The impact of big data on supply chain resilience: the moderating effect of supply chain complexity

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Abstract

Big Data represents a new era in data exploration. Less is known on how big data impact on supply chain resilience. This paper explores the relationship between big data and supply chain resilience with considering the mediating role of supply chain visibility and the moderating role of supply chain complexity. Based on Data obtained from Chinese manufacturing firms, the analysis shows there is a direct relationship between big data and supply chain resilience. Big data also enhance supply chain resilience by improving visibility. However, contrary to the hypothesis supply chain complexity moderate the relationship but in a negative direction.

Keywords: Supply chain resilience, Big data, Supply chain visibility

Introduction:
In a more global world supply chain disruptions such as natural disasters, political turmoil, fuel crises, diseases and terrorism have a greater geographic dispersion (Chen et al., 2012). At the same time, supply chains are designed to reduce costs through tighter coupling and reduced inventory levels creating greater vulnerabilities. Building a more resilient supply chain aims at minimizing the devastating effects of risks. However, the majority of the existing literature focuses on conceptual discussions, definitions and constructs of supply chain resilience (SCRES) and offers limited guidance on how to achieve it (Ali et al., 2017). To build and operate a resilient supply chain, it is crucial to

understand which firm resources and how they benefit on SCRES (Brusset and Teller, 2017). The review paper of Tukamuhabwa et al. (2015) summarize 24 different SCRES strategies and conclude that information technology is an indispensable resource for most of these strategies. With IT development, the field of “big data”, characterized by increasing creation of massive amounts of data through an extensive array of several new data generating sources, has emerged as the new frontier (Goes, 2014). According to information richness theory, greater amount and richer information will be more effective for dealing with uncertainty (Daft and Lengel, 1986). Therefore, big data improves the ability of firms to see through and monitor the entire supply chain, which can help to identify potential threats, signal potential disruptions and improve resilience. So far, the relationship between big data and SCRES has not been addressed, especially no empirical evidence is documented in the literature. Our research aims to fill this research gap by investigating the question: how does big data influence SCRES? We argue that big data as a resource improves visibility and subsequently SCRES. Additionally, we investigate the contingent effect of supply chain complexity on the relationships between big data and SCRES as supply chain complexity creates greater uncertainty (Brandon-Jones et al., 2014) and therefore a situation where big data has an even larger effect on improving SCRES.

In developing our paper, we define SCRES as the capability of a firm’s supply chain to proactively plan and prepare for unexpected events, respond adaptively to disruption and recovery from them by maintaining continuity of the supply network operations (Ponomarov & Holcomb 2009. We consider big data as data volume and variety which show the ability of a firm to capture data in a large amount from different sorts of sources and formats, and contain multidimensional data fields (Russom, 2011). Visibility is regarded as the extent to which the information shared and knowledge of the status entities transiting the supply chain, captured in timely messages about events (Pettit et al., 2013). With regard to supply chain complexity, we relate to the number of suppliers of buyers (Vollmann et al., 2005).

This study contributes to offer theoretical reasoning and empirical evidence of the relationship between big data and SCRES with considering the mediating effect of visibility and the moderating effect of supply chain complexity. It is one of the first in-depth studies that explore how big data influence SCRES. In this paper, contrary to most papers dealing with the subject of resilience, we provide managers insight to understand how the decisions and practices they apply, the resources that they build upon contribute to the resilience of the supply chain to which their firm belongs. This insight is useful to help them to prioritize data capturing further adapt efforts on the face of complexity.

