have checked the efficacy of the various measures we have planned with the aim of creating a more effective overall system [PI5, 1]…"

Even though this is just excerpt, it should be enough to demonstrate the procedure.

So, we calculate average values by counting present practices and dividing by the total number of practices as follows. PI=(PI2+PI3+PI4+PI5)/5=4/5=0.80; PE=(R11)/4=0.25; RI=(R52)/5=0.20; we do not have RE in this excerpt. Performance=sum(all measures)+15= (1+-1+15)=15.

*Since the particular incident is regarded as disruption scenario type III, the weighted performance, X_Perf=15*3=45.*