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Data-driven supply chain capabilities and performance: A resource-based view

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A B S T R A C T

Despite the importance and relevance of data-driven supply chains, there has been very limited empirical research that investigates how big data-driven supply chains affect supply chain capabilities. Drawing on the resource-based view, this study explores the effect of data-driven supply chain capabilities on financial performance. The data for this study were gathered from China's manufacturing industry and analysed using structural equation modelling. The results indicate that a data-driven supply chain has a significant positive effect on the four dimensions of supply chain capabilities. Coordination and supply chain responsiveness are positively and significantly related to financial performance.

1. Introduction

Nowadays, firms invest heavily in information technology, e.g., enterprise resource planning, radio frequency identification, etc., to track merchandise and operations, automate transactions, and optimize inventory levels and other supply chain decisions (Chae et al., 2014; Fosso Wamba, 2012; O'dwyer and Renner, 2011; Yu, 2015). These technologies generate large amounts of data flowing in real time into every area of the global economy (The Economist, 2010). The scale of the data creation is substantial with approximately 2.5 exabytes of data generated every day in 2012, and that volume is doubling every three years (Libert, 2013; McAfee and Brynjolfsson, 2012). This data includes a burgeoning volume of transactional data associated with trading partners (Manyika et al., 2011). Properly harnessed, the scope and scale of this data have the potential to revolutionize supply chain performance, possibly through supply chain capabilities (Fosso Wamba et al., 2015; Waller and Fawcett, 2013). Supply chain managers leveraging the data coming into the system can derive useful insights toward improvements to supply chain capabilities and competitiveness (Davenport, 2006). In fact, supply chain managers are increasingly viewing such data as a critical source of value creation and competitive advantage (Tan et al., 2015) since it is the data that enables them to gain visibility into expenditures, identify trends in costs and performance, support process and planning control, capacity and inventory monitoring, and production optimization (Davenport, 2006; Hazen et al., 2014; Tan et al., 2015). While some leading manufacturing firms (such as Dell, Apple, Sony, Samsung, Volvo, and BMW) are actively employing big data to improve supply chain processes and open up new business opportunities, many firms are still in the early stage of adoption because of a lack of understanding of big data and how to manage it (Kwon et al., 2014; Manyika

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et al., 2011; Sanders, 2014). Recently, practitioner articles and consultancy white papers have reported the potential benefits from big data to generate tremendous opportunities for competitive advantage in firms (e.g., Libert, 2013; Manyika et al., 2011). Despite the importance and relevance of data-driven supply chains (DDSC), there is a dearth of research addressing the effect of DDSC on supply chain capabilities and performance (Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013), thus calling for its theoretical development (Chae et al., 2014).

Grounded in the resource based view (RBV), the research herein investigates the relationship between DDSC and supply chain capabilities (SCC), that in turn influence financial performance; SCC referring to "the ability of an organisation to identify, utilize, and assimilate both internal and external resources to facilitate the entire supply chain activities" (Wu et al., 2006, p. 494). The RBV attributes superior business performance to the effective use of resources and organisational capabilities (Barney, 1991; Wernerfelt, 1984); capabilities being broadly defined as "complex bundles of skills and accumulated knowledge that enable firms to coordinate activities and make use of their assets" (Day, 1990, p. 38). Supply chain researchers have recognized organisational capabilities as an important source of an organisation's operational strengths and competitive performance (Huo, 2012; Peng et al., 2008; Yu et al., 2014). Supply chain management has emerged as a vital competency that depends on companies developing specific capabilities such as the ability to build strategic relationships with customers and suppliers, information sharing among supply chain partners, and flexible and quick responses to market demands (Huo, 2012; Wu et al., 2006). From an RBV perspective, this implies that DDSC are an important intangible firm resource (Hazen et al., 2014; Waller and Fawcett, 2013). DDSC and SCC are each thought to be part of an emerging competence that will transform the way in which supply chains are managed and designed (Hazen et al., 2014; Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013).