Theoretical background and hypotheses development

Big data

Big Data represents a new era in data exploration but as a concept it is nascent and its origins are uncertain. Laney (2001) suggested that Volume, Variety, and Velocity (the Three V's) are the three dimensions in data management, which have become the common framework to describe big data (Chen et al., 2012; Kwon et al., 2014). Volume refers to the amount of all types of data generated from different sources (Hashem et al., 2015). Variety refers to the structural heterogeneity in a dataset. Technological advances allow firms to collect various types of structured data (traditional text/numeric information), semi-structured data, such as XML and RSS feeds and unstructured data (audio, video, images, text and human language). Velocity refers to the rate at which data are generated and the speed at which it should be analyzed and acted upon (Gandomi and Haider, 2015). The first two dimensions are connected to the data capturing of firms while velocity more focuses on data analytics. While some researchers have explored the linkage between the implementation of big data analytics and competitive advantage (Akter et al. 2016; Ji-fan Ren et al. 2017; Frisk and Bannister, 2017), there is limited empirical research on big data capturing. However, as stated by Pat Helland from Microsoft:" If you have too much data, then 'good enough' is good enough". One of the fundamental reasons for Big Data phenomenon to exist is the current extent to which information can be generated and made available (Hashem et al., 2015). Thus, in the research we focus on volume and variety in data capturing.

Supply chain resilience

Most definition of SCRES consist of two dimensions: one is to reduce the possibility to be disrupted before the turbulence, the other is to respond and recover rapidly post the disruption (Jüttner & Maklan, 2011; Ivanov et al., 2014; Hohenstein et al., 2015). Wieland & Wallenburg's (2012) summarized it similarly into mitigating of vulnerabilities in a proactive or reactive manner. Therefore, SCRES refers to "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function" (Ponomarov & Holcomb 2009, p.131). By following this definition, our study focuses on both preparation and response phases as part of resilience.

Supply chain visibility

Supply chain visibility has been conceptualized by prior studies as a capability to facilitate the prediction of risks (Rai et al., 2006) and to reduce the negative impacts of a supply chain disruption (Christopher and Lee 2004). Visibility is concerned with the information flow in terms of inventory and demand levels within the supply chain at a given time (Braunscheidel and Suresh 2009) and enables supply chains to be more transparent (Christopher and Lee 2004) based on information technology. With extensive visibility in place, organizations have a smoother information flow and can quicker access and share information between partners in their supply chain (Jüttner & Maklan 2011). In this paper supply chain visibility is regarded as an ability for a company to acquire knowledge of the status of operating assets and the environment in the supply chain (Pettit et al. 2013) as well as to detect the status of the supply chain (Jüttner and Maklan 2011).

Supply chain complexity

Supply chain complexity is considered as the context variable to change the environment in which supply chain activities works and makes managing supply chains more challenging (Gimenez et al., 2012). Various researchers have developed lists of supply chain complexity sources, i.e. solely supply base complexity (Choi & Krause, 2006), the manufacturing plant (Martinez-Olvera, 2008) or a two stage supply chain (Sivadasan et al., 2010). Our research focuses on the complexity derived from inter-organizational characteristics of a supply chain including upstream and downstream complexity. Socio-technical systems, like supply chains, are considered to be complex when they are "made up of a large number of parts that interact in a non-simple way" (Simon, 1962, p. 468). This definition motivates to consider supply chain complexity as the amount of entities engaged in the supply chain. To be more specific, we see supply chain complexity as being related to the number of suppliers and buyers (Vollmann et al., 2005).

Hypotheses development

A large volumes of a wide variety of data can provide better insights into a changing environment. By being capable of observing these changes in the environment or (potential) disruptions of the supply chain, a firm can alter its strategy or processes like changing their product mix to act upon this changes (Swafford et al., 2008). The benefit of gathering huge amounts of data includes the creation of hidden information and patterns through data analysis (Hashem et al., 2015) and it is expected that a firm can interact with its supply chain partners by using these data. The data from different resources such as APS, RFID, sensors, smartphones or social networks would help to improve operational efficiency and order, part and product traceability (Gunasekaran & Ngai 2004). By improving tangible-products traceability, organizations can see from one end of the supply chain to another. Therefore, if a firm has integrated their IT inter-organizationally, the capabilities of altering its product flows will be enhanced, which leads to a better capability to adapt or respond towards (potential) disruptions and thereby enhancing SCRES. Thus, we posit the following:

H1. *The implementation of big data capturing is positively related to supply chain resilience.*

Ngai et al. (2011) find that the importance of ICT competence to an organization depends on the scale of the organization. For example, a small-scale organization has a comparatively simple supply chain and may therefore not require advanced ICT competence to support SCRES. In contrast, in a large-scale organization with a sophisticated supply chain, advanced ICT competence is extremely important to support SCRES. Therefore, it implies that the influence of big data capturing capability changes with the sophistication of the supply chain. More suppliers and buyers in a supply chain contribute to a higher level of supply chain complexity with a more complex construction. To manage supply chain complexity, more 'information generation and dissemination' (Wong et al., 2015, p. 4) is needed. Thus, we expect the following

H2. *Supply chain complexity moderates the positive relationship between big data capturing implementation and supply chain complexity, such that the relationship becomes stronger when supply chain complexity is high rather than low.*

Grounded in the Resources-Based-View and dynamic capabilities approach, Brusset and Teller (2017) develop a theoretical model to indicate that resources in the supply chain firstly improve lower-order capabilities e.g. supply chain visibility and then the operational capabilities such as resilience. Similarly, Brandon-Jones et al. (2014) argue from the RBV perspective that SCRES can be understood as performance outcomes and supply chain visibility is regarded as capability that may reduce the negative impacts of a supply chain disruption. According to the RBV, organizational capabilities defined as a higher order construct which relies on the resources (Wu et al., 2006) influence performance or lead to sustained competitive advantage (Newbert, 2007). Thus, big data capturing implementation regarded as a kind of IT resources firstly improves supply chain visibility and then benefits SCRES. A large volume of a wide variety of data can accelerate and visualize flow of information, products and finance. This attribute indicates that big data capturing implementation would enhance the visibility of a supply chain as it makes it possible to visualize and see through the chain based on its positive impact on traceability, forecasting, and information flow. Furthermore, improved supply chain visibility capability may reduce both the probability and impact of a supply chain disruption and therefore lead to enhanced resilience (Christopher and Lee 2004; Brandon-Jones et al., 2014). Thus,

H3: *Big data capturing implementation has a positive relationship with supply chain resilience via supply chain visibility.*

Figure 1 summarizes the hypotheses in the conceptual model of this study.

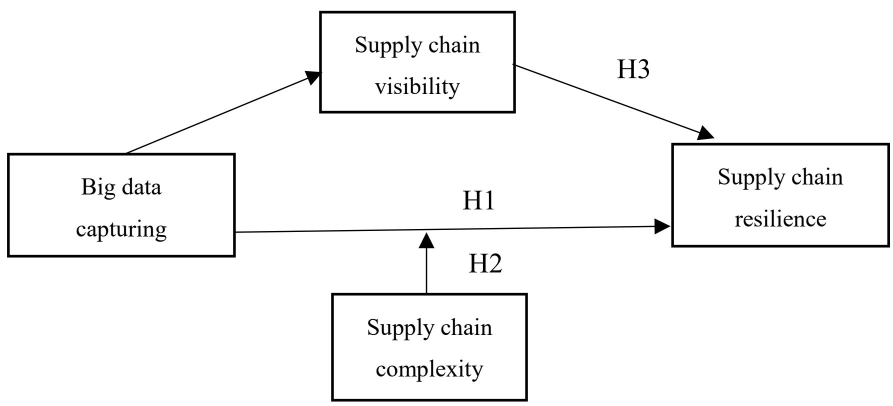

Figure 1 –Conceptual model

Methodology

A survey was developed and administered to test the hypothesized relationships between the constructs. The measurement of big data capturing implementation includes two aspects: volume and variety by following the definitions of Wamba et al. (2015) and Cecere（2012). The items used to measure SCRES and visibility were adapted from Wieland & Wallenburg (2012) and Pettit et al. (2013). Supply chain complexity is measured as the numbers of suppliers and buyers (Vollmann et al., 2005). The original survey questions were translated from English to Chinese and then back to English by SC academics to ensure that the contents of the English and Chinese texts are aligned.

Furthermore, we invited several academic researchers in the field of Operations Management to edit and improve upon the questions. Pilot tests were taken for the Chinese questionnaire. The informants were asked to provide feedback on the readability of the questions, confusion of questions and any mistakes. Meanwhile, their completion time was recorded.

The initial target population is based on the data pool of one of the largest Chinese survey online platform (www.sojump.com). This online survey platform has 2.6-million companies in its data pool. Sojump.com is a top professional survey site in China. It achieves very high reliability by controlling the uniformity of IP addresses, accounts and respondents' detailed information. Sojump.com partners with its respondents, who are dispersed in various industries. We selected respondents based on the following criteria: 1) at least 50 employees in the company, 2) respondents are in a supply chain-related position, and 3) respondents are from manufacturing firms that have their own production lines. The starting population was collected in the following sectors via NACE code: Manufacture of food and beverages (C.10-11), Manufacture of chemicals and chemical products (C.20), Manufacture of electrical equipment (C.27), Manufacture of motor vehicles, trailers and semi-trailers/ other transport equipment (C.29-30), Manufacturer of textiles (C.13), Manufacture of other non-metallic mineral products (C.23).

Based on the data pool from sojump.com, we originally distributed 380 surveys. The target respondents were reached through social media and/or email. Within four weeks, 157 questionnaires were returned and 142 of those questionnaires are valid. The respondent rate is therefore 37.37%. To check for differences between early and late responders, a one-way ANOVA analysis was conducted on two control variables, firm size and firm turnover. The 30 earliest and 30 latest respondents were selected to conduct comparisons. The results were (1) firm size: $F = 0.572$, $p = 0.685 > 0.05$; (2) firm turnover: $F = 0.573$, $p = 0.671 > 0.05$. From the p-value, there is no significant difference between the responses, therefore, non-response bias is not considered a problem with the data (Karlsson, 2010).

Data analysis

To determine the quality—i.e., the validity and reliability—of our multi-item constructs, we conducted an exploratory factor analysis (EFA). Kaiser-Meyer-Olkin (KMO) examines sample adequacy, while Bartlett's test examines relationships between items. The model corresponds to a KMO value of 0.912, which indicates a satisfactory adequacy for factor analysis. The p-value of Barlett's test is $<.001$, which indicates correlated items for each factor. In addition, a principal component analysis (PCA) was conducted to test the retention of factors. The factor loadings are commonly accepted when they exceed a .40 standard, which means that it is not necessary to remove items to improve model fit (Anderson and Gerbing, 1988). Finally, we checked Cronbach's alpha value, which determines the reliability and consistency of a set of items. An acceptable Cronbach's alpha value should exceed .70. The result of the principal-component analysis is presented in Table 1.

Table 1-Factor analysis

Items	1	2	3
F1: Big data capturing Cronbach's α = .844			
Collect business data from traditional systems (like ERP, transport management system, etc.)	.597		
Collect data from mobile devices (e.g., smartphones, laptops, POS, etc.)	.664		
Collect data from social media (e.g., Wechat, Webo, etc.).	.562		
Records structured data (e.g., Transactional data, Time phased data).	.584		
Records unstructured data (e.g., video, audio, networking data)	.741		
Records semi-structured data (e.g., web-log)	.774		
F2: Supply chain visibility Cronbach's α = .753			
We have information systems that accurately track all operations.		.740	
We have real-time data on location and status of supplies, finished goods, equipment, and		.753	
We have effective Business Intelligence gathering programs.		.688	
We have regular interchange of information among suppliers, buyers, and other external		.599	
F3: Supply chain resilience Cronbach's α = .889			
Systematic identification of sources for such disruptions.			.716
Assessment of both own risks and risks of important suppliers and buyers.			.648
Assigned persons responsible for the management of such risks.			.644
Continuous monitoring of developments that might promote such disruptions.			.685
Material flow would be quickly restored.			.738
It would not take long to recover normal operating performance			.708
The supply chain would easily recover to its original state			.680
Disruptions would be dealt with quickly			.602
Eigenvalue	1.400	1.070	7.934
Percentage of variance explained (%)	7,776	5.943	44.077

Results

Multiple regression was used to examine the hypotheses. The individual variables and the variates were checked for linearity, homoscedasticity, and normality. The variance inflation factors associated with each regression coefficient ranged from 2.621 to 2.802, showing no relevant multicollinearity. The number of employees and annual sales are included as control variables. H1 refers to the direct effect of the implementation of big data capturing and SCRES. The result shows big data capturing has a significant impact on SCRES (β=0.622, $p < 0.01$), thus H1 can be accepted. H3 is tested following the approach suggested by Baron and Kenny (1986). First, big data capturing have significant relationships supply chain visibility (β=0.595, $p < 0.01$). Second, visibility has a significant positive effect on SCRES (β=0.247, $p < 0.01$). Finally, the results show that adding the mediator in the regression significantly reduces the effect of electronic linkages, as is confirmed by the Sobel test. The change of β-coefficient is from 0.622 ($p < 0.01$) to 0.475 ($p < 0.01$) shows that information sharing partly mediates the effect of big data capturing. Thus, H2a is supported. The result shows that the interaction effect between the big data capturing and complexity with SCRES is significant but the value of β-coefficient is negative (β=-0.134, $p < 0.05$), which partly supports H2.

Examining the individual items of big data capturing results yields some additional insights. All the three data resources, which are collecting data from traditional systems, mobile devices and social media, have significant relationship with SCRES. The data captured from traditional systems has the strongest impact on SCRES (β=0.270, $p< 0.01$), followed by data from mobile devices (β=0.257, $p< 0.01$) and social media (β=0.235, $p<0.01$). Structured data (β=-0.341, $p<0.01$) improve SCRES more than semi-structured data (β=0.269, $p < 0.01$) while unstructured data has no significant relationship with SCRES (β=0.079, n.s.).

Conclusion and Discussion

This paper explores how the implementation of big data capturing impact on SCRES. The results show that there is a direct relationship between big data capturing and SCRES. Meanwhile the impact of big data capturing on SCRES is mediated by supply chain visibility. With regarding to the influence of supply chain complexity, the result shows supply chain complex moderate the relationship between big data capturing and SCRES but in a negative way, which means the higher the complexity the less the beneficial effects of big data capturing on SCRES, which is opposite to our hypothesis. When less capacity is available to generate and disseminate information with supply chain partners, it is expected that the firm has a reduced capability of acting and responding fast to changes in the environment. Even if the data has been captured to a large extent, employees working at firms which are facing high complex environments might find it difficult to act on this information (Blome et al., 2014). A possible explanation for this is that employees are overwhelmed by the amount of data being shared to such extent that sense-making of this data is hindered, therefore weakening supply chain flexibility capabilities. The result of detailed analysis indicates that the data captured from traditional systems or the traditional way (structured formats) contributes more than mobile devices or semi-structured format which are with more "big data" characteristics. Furthermore, it seems unstructured data e.g. video, audio, networking data does not benefit SCRES. These findings imply that organizations much convert data into valuable insights and later actions. The diversity of data types especially with "big data" characteristics is one of the challenges that organizations need to tackle in order to make value out of the extensive informational assets available today.

We feel that progressing along the lines of this paper might be an interesting line of research that has both theoretical and managerial implications. As far as academic contributions, it helps understand the relationship between the implementation of big data capturing and SCRES and the role of supply chain visibility and complexity, which has not been explored before by empirical study according to our knowledge. For practicing managers, our research could help better understand how to achieve more SCRES.

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