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Do not expect others do what you should! Supply chain complexity and mitigation of the ripple effect of disruptions

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Abstract

Purpose – Recent studies have argued that companies may actively implement practices to mitigate disruptions in their supply chain and reduce the extent of damage on performance. Other studies have shown that disruptions may propagate in supply chains, leading to consequences that are more negative and raising doubts on the effectiveness of mitigation strategies implemented downstream. This study investigates the influence of supply chain complexity on the two phenomena and their interplay, taking a focal company's perspective.

Design/methodology/approach – A systematic procedure for data collection, encoding and aggregation based on incident data mainly from secondary sources was used. Multiple regression models were run to analyse direct and moderation effects involving resilience, distance of impact location from trigger point, and supply chain complexity on weighted performance change.

Findings – Supply chain complexity is found to have positive moderation on the ripple effect of disruption. Resilience capability remains to have dominating direct positive effect in mitigating disruptions when supply chain complexity is taken into account.

Research limitations/implications – This study extends the research discourse on supply chain resilience and disruption management with focus on the supply side. It demonstrates that, along with the severity of the disruption scenario, the ripple effect must also be considered when analyzing the benefits of resilience practices implemented by the focal company.

Practical implications – Complexity in the supply chain can only help to smooth-out the rippling effects of a disruption, which go largely beyond supply-demand unbalances and lead time fluctuations. To mitigate it better, the focal company has to act proactively with adequate resilience practices, which also connects to the importance of better visibility across multiple supply chain tiers.

Originality/value – To the best of the authors' knowledge, this is the first study that empirically tests the benefits of resilience practices and the ripple effect of disruptions under the moderation role of supply chain complexity.

Keywords – supply chain complexity; disruption; ripple effect; resilience; resource-based view

Article classification – Research paper

1 Introduction

Recent supply chain reports have indicated that there is a growing trend of disruptions happening in different supply chains. A large number of disruptions are triggered multiple layers upstream supply chains. For example, in 2013 some 58% of disruptions were triggered at tier 1, in 2017 this percentage reduced down to 44%, implying that up to 56% took place at tier 2 or higher (BCI, 2013, 2017). Several studies agree that swift actions and better visibility along the extended supply chain are needed to mitigate such disruptions, although how this can be done effectively is a concern with ongoing investigation.

Supply chains are getting more and more complex from time to time that could lead to both positive and negative consequences. Aitken et al. (2016) suggest that complexity in supply chains could have strategic benefits to competitiveness. High product customisation and customer diversity prescribed in business strategy are examples of strategically relevant complexities for driving superior advantages over competitors. Such complexity drivers need to be absorbed rather than reduced or avoided (Aitken et al., 2016). Supply chain complexity could also contribute to increased severity of disruptions (Brandon-Jones et al., 2014; Craighead et al., 2007). Other studies indicate that complex supply chains (e.g. with multiple nodes) could be more resilient to disruptions such as those triggered by climate change (Lim-Camacho et al., 2017). However, the potential moderation influence of complexity on disruption dynamics and management is still under-researched and the mechanisms of its influence on performance recovery are largely unknown. Increasing frequency and unwanted consequence of disruptions occurring in supply chains demand a better understanding of the values and possible drawbacks of supply chain complexity in disruption management. However, only a few studies have touched upon this issue in relation to developing capabilities for mitigating disruptions triggered upstream tiers and rippling out in a supply chain network.

Resilience can be thought of as the capability of a business firm to prepare for, respond to and recover from unexpected upstream supply chain disruptions by returning to, or maintaining continuity of, operations at the desired level (Ponomarov and Holcomb, 2009). On one side, studies have argued that the level of resilience capabilities required to bring about an upward change on performance after disruption must be proportional to the severity of the disruption (Birkie et al., 2017); on the other, different studies argued that having high resilience capabilities is not enough for effectively coping with disruptions (e.g. Li et al., 2017). However, none of these studies accounted for the influence of ripple effect. According to Ivanov et al., (2014) , ripple effect in the supply chain occurs when “disruption propagates from the initial disruption point to the supply, production and distribution networks”.

Birkie et al. (2017) investigated the direct influence of supply chain complexity on the effectiveness of resilience practices in recovering from disruption only. On the side of ripple effect, recent studies include Ivanov et al. (2017) who have made investigations on the phenomenon. Our current study builds on these two papers as well as related research in the domain with an aim to investigate the interplay between supply chain complexity and the focal company's resilience capabilities on mitigating the ripple effect of disruptions, towards reduction of performance degradation.

The remainder of the paper is organised as follows. The next section establishes the theoretical underpinning of the study. It presents brief literature review and introduces hypotheses. The third section describes the methodological details followed in conducting the study. Findings of the research are presented subsequent to that. Based on the detailed discussion held in the fifth section, conclusions are drawn in the last section.

2 Theoretical background and hypotheses

2.1 Ripple effect of disruptions

Supply chain disruption is a phenomenon in which unexpected events happening at a point in a supply chain affect performance of a firm, or have a potential to do so (Craighead et al., 2007). If disruptions cannot be timely recovered where they emanated, they may propagate in different directions affecting performance of multiple entities in the extended network (Swierczek, 2014). Indeed, supply chain costs tremendously increase in consequence of higher severity and longer duration of disruption (e.g. Ivanov, 2017).

It can be inferred from the definition of ripple effect that the distance from initial strike point to where consequences are measured (e.g. Kim et al., 2015) can be used as a proxy to estimate ripple effect. The time it takes to recover from consequences of a disruption originating at a point in a supply chain can also be another way of estimating ripple effect (Ivanov, 2017). These approaches tend to complement each other. However, they have different data and researcher engagement needs. For the latter approach, one would require very close and preferably real time follow up of events to properly map what has happened over an extended duration. The former is easier to manage as possible propagations can be mapped ex-ante, and is more suitable, especially for studies like the current one, that rely on secondary data.

Another way of capturing the ripple effect is using the duration of disruption prevalence at different nodes in the direction of ripple propagation. This approach follows the idea of the bullwhip effect which describes phenomenon of order-variance amplification upstream a supply chain (e.g. Ivanov, 2017). However, bullwhip effect and the ripple effects of disruption have important differences in terms of scope and scale.

In terms of scope, ripple effects cover a larger number of risk categories (Chopra and Sodhi, 2004) than just demand and lead time fluctuations involved in bullwhip effect (Schmitt et al., 2017). Amplification of demand variations often moves upstream in a value chain, while disruptions may propagate in multiple directions (Swierczek, 2014). Bullwhip effect often arises due to lack of information sharing or conscious decisions and over reactions by supply chain actors to manage and adjust their own level of activity and inventory levels (Schmitt et al., 2017) whereas multiple sources of uncertainties can cause disruptions (Chopra and Sodhi, 2004) with rippling effects along the value chain.