Consistent with the RBV, effectively leveraging a resource such as big data can lead to significant profit (Libert, 2013; Manyika et al., 2011; McAfee and Brynjolfsson, 2012). It has been suggested that big data applied to supply chains will continue to reduce business costs and create competitive advantages via improved supply chain operational effectiveness and efficiency (Manyika et al., 2011; Sanders, 2014). Despite the importance of big data to business success, many managers are not taking advantage of it. For example, research from The Conference Board and Stanford University shows that only about 7 percent of boards incorporate big data into their decision making (Libert, 2013). One of the main reasons is that most companies do not manage well the information they already have. They do not know how to organize and analyse it in ways that enhance understanding of markets and then make operational and product changes in response to new the insights generated (Ross et al., 2013). Until a company learns how to use data to support its operating decisions, it will not be in a position to benefit from big data (Libert, 2013; Ross et al., 2013). Thus, a major challenge for supply chain managers is to understand the linkage between big data, SCC, and the delivery of better business performance. Unfortunately there has been a lack of practical guidance assisting managers in developing valuable insights from data to drive improvement in supply chain capabilities or business performance (Libert, 2013; Schoenherr and Speier-Pero, 2015; Tan et al., 2015; Waller and Fawcett, 2013).

This study aims to extend existing supply chain and big data research. More specifically, we develop a construct to measure DDSC. Additionally, consistent with the research of Wu et al. (2006), we conceptualise SCC as a four dimensional construct, i.e., information exchange, coordination, interfirm activity integration, and supply chain responsiveness. By disaggregating SCC into its constituent parts, this study can contribute to building a more granular understanding of the nature of the relationships between DDSC, each SCC dimension, and financial performance. After presenting the hypothesized relationships and the methodology used to test them, we present the findings from this study and offer insights to managers into how big data can be deployed to build data-driven supply chain capabilities for performance improvement.

2. Theoretical background and hypothesis development

2.1. Resource-based view (RBV)

The resource-based view of the firm (RBV) suggests that firms possessing resources that are valuable, rare, inimitable and non-substitutable can achieve sustainable competitive advantage by using them to implement strategies that are difficult for competitors to duplicate (Barney, 1991; Peteraf, 1993; Wernerfelt, 1984). The RBV considers a firm to be a bundle of resources and capabilities (Wernerfelt, 1984), and this vantage point has proven to be an influential theoretical framework for understanding how competitive advantage, and by extension financial performance, is achieved (Corbett and Claridge, 2002). In general, capabilities relate to the ability of the firm to use its resources "to affect a desired end" and are analogous to intermediate goods generated by the firm using organisational processes to provide "enhanced resource productivity" (Amit and Schoemaker, 1993). In contrast to resources, capabilities are embedded in the dynamic interactions of multiple knowledge sources and are more firm-specific and less transferable; hence they may lead to competitive advantage (Peng et al., 2008). Capabilities can be broadly categorized into those that relate to performing basic functional activities of the firm and those that guide the improvement and renewal of the existing activities (Collis, 1994). The RBV holds that firms will have different resources and varying levels of capability in regards to resource exploitation. Firm survival depends on the ability to create new resources, build upon existing capabilities, and make the capabilities more inimitable (Peteraf, 1993).

2.2. Data-driven supply chains

Today's supply chain professionals are inundated with data that potentially enables new ways of organizing and analysing supply chain processes to drive supply chain performance (Hazen et al., 2014). Big data refers to data that is in such volume, velocity, and variety that typical computing infrastructures cannot process it (Lycett, 2013; McAfee and Brynjolfsson, 2008). The use of big data is an evolving phenomenon reflecting the increasing significance of data in terms of its burgeoning volume, variety, velocity, value, and veracity (Fosso Wamba et al., 2015; McAfee and Brynjolfsson, 2012). In the context of supply chains, consistent with Waller and Fawcett (2013), we consider a DDSC to be those that use big data as the basis for quantitative and qualitative techniques aimed at improving supply chain competitiveness. While data is growing in importance as a driver of better decision making and improved business performance for those firms able to leverage it (Stank et al., 1999), it has been suggested that not all firms are able to translate investments in computational infrastructure into performance gains (Taylor, 2003).