Another difference between bullwhip effect and ripple effect relates to scale. Performance implications of ripple effects from disruptions are often beyond expected routine fluctuation thresholds, and often long lasting (e.g., Schmitt et al., 2017; Sheffi, 2007). The extent and causes of uncertainties discussed in ripple effect are often much more pronounced than the day-to-day fluctuations that a stable supply chain network would naturally address with routines. For example, sharing information on customer demand along the supply chain could considerably reduce bullwhip effect (e.g. Ouyang, 2007) but this remedy alone may not be enough to address the multitude of incidents causing serious disruptions in supply chain operations.

The propagation and severity of consequences from disruption depends on several issues including proactive measures put in place and recovery efforts employed by different supply chain actors. Such influence coming from disruptive incidents can be measured at different locations (or nodes) than where the incident is triggered (Craighead et al., 2007; Kim et al., 2015; Swierczek, 2014). The location where a disruption triggers, how many and which supply chain actors are connected to the disruption are all important issues in disruption dynamics and mitigation (Greening and Rutherford, 2011), even though the attention given to them in research is limited. Therefore, the location where consequences of the disruption are measured relative to trigger point, and their relative distance, becomes the focus of attention in a disruption propagation study. For the purpose of the present study, we refer to this measurable element as *"supply chain distance"*. The primary focus of supply chain distance is the number of interconnectedness and interactions among actors involved between the extreme points rather than the geodesic distance between the same on the globe.

2.2 Supply chain resilience against disruptions

Resilience can be seen as the dynamic capability to mitigate disruptions and their negative consequences on different performance aspects (Dabhilkar et al., 2016; Liu and Lee, 2018). Considering that dynamic capabilities can be formed from intentional and interrelated practices undertaken by a business firm (Ambrosini et al., 2009), several studies have advanced the notion of resilience as a multidimensional capability (Adobor and McMullen, 2018; Datta, 2017) formed from routine practices which can act on other lower level practices and physical assets in dealing with disruptions. For example, Ambulkar et al. (2015) used such notion of practice routines in their study of developing a measurement model for resilience; *maintaining high situational awareness* and *learning from even small disruptions* are examples of resilience practices mentioned in their study.

Dabhilkar et al. (2016) have furthered the idea of practices enabling resilience capabilities. Their classification of practices forming resilience capabilities (proactive-internal, proactive external, reactive-internal, and reactive-external) is used in the current study to bundle resilience practices. Proactive versus reactive captures the temporal dimension—when a practice is implemented with reference to the time that a disruption happens, i.e. proactive if implemented before, reactive otherwise. Internal versus external distinguishes if the practices have to do with actions and resources within the firm's boundary, or if they have to do with external actors. As disruptions are often unanticipated, no one of these categories would be sufficient in dealing with disruptions; a combination of them, mostly all, would be needed. However, it follows from resource-based view (RBV) that constituents of each bundle of practices could be unique to the firm under consideration, and should be tailored to the specific disruption situation (e.g. Li et al., 2017).

Some studies have shown that the effectiveness of resilience capabilities in mitigating disruptions is dependent on context factors such as supply chain complexity. Complexity in a supply chain can be described in terms of detail and dynamic forms (Bode and Wagner, 2015; Tokui et al., 2017). Detail complexity refers to the variety and number of components as well as the strength of their interactions in the system (Serdarasan, 2013). Dynamic complexity describes uncertainties and randomness that prevail in a supply chain, such as changing tastes and preferences of customers or the rate of new product events. The scope of this study does not address dynamic complexity.

Detail supply chain complexity drivers are further classified in this study into three categories: size, product portfolio, and supply dispersion (Birkie et al., 2017; Bozarth et al., 2009). Annual turnover and number of employees constitute size. Product portfolio is formed by number of product brands, product lines, and number of customers (Bozarth et al., 2009; Brandon-Jones et al., 2014; Perona and Miragliotta, 2004). Number of production facilities, number of suppliers, and number of legal entities are grouped under supply dispersion.

How such complexity drivers influence the effectiveness of strategies the focal company adopts to recover from supply chain disruptions is a point of interest in this study. As a matter of example, we may consider a product diversification strategy, that often implies reduced demand and market risks (Kleindorfer and Saad, 2005). In the context of supply chain activities such diversification normally implies a larger number of suppliers and customers, including geographic dispersion (e.g.

Tokui et al., 2017). Thus, the same attributes of diversification also make the supply chain more complex. Companies that have diverse supply base are argued to have faster performance recovery (e.g. Tokui et al., 2017), though the same aspect could worsen ripple effects of disruptions.

Craighead et al. (2007) are probably the first to discuss both supply chain complexity and resilience capabilities in one study, however, they do not provide analysis on a possible link between the two. Possible multifaceted relationship between resilience and supply chain complexity can be inferred from recent studies. For instance, complexity in the supply chain could trigger unexpected events and disrupt operations, as highlighted by Bode and Wagner (2015), and Brandon-Jones et al. (2014). More recently, Birkie et al. (2017) discussed not only the positive direct impact that supply chain complexity has on performance recovery after a disruption, but also that it has positive moderating effect on the relationship between resilience and performance.

2.3 Research hypotheses

Different studies on the ripple effect of disruption have so far argued that the overall negative implications of a disruption continue to cumulatively increase as they propagate from source to supply, production and distribution networks (Ivanov et al., 2014). That is, the further the distance between a source of disruption and point of consequence measurement, the more severe the unwanted consequences on performance. This implies that chances of getting relatively worse performance are higher as disruptions are triggered upstream the supply chain in relation to a location of unmitigated supply chain disruption. As an example, a simulation study has shown that service level reduces as disruption propagation increases (Ivanov, 2017).

It is also shown that disruptions not mitigated close to the source (i.e. lack of resilience capabilities along the supply chain) have much worse influence on revenue performance of supply chains compared to when same resilience capabilities were applied closer to the disruption trigger point (e.g. Trucco et al., 2018). This implies that by making the disruption propagation shorter, the potential effectiveness of efforts to keep performance up during a disruption becomes higher, and so does the ripple effect.

Many studies on supply chain complexity reported only direct impact on performance; even so, there are mixed views on how complexity may affect performance. For example, Bozarth et al., (2009) have found negative or no significant impact of detail complexity on manufacturing performance. Limited number of studies exist that address moderation role of supply chain complexity on operations performance. For example, the moderating role of detail complexity on the lean operation-performance link was found to be negative (Azadegan et al., 2013) under “no disruption” operation conditions. We do not have evidence if this relation prevails under situations of supply chain disruption as well.

Increased complexity may arise as a result of dealing with too many alternatives, redundancies, configuration options and dynamism, which are also potential sources of resilience capability in mitigating disruptions. At the same time, those complexities could challenge smooth recovery. For instance, multiple sourcing bases could imply both a potential for better performance recovery (Dabhilkar et al., 2016) as well as a challenge of complexity in coordination (Sokolov et al., 2016) that in turn may degrade performance. In a recent study, Birkie et al. (2017) indicated that supply chain complexity positively moderates the resilience-performance link upon disruption. However, that study has limitations, as it did not consider the influence of the ripple effect. With this argument, the first hypothesis is introduced as baseline.

H1: Supply chain complexity moderates the resilience-performance relationship.

If ripple effect prevails, as argued in previous studies, then it is worth investigating how it may be influenced by supply chain complexity. However, there are almost no studies primarily investigating the possible moderating role of supply chain complexity on the ripple effect. To the best of our knowledge, Ivanov et al., (2014) is the closest paper with implications that supply chain complexity may lead to disruptions and subsequent ripple effects. In studies that have somehow tried to capture the influence of complexity in connection with the ripple effect, performance implications and disruption management, some indicative arguments can be taken. While one can understand that the influence of supply chain complexity is plausible, the forwarded arguments imply contradicting directional of influence. For example, increasing complexity in supply chain (i.e. adding suppliers, buffers, and redundancies) could reduce the propagation of disruptions and their consequences (Hendricks and Singhal, 2005; Sheffi, 2007). However, adding more nodes or actors in a supply chain network could have the opposite effect especially if node criticality is high (Craighead et al., 2007; Kim et al., 2015). Source diversification as a driver of supply chain complexity could be better than "over dependence" of actors with intense integration (Swierczek, 2014). Finally, it has been demonstrated that complexity is associated with higher vulnerability of the supply chain to disruptions (Bode and Wagner, 2015).

Table 1 briefly illustrates findings from selected studies considered to be close to the current study in terms of research focus. It also indicated the inclusion of the three constructs brought together in a single study as a research gap this paper aspires to address. Given the indicative arguments mentioned before, we find it interesting to check if a moderating role of supply chain complexity is significant; and if it does, what the direction of moderation is on the ripple effect of disruption. Accordingly, we set forth the second hypothesis.

H2: Supply chain complexity moderates the ripple effect.

Figure 1 depicts the proposed hypotheses in this study.

Table 1. Summary of gap in recent studies and relation to the current study

Relationship addressed	**Ripple effect**	**Complexity**	**Resilience**	**Sample reference**	**Operationalisation**
Qualitative discussion and propositions based on the characteristics of a supply chain, complexity being one, affecting severity of disruptions	--	Yes	Yes (as recovery capability only)	Craighead et al., (2007)	Complexity as the sum of the number of nodes and the number of backward, forward and within-tier flows in a given supply chain
Ripple effect reduces operational performance - Implied that supply chain complexity could lead to more disruptions and propagation	Yes	---	---	Ivanov et al., (2014)	Rippling effects captured as propagating (unexpected) fluctuations
Resilience capabilities improve performance affected by disruption	---	---	Yes	Dabhilkar et al., (2016)	Resilience using set of practices, performance using cost, quality, speed, dependability flexibility
Complexity moderates resilience-performance relation	---	Yes *also as moderator of resilience*	Yes	Birkie et al., (2017)	Complexity as a set of static (detailed) complexity factors synthesised from literature
Complexity moderates the ripple effect and resilience-performance relation	**Yes**	**Yes;** ***also as moderator of :*** ***- Resilience (H1)*** ***- Ripple effect (H2)***	**Yes**	**Current study**	**Supply chain distance as proxy for measuring rippling effect; it aims to bring the interplay of the three variables on performance after disruption**

Please insert Figure 1 about here

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3 Research methodology

3.1 Methodological overview

A multi-method approach was used in this study. A systematic process was followed involving five steps: *surfing, sorting, encoding, aggregation,* and *regression, following the work in* Birkie et al., (2017). The approach was primarily inspired by event study approach used, for example, by Hendricks and Singhal (2005).The first three steps were part of data collection and collation. The remaining two steps were for the data analysis part. Figure 2 illustrates the data collection and analysis process along with corresponding sources and approaches.

Please insert Figure 2 about here

Data was collected mainly from secondary sources based on critical incident technique (CIT). CIT focuses on incidents as references for an inquiry (Butterfield, 2005; Flanagan, 1954) and aimed to examine situations that deviated from what was expected. Supply chain disruptions occur unexpectedly, and affect (or challenge) the fulfilment of intended supply chain functions and performance. CIT, therefore, becomes a suitable study method. In a critical incident study, phenomena—such as disruption incidents—that lead to or had a potential of deviating in achievement of some target or objective, are considered critical (Flanagan, 1954).

CIT is merited for data collection and analysis of incidents in retrospect. Initial development of the technique was concerned with primary data collection from people directly involved with a critical incident (Flanagan, 1954). Recent developments in CIT include the use of retrospective secondary data sources and the application of more advanced statistical analyses (e.g. Butterfield, 2005).

Considering that the research framework in this paper uses formative second order constructs, partial least square analysis has been found suitable for statistical analysis. However, recognising the recent debates on the limitations of PLS (e.g. Rönkkö et al., 2016), we have started the statistical analysis by first doing ordinary covariance based analysis using SPSS software.

In this study, supply chain complexity is considered as a second order construct comprised of formative measures. To approximate this formative nature in SPSS, the measures were aggregated to their complexity sub-categories using unit-weight average based on standardised scores. Factor analysis was followed to obtain a supply chain complexity score based on these sub-categories (see Appendix 1). Then, regression analysis was done to estimate direct and moderation influences. Having obtained initial results, PLS-based analysis was followed to estimate and explain not only regression results but also relative strength of sub-categories (sub-indices) in forming supply chain complexity.

3.2 Data collection and encoding

Data collection was started by surfing news items and announcements about supply chain disruption incidents, from relevant media outlets – specifically: Bloomberg, Financial Times, Reuters, NewsWeek, and CNNMoney. The search covered a time horizon ranging from 2007 to 2015. The initial list of candidate disruption incidents, more than 110, was organised based on reports on companies that have been affected by disruptive incidents in their supply chain. The initial news items identified disruption incidents (what happened, when, where, etc.) and companies affected by them. Then additional data was sought from the identified companies regarding proactive and reactive resilience practices, performance changes in the reporting year the incident happened. Further data regarding incident details (i.e. trigger point, time of incident, severity), supply chain complexity elements were collected as well.

Annual and quarterly reports were primary references. Interviews and communications (e.g. press releases) by the company management were additionally considered when available. Company websites also supplemented with some additional details, including supply chain complexity issues that could not be found in annual reports, such as number of production facilities.

As a next stage of study, sorting was done. That is, incidents for which no enough details were reported by the companies on variables of interest in this study were excluded. The final list of incidents went down to 71 owing to lack of enough details especially on supply chain complexity measures and supply chain distance. In this study, supply chain distance has been conceptualised as the smallest number of nodes and arcs between disruption-trigger location and the focal firm (i.e. the node at which information about performance variation was collected). In order to measure this in a simple way, we have used an arc-node unit as proxy. The main reason for considering the pair is that performance is usually measured at nodes, while arcs are possible trigger points for disruptions.

Disruptions obviously have different severity levels. Major disruption due to hurricane is more devastating and more demanding to recover compared to minor and unavoidable operations discontinuities (Kleindorfer and Saad, 2005). Such variation among different incidents in terms of severity were considered to weigh the potential performance change implication. Classification of “disruption scenarios” suggested by Birkie (2016) was used for this purpose. Severe disruptions (Type III) that involved high unpredictability, multiple actors being affected simultaneously, potential or eminent hazard to human health and well-being are dominant in the sample at 52%. Minor disruptions that have high predictability, low scale of influence (Type I) accounted for only 7% of the incidents in the final sample. The remaining incidents were of type II severity. See Appendix 2 for the full definition of the three disruption scenarios. As can be seen in Table 2, the dominant part of data came from the automotive and consumer electronics manufacturing sectors, but other sectors, ranging from chemical to utilities and services, are represented as well in the final sample.

Table 2. Dataset stratification on industry

(a) Industry	Frequency
Electronics & electrical items	27
Automotive	23
Chemical/pharma	8
Industrial goods	6
Leisure and personal goods	5
Utilities and services	2
Total	**71**

In the third step, the descriptive details compiled from the aforementioned sources were encoded to corresponding variables based on a scheme developed in earlier stages of the study. Figure 2 shows the encoding approach. The following paragraphs illustrate the encoding procedure followed for the main constructs in this study.

As previous studies indicated, disruptions may propagate forward or backward in reference to direction of an affected flow- material, information or financial flow (Swierczek, 2014). All the incidents included in this study had major implications on material flow, even though in some cases information and financial flows were also affected. We, therefore, took the direction of material flow as reference and the discussion offered in the present study is intended to draw implications for the management of the physical flow only. Supply chain distance is positive for disruptions emanating upstream the supply chain, and the focal firm where performance is measured is downstream in the value chain. For example, a fire inside a factory of the plant to which performance consequences are estimated would imply a supply chain distance equal to zero. An incident triggered at third tier supplier is represented as a distance of +3. If the supply chain disruption were caused due an event close to an immediate customer of the focal firm where performance change is estimated, then supply chain distance would become -1. If an incident is triggered at an arc (for instance, something happens to a cargo while being transported by sea), the remaining portion of the arc is counted to the node-arc proxy as long as it is outside of the boundary of the firm in the supply chain closer to the focal firm. The actual values in the collected data for supply chain distance variable ranged from -2 to 4. This simply means that incident trigger positions varied from second-tier customer to fourth-tier supplier in reference to a "focal" firm for which performance variation due to disruption is being measured.

For the other variables in this study, the operationalisation used in Birkie et al. (2017) was employed as follows. (1) The nineteen individual resilience practices were captured in binary: 1 if evidence of that practice being employed was found, 0 otherwise. (2) Change in individual performance measures (fifteen of them) was captured as -1, 0, +1 for reduction, no change, and increase respectively, where positive numbers represented favourable change to the firm in each case. (3) For supply chain complexity, variables were captured using Likert-scale representing predefined intervals of values for each. This scaling avoided the need for highly accurate figures, which were not available for most of the incident cases. For suppliers and customers, we had to use a single cut off point based on average of values collected. Appendix 3 shows the scaling scheme.

3.3 Data analysis

As a general starting point, all the three constructs of interest (resilience, supply chain complexity, weighted performance) were estimated based on unit-weight aggregations of standardised scores in their constituent observed variables. For this purpose, all variables have been transformed into standardised normal distribution scores prior to aggregation.

Aggregation to sub-indices and second order constructs for resilience and supply chain complexity was done by factor weights following the logic in formative constructs. Supply chain complexity items were organised into four sub-indices after doing an initial partial confirmatory analysis. Standardised scores of sub-indices were used before proceeding to next level of analysis. Table 3 shows the weights of formative first order items (sub-indices) on the respective second order constructs (indices) of complexity. The scores obtained for sub-indices have been used to obtain the index for supply chain complexity. Resilience practices were aggregated into four bundles according to Dabhilkar et al. (2016): proactive-internal, proactive-external, reactive-internal, reactive-external (Table 4).

Performance values have been aggregated using unit weight summation followed by linear transformation of values to a non-negative range. The five performance objectives – quality, cost, speed flexibility, and dependability – had 2, 5, 4, 2 and 2 measures respectively. Therefore, one could view the aggregated performance is being weighed by the count of underlying measures, indicating the usual dominance of cost objective. The aggregated performance was then weighted by a proportion of 3:2:1 for severe (type III), medium (type II), and minor (type I) classification to capture variation of disruption severity, in respective order (Birkie, 2016). Appendix 4 provides a simplified example of the coding procedure employed, building on earlier studies.

Table 3. Factor weights of measures forming supply chain complexity sub-indices

Measure	Mean (*s.d.*)	Product portfolio	Supply dispersion	Size
Product lines	3.14 (*0.98*)	0.378*		
Brands	1.97 (*1.41*)	0.299		
Customers	1.65 (*0.48*)	0.729**		
Production facilities	3.29 (*1.52*)		0.553**	
Suppliers	1.64 (*0.48*)		0.739**	
Entities	2.10 (*0.80*)		0.054	
Turnover	5.09 (*1.36*)			0.380
Employees	5.87 (*0.98*)			0.693**

$^{*}p < 0.05$, $^{**}p < 0.01$

The weights for the sub-indices and subsequent regression path coefficients (Tables 2 and 3) have been estimated using formative-formative item relations in SmartPLS version 3 (Ringle et al., 2015).

Table 4. Weights of sub-indicators forming second order factors

Sub-indicators	Mean (*s.d.*)	Supply chain complexity	Resilience
Product portfolio	0.00 (*1.01*)	0.389**	
Supply dispersion	0.00 (*1.01*)	0.361**	
Size	0.01 (*1.00*)	0.391**	
Proactive internal	0.44 (*0.31*)		0.370**
Proactive external	0.46 (*0.26*)		0.326**
Reactive internal	0.51 (*0.27*)		0.455**
Reactive external	0.55 (*0.24*)		0.287**

Notes:1) $^{**}p < 0.01$

2) Mean values and standard deviations for supply chain complexity sub-indices were calculated based regression standard scores of the latent sub-indices

With the use of partial least square (PLS) approach it was possible to easily perform moderation analysis involving second-order formative constructs. The use of PLS also made it easier to handle complex models for which measurement model un-identification is a challenge. Consistent PLS routine was run for the computations. While results reported in this study were based on PLS analyses, we have checked and found that the general pattern of regression and values of path coefficients for inner model remained similar in covariance-based regression tools.

The aggregate scores of main constructs were used to run initial multiple regression models consisting of direct effects alone (model M1), and including moderation influences (model M2). This was necessary to ensure if the proposed model worked in its "coarse formulation" before proceeding to estimation and analysis involving supply chain complexity as second order variable with its three detail complexity sub-indices. Table 5 provides the correlation among the four constructs of interest based on standardised scores.

Table 5. Correlations among constructs

Constructs	1	2	3
1 Resilience			
2 Supply chain distance	-0.153		
3 Supply chain complexity	-0.097	0.012	
4 Weighted performance	0.448**	-0.340**	0.149

** $p < 0.01$

4 Research findings

As described in the methodology section, the structural model was initially run without and with moderation influences in a covariance-based structural modelling (CB-SEM) as suggested by Peng and Lai (2012). This was done as possible comparison because second order PLS is computed in two steps as described earlier: (1) estimation of the first order and second order indices, (2) using standardised weights obtained in step one for the second order latent variables in estimating the structural model. This second step essentially became independent of the first step making a covariance-based estimation a possibility. In so doing, the corresponding coefficients and their significance levels were found to be fairly close in the PLS and unit weight estimation models despite the methodological differences. A key difference observed is the slight variation on the marginal significance (at $p<0.1$ level) of the two moderation effects.

In the first CB-SEM model with only direct effects, resilience and supply chain distance respectively showed positive (*path coefficient*, $\beta=0.43$, $p<0.01$) and negative ($\beta=-0.27$, $p<0.05$) influences on weighted performance. Direct effect of supply chain complexity on performance appeared positive ($\beta=0.19$, $p<0.1$). This model captured about 28% of variance. With the introduction of supply chain complexity as a moderator to the other two variables in the CB-SEM model, the explained variance increased to 30.5%. In this second initial model both the direction and significance of direct effects of resilience and supply chain distance remain unchanged. While supply chain complexity becomes no more significant as a direct influencer of performance change, marginal significance was observed on moderation effect. We then continued with detail analysis with PLS considering formative constructs.

In reporting and validating the PLS model in this study, the guidelines provided in Peng and Lai (2012) for assessing PLS with formative indicators and constructs were used whenever applicable. Accordingly, the formative item weights were checked for multicollinearity. All VIF values were well below the conservative threshold of 3.3, indicating a low level of multicollinearity. As reported in Table 3, each item weight, with the exception of entities, is greater than the suggested value of 0.10. The sign of all items in the table are positive, consistent with what would be theoretically expected. When it comes to the significance of the formative items, three of the eight items did not pass the 0.05 significance test. However, we decided to keep them because of their indispensable aspects (i.e. turnover in size measurement) and considering that the sample size of our study could be the reason for underestimation.

Table 6. PLS second order model path coefficients to weighted performance

	Path coefficient (β)	
Constructs	M1	M2
Supply chain Distance	**-0.223***	**-0.276***
Resilience	**0.442****	**0.392****
Supply chain Complexity	**0.186***	0.086
Supply chain Distance *X* Supply chain Complexity		**0.210**†
Resilience *X* Supply chain supply chain Complexity		0.166
Variance explained	*0.260*	*0.270*

Note: $^{\dagger} p < 0.1$, $^{*} p < 0.05$, $^{**} p < 0.01$

The measurement and structural models were run with the bootstrapping routine using 2000 resampling times provided as default in SmartPLS to find significance levels. The significance values reported in Table 4 come from this procedure.

The significance levels for the two models provide evidence that resilience to weighted performance and supply chain distance to weighted performance path coefficients remain significant in both M1 and M2 (Table 6), while supply chain complexity loses significance of its direct influence when the moderations are introduced. The moderation of supply chain complexity on the ripple effect is significant at 10% level, rather than the conventional 5% value.

The amount of variance explained grew from 26% to 27% when moderation influences were introduced (in M2), indicating that consideration of the moderation effect captured small additional variance in the dependent variable. However, the direct effect path coefficient for supply chain complexity reduces considerably. Therefore, this variable becomes only a moderator. Supply chain complexity appears to significantly positively moderate the effect of supply chain distance on performance. Moderation on resilience is not significant; however, its standardised path coefficient is somehow close to moderation on the other variable.

The estimation of direct and moderation effects has been achieved with good structural model fit. In Table 6, the model with moderation influences well fulfils the conventional thresholds put to claim good model fit. SmartPLS provides four indicative statistics of model fit: standardised root mean residual (SRMR), normalised fit index (NFI), squared Euclidean distance (d_ULS) and geodesic distance (d_G). The last two are extracted using bootstrapping, and measure the discrepancy between the empirical covariance matrix and the results of the composite factor model. Small discrepancies are needed for a better fit. This is tested by non-significant ($p > 0.05$) value corresponding to d_G and d_ULS. NFI close to 1.0 and SRMR close to zero indicate good model fit. Rule of thumb values suggested for good are NFI>0.9, SRMR<0.08, p of d_G and p of d_ULS > 0.05. Second order formative PLS models are neither required nor expected to fit any better than their first order counterparts (Wilcox et al., 2008). Even so, the model seems to have good fit with NFI=0.997, SRMR=0.007, and non-significant *p* values for geodesic and square Euclidean distances.

5 Discussion

A few studies have investigated the ripple effect of disruption on performance degradation; because of its prevalence, some have argued that mitigation of supply chain disruption requires close collaboration with partners at different tiers (Norrman and Jansson, 2004). This rippling effect also implies that a category of supply chain risk may induce another as propagation continues along different nodes and arcs in a supply chain with potentially devastating outcomes.

The negative consequences of disruption propagate out and broad with possibly growing intensity and amplitude unless supply chain actors do not undertake mitigation actions. Hidden dependencies far out in the network could be easily overlooked in extended supply chains. Longer supply chain distance might also cause unwanted consequences on multiple performance objectives at one or more of the focal company’s factories. Supply chain literature vastly discusses the reduced visibility that companies have to their multi-tier suppliers and its negative impact on supply chain performance or how visibility implies better disruption mitigation possibilities (Kleindorfer and Saad, 2005; Scholten and Schilder, 2015). A lower visibility tends to decrease operational efficiencies and is therefore associated with lower resilience (Craighead et al., 2007; Scholten and Schilder, 2015).

Furthermore, some scholars posit that supply chain complexity is a possible reason for ripple effect of disruptions (e.g. Ivanov et al., 2014). In the current study, theoretical arguments have been offered in favour of considering supply chain complexity as a possible moderator (rather than a main cause) of the ripple effect, together influencing performance.

Even though several studies have already argued that the ripple effect negatively influences performance, the current study analysed the phenomenon with a new operationalisation, using supply chain distance. The negative impact of supply chain distance on performance is apparent as shown in model M1 of Table 6. This enables to focus discussion in the subsequent paragraphs on moderation effects of supply chain complexity.

5.1 The positive effect of supply chain complexity on the ripple effect

In view of the extant literature, the results of the current study imply that the influence of supply chain complexity on performance under disruption come dominantly through moderation rather than as direct effect. This is partly explained by the fact that earlier studies did not consider the ripple effect and supply chain complexity together in one model.

The present study shows that supply chain complexity has a significant positive moderation on the (negative) impacts of ripple effect of disruptions. That is, higher supply chain complexity generally smooths out the ripple effect more effectively. The moderation could materialise in terms of reducing the chances of disruptions from propagating, or reducing the severity of the consequences or both. This idea reinforces and better explains what has been found out by Ambulkar et al. (2015) regarding better disruption orientation for better mitigation of disruptions.

Disruptions triggered far upstream are more likely to negatively affect performance in a supply chain. The negative consequences may switch from one performance objective to the other as the disruption propagates downstream (for example, a quality problem at a multi-tier supplier often causes delivery delays by company downstream. This in turn could hinder flexibilities that could be priorities for customers). However, the effect can be considerably lessened with larger organisational footprint, supply dispersion, or broader product portfolio. That is, a disruption that rippled from a distant trigger point can be smoothed out by alternate sourcing or by diverting production to a different location, and disruptions triggered close to the focal firm can be directly addressed by immediate resources brought with complexity, such as a large number of multi-skilled workforce. Several examples illustrate how firms used their day-to-day decision processes and logics on supply chain complexity attributes for mitigating disruptions triggered upstream or downstream in their supply chain.

The findings in this study explain the influence of complexity on mitigating supply chain disruptions further building on prior research (e.g. Birkie et al., 2017; Brandon-Jones et al., 2014;

Lim-Camacho et al., 2017). In the current study, the moderating role of supply chain complexity on the ripple effect-performance link outweighs both the direct positive impact it would have on performance and its moderating role on the resilience-performance link. Therefore, well designed and managed complexity in supply chain is very likely to limit the propagation of disruptions instead of snowballing unwanted consequences forward, which indirectly helps the resilience capabilities of the focal company becoming more effective on the residual performance degradation. It might even be possible to observe positive coefficient of supply chain distance on performance at higher values of complexity. It is not within the scope of this paper to provide detailed qualitative explanations of how this can be achieved in practice.

5.2 The effectiveness of resilience practices

Resilience capabilities against disruptions formed from routine practices (Dabhilkar et al., 2016) have shown persistence on different disruption situations. In the current study, such capabilities are argued to have helped reduce severity of and recover performance irrespective of the trigger positioning; the correlation of resilience and performance recovery remains positive and significant when disruptions initially outbreak within the boundaries of the firm or far away from it. This result confirms and generalises what has been achieved by prior research (e.g. Birkie et al., 2017; Trucco et al., 2018).

Overall, this study has shown that the ripple effect is an important prevailing phenomenon in supply chain disruptions and needs careful consideration. Supply chain complexity seems to smooth out the unwanted rippling effects of disruption and its effect seems outweigh the resilience-performance link broadly discussed in earlier research. Table 7 provides summary of the main results in terms of the proposed hypothesis.

Li et al. (2017) argue that having too high resilience capability is not necessarily a good thing, especially when there is lack of accurate information. Results in the current study suggest that higher resilience, with broader range of practices, is still a good thing. If we equate longer supply chain distance with lack of accurate information (visibility), the results may be perceived to contradict Li et al.'s (2017). However, the simulation study in Li et al. (2017) explicitly incorporates variable cost of resilience capabilities. The current study captures such costs only implicitly (as changes) in the cost performance metrics.

The moderation coming from supply chain complexity does not seem to change the positive link between resilience practices and performance recovery so much when ripple effect is taken into account. This is in contrast with earlier research where, without consideration of the ripple effect, complexity was found to have significant partial moderation influence on resilience (Birkie et al., 2017).

Among the resilience practices (sub-indices in the model), the internal bundles have higher weights than external ones. This is a confirmation of earlier studies that better resilience capability against disruptions is achieved when embedded starting from what the focal company can easily control and reallocate as appropriate– both proactively and reactively. An additional observation from factor weights analysis is that the external resilience capabilities are better effective when dealt with proactively rather than reactively. This is practically easy to understand as it means that companies leverage relationships and wisdom accumulated over time, before a disruptive incident happens, also to affect resources and capabilities in the extended supply chain post trigger of disruption (Brandon-Jones et al., 2014; Dabhilkar et al., 2016; Scholten and Schilder, 2015).

Table 7. Summary of moderation analysis results with SmartPLS

Hypothesis	Findings
H1: Moderation on resilience to recover performance	***Rejected*****:** the moderation influence of supply chain complexity on the resilience-performance relationship does not appear to be sufficiently significant in the second order construct model. The sign of moderation is positive, consistent with an earlier study.
H2: Moderation on the ripple effect of disruption	***Supported*****:** supply chain complexity positively moderates the ripple effect. The moderation is partial (also in H1); the direct negative effect of supply chain distance to performance (i.e. ripple effect) remains significant even with the moderation influence. Complexity makes performance better even if ripple effect prevails

6 Conclusion

The aim of this study was to investigate how the positioning of initial trigger in the supply chain to disruption affects performance recovery. In this regard, we found that disruptions triggered far upstream a supply chain could have rippling performance implications to a company downstream the chain. Resilience practices prove to be useful in mitigating disruptions despite the position of trigger. More importantly, the study has analysed the moderating role of supply chain complexity on effectiveness of resilience practices as well as on the ripple effect of disruption. Strong evidence of positive influence was found for the latter.

6.1 Theoretical implications

The findings obtained in this study inform theory on the phenomenon of the ripple effect for better management and mitigation of disruptions. This study provides explicit operationalisation of the ripple effect of disruption using supply chain resilience as proxy. It also modelled the moderating role of supply chain complexity both on the effectiveness of resilience capabilities and on the ripple effect in a single moderation model. It adds to the discussion of the seemingly conflicting influences of supply chain complexity. Prior research recognised that supply chain complexity is a source of, or a contributor to disruptions (e.g. Brandon-Jones et al., 2014), but also revealed that it positively contributes to mitigate performance loss under disruption both directly and indirectly, via the moderating role on the effectiveness of resilience capabilities (Birkie et al., 2017). Our findings expand on previous results and better clarify the contribution of complexity in mitigating supply chain disruptions, by revealing its significant smoothing influence on the ripple effect. Ripple effect, supply chain complexity properties, and their interplay is a key aspect that should not be overlooked to fully understand the resilient behavior of actors in a supply chain struck by a disruption event. This implies that of different resilience practices for managing disruptions may not be equally useful for disruptions that ripple out differently.

Looking at the attributes of complexity, the implication is that having more resources (e.g. size) is not particularly more important than having diverse resources (e.g. supply dispersion). This is in agreement with earlier research in the domain of supply chain resilience. Therefore, all companies, small or big can have the opportunity to leverage good benefits of complexity attributed from different elements in dealing with propagating disruptions. More interesting in this study is that such diverse resources could help in better mitigating the propagation of a disruption. In view of contingent resource based view, this implies that the extent of competitive benefit obtained from capabilities and physical assets, including risk management infrastructure, is contingent on prevailing conditions. Therefore, while the concept of resilience capabilities and bundling of practices forming them holds, the combination of the specific practices for effective recovery depends on the nature and extent of the propagating disruption.

6.2 Managerial implications

The positive role that supply chain complexity plays in mitigating disruption of flows, and particularly in smoothing down its rippling effect, can be leveraged by managers as a strategic capability, thus should be taken into proper consideration when trying to influence the design or the drivers of complexity in their supply chain. Managers could consider how actions increasing supply chain complexity at the same time could help to embed redundant or flexible capabilities that can be activated when ripple effect of disruption is eminent. Practitioners may adjust their investment choices towards embedding capabilities at "disruption prone" upstream tiers in their supply chain network. It is imperative that practitioners actively try to restrain disruptions local to where they emanated rather than waiting to manage disruption and unwanted consequences that have spread out to the larger system. The resources demanded and the effectiveness of efforts would not be any better, if not worse by waiting. Complexities in supply chain may be employed to serve this strategic purpose of containing disruptions early on local to where they originate.

On the other hand, when supply chain complexity is limited or reduced, firms would require either: i) increased visibility for early detection of upstream or downstream disruptions; ii) additional efforts for enhancing specific resilience practices (internal reactive or external proactive). Managers can consider relational capabilities and resources for mitigating future disruptions. We think this is very essential as proper management of eminent and potential disruptions has proven to be a source of competitive advantage and drives more customer value.

Finally, recent studies provided indication that detail complexity drivers may give rise to dynamic complexity as well (e.g. Aitken et al., 2016; Serdarasan, 2013). Another managerial implication in light of this argument is that, the need to manage a complex supply chain could provide with practices that intrinsically have the properties and the ability to contribute towards dampening disruption propagation.

6.3 Study limitations and future research

In this study, we assumed that a single disruption with a clearly known point of trigger is propagating across a supply chain network. However, this may not be true in many real situations; it is possible that actors at different tiers are concurrently affected resulting into more complex events, where the manner of the propagation is less clear and multiple conjoint triggers could attribute same consequence being estimated. A detail discussion with informants with direct involvement in disruption management could help in the future to address these limitations as well as discussing a stronger argument of causality.

Future research may address forward and backward propagating disruptions separately, and investigate which practices lead to better performance in which disruption propagation circumstances. This kind of analysis would require a significantly larger sample. Furthermore, it may be of interest to investigate how the efforts to build better resilience by different firms could complement performance improvement along the extended supply chain rather than focusing just on the performance of the focal company. Besides, considering the costs of implementing resilience practices at different nodes of supply chains could be an extension of the investigation in this paper, as it may shed light on justification for possible collaborative resilience capabilities planning to manage disruptions.

Some studies have shown that excessive mutual dependence of firms in a supply chain that results from supply integration may lead to more chance of disruption propagation (e.g. Swierczek, 2014). In light of such studies, and considering the theoretical lens contingent RBV, an interesting debate emerges as to how to strike optimal position between strong interdependence and too much lack of visibility of a firm's supply chain. This is a concern for production systems given the technological transformation, data-connectedness and automation on one hand, and extreme conditions of uncertainty and disruption that businesses are dealing with lately. Which of a firm's practices (and thus capabilities) would help to address this dilemma could be a point of interest for future investigation.

Studies have shown that interesting interplay exists between the detail and dynamic complexity (Fernandez Campos et al., 2019). However, no prior empirical study has investigated this interplay, or the mechanisms and implications of such a relationship in the supply chain literature. Understanding these underlying mechanisms in view of supply chain resilience could be an interesting future research undertaking too.

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Appendices

Appendix 1: Factor analysis for complexity using SPSS

Sub-category	loading	Cronbach's α
Size	0.71	0.71
Product portfolio	0.53	
Supply dispersion	0.70	

Appendix 2: Description of the disruption scenario classifications (source: Birkie 2016)

Type III

- Destruction of company's own key assets or key components suppliers
- Event affecting multiple suppliers, competitors or customers
- Actual/potential damage to people's health and well-being, biological/hazardous substance involved
- High unpredictability: "suddenness" or unexpected characteristics of event
- Depth: multiple tiers in the chain or multiple actors in the same tier affected

Type II

- Inoperability of facilities without major damage of assets (e.g. due to precautionary shutdown, strike)
- Destruction of utility assets (e.g. communication infrastructure, power line)
- Damage to multiple products or inputs without processes being affected
- A few sourcing bases among many affected
- Little predictability: little preparation time for the incident
- Extended delays (e.g. due to bankruptcy)
- "Abnormal accidents" in work area

Type I

- Only a few of the product/input range damaged
- Fairly predictable: some time to preparation for the incident. For example, notified workers' strike
- Short delays in logistics or internal operations (not more than two weeks)
- "Normal accidents" in work area
- More than expected demand
- Information exchange problem

Appendix 3: Scheme for encoding collected data. (Source: Birkie et al., 2017)

	Measure							
Scale	Employees (FTE)	Turnover (million USD)	Product lines (count)	Production facilities (count)	Legal entities (count)	Major brands (count)	Number of suppliers*	Number of customers*
1	< 100	< 50	1	< 3	1	1	<100	<3000
2	100-500	50-100	2-4	3-10	2-5	2-5	>100	>=3000
3	500-1500	100-500	4-7	10-25	5-10	5-10		
4	1500-5000	500-5000	7-10	25-60	10-15	10-15		
5	5000-25000	5000-25000	10-15	60-100	15-25	15-25		
6	25000-100,000	25000-100000	15-20	100-250	25-50	25-50		
7	> 100000	> 100000	> 20	> 250	> 50	> 50		

* Based on average values from collected data

Appendix 4. Illustrative example for the coding and aggregation procedure

Consider this disruption incident. A natural disaster affected a second-tier supplier of a manufacturer whose performance change due to disruption is being estimated *[supply chain distance=+2]*. It was identified from annual report that six performance metrics, of a total 15 items, were negatively affected and one metric has improved in the reporting period in which the disruption occurred [so, average performance change=15-6+1=10]. The supplier's production facility, which served several manufacturers was damaged and halted production for several weeks due to the disruption [disruption scenario type III; weighted performance=10*3=30].

Items of the supply chain complexity identified during data collection were as follows. Number of employees- more than 100000 (scale= 7, see Appendix 3); turnover for the year was 10 billion USD (scale=3); production was being done in 20 facilities globally (scale=3); the products were marketed in one of the three brands (scale=2); the company managed hundreds of suppliers and (scale=2) and some 5000 major customers (scale=2).

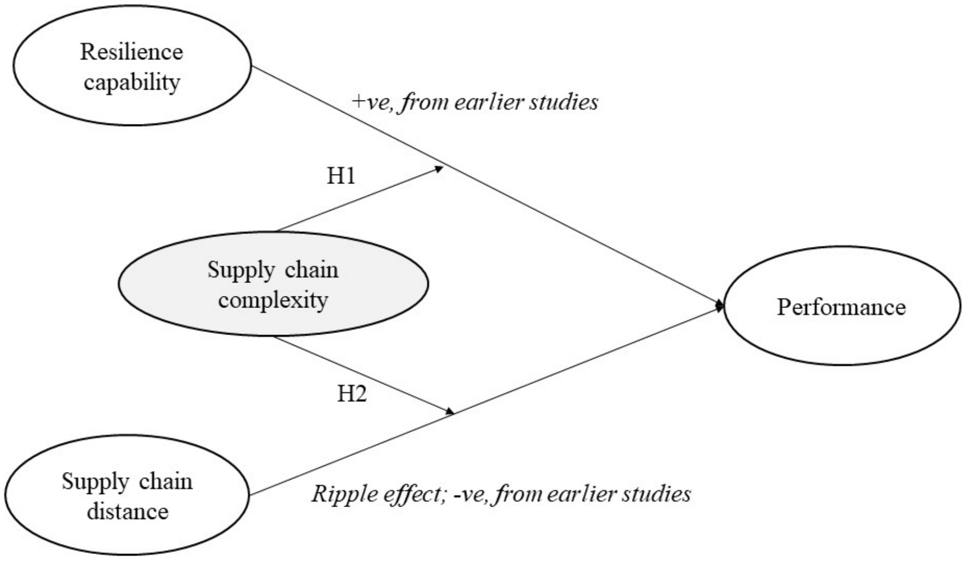

Figure 1. Study framework and hypotheses

254x190mm (96 x 96 DPI)

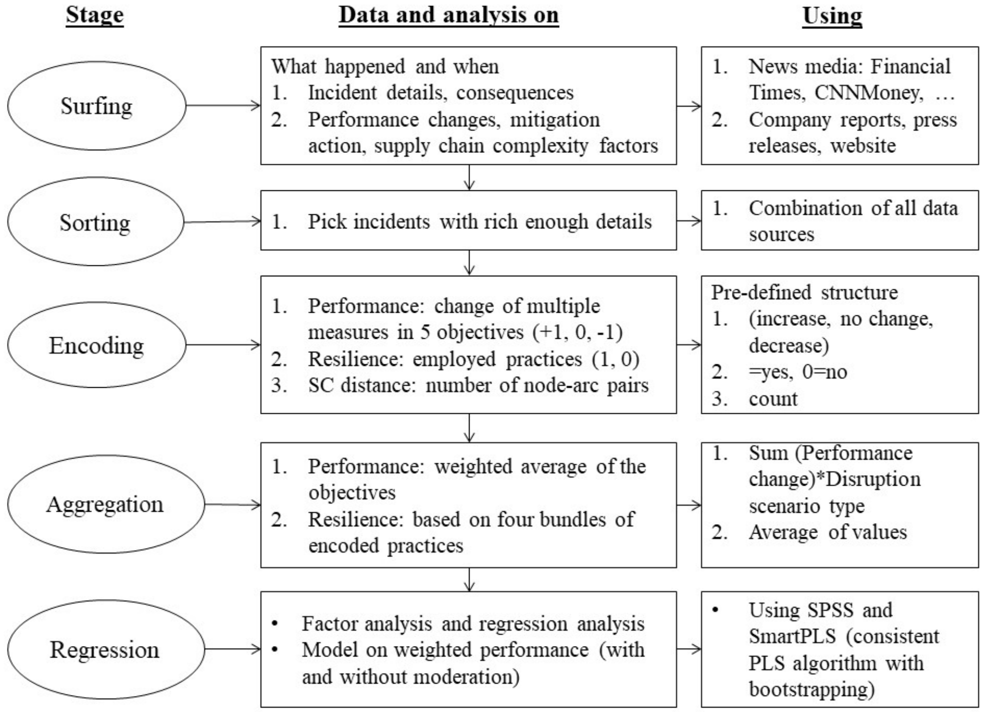

Figure 2. Illustration of the research process

254x190mm (96 x 96 DPI)