In the context of the RBV, the ability to leverage big data can be considered one of a firm's assets (Marchand et al., 2000) as it is a reflection of a firm's strategic intent, and can become unique and difficult to replicate in the near to intermediate term (Philip and Booth, 2001). Some firms are already harnessing big data to gain new insights and identify business opportunities or to understand elements of product and process design, suppliers and customers, and market demand (Schoenherr and Speier-Pero, 2015; Tan et al., 2015). For example, Hopkins and Brokaw (2011) describe how its use enhanced call centre responsiveness. The nascent successes with an apparent potential of successful exploitation of big data have led industry practitioners to claim that leveraging big data is the next 'blue ocean' in nurturing business performance (Kwon et al., 2014). Deploying a big data strategy to the supply chain could potentially lead to improvements in efficiency and effectiveness through activities such as monitoring the location, transfer and acceptance of products and services, advanced demand forecasting and supply planning, and understanding behaviour of customers and suppliers (Davenport, 2006; Davenport et al., 2012; Kwon et al., 2014; Waller and Fawcett, 2013).

Firms can use big data to inform the different supply chain functions, e.g., purchasing, production and operations, distribution, marketing and sales, and after-sale service (Hopkins and Brokaw, 2011; Sanders, 2014). Using real-time data in supply chain processes, firms can manage demand planning across extended enterprises and global supply chains while reducing defects and rework within production plants (McAfee and Brynjolfsson, 2008; Waller and Fawcett, 2013). Through DDSC, firms can develop a collaborative relationship with customers and suppliers based on a deep understanding of market demands, which can enable the supply chain to respond more quickly and effectively to changing customer and supplier needs (Sanders, 2014). DDSC can also impact production and operations processes by enabling higher efficiency in product design and development, quality improvement, and better balance between demand and capacity through the collaborative relationships and information sharing with supply chain partners (Sanders, 2014). For example, big data can help manufacturers reduce product development time by 20–50% and eliminate product defects prior to production through simulation and testing (Manyika et al., 2011).

Achieving supply chain effectiveness and efficiency improvements requires access to data from different functional areas of an organisation and from different supply chain partners (Huo, 2012; Sanders, 2014; Wu et al., 2006; Yu, 2015). But, the challenge is that different supply chain members may use different information systems and technologies and be constrained to only access their own silos of data. In order to use the data to maximize profits, information must be shared across processes not only within the organisation, but also outside the organisation, thus providing a real end-to-end process view to all supply chain partners. In a data-driven supply chain process, information is shared across the entire supply chain to connect supply chain partners and provide end-to-end supply chain data access (Sanders, 2014). To be most impactful, it should be embedded into organisational processes (LaValle et al., 2011) since the number of activities and entities a manager must track continues to grow faster than the ability to manage them (Akkermans and Van Wassenhove, 2013). To continue improving supply chain effectiveness, manufacturers will need to leverage large supply chain datasets. For example, firms could improve demand forecasting and supply planning by using their own data and supplement with customer and supplier data such as raw material data, delivery data, promotion data, and inventory data. Such DDSC enable firms to build strategic collaborations with supply chain partners and conduct more efficient coordination activities with business partners. Overall, DDSC enable firms to achieve dramatic improvements in managing the complex, global, extended value chains in more innovative and precise ways, such as through collaborative product development based on customer data, advance demand forecasting and supply planning, and lean operations and production (Waller and Fawcett, 2013).

As mentioned above, DDSC firms can develop a more thorough and insightful understanding of their supply chain management practices, which may lead to enhanced information exchanges, supply chain coordination and integration, and greater supply chain responsiveness. Accordingly, this study examines how DDSC affect SCC through the testing of the following hypotheses:

H1. Data-driven supply chains have a significant positive effect on (a) information exchange; (b) coordination; (c) activity integration, and (d) responsiveness.

2.3. Supply chain capabilities

SCC includes using both internal and external resources/information to facilitate supply chain activities (Amit and Schoemaker, 1993; Collis, 1994; Wu et al., 2006). SCC can be used to gain a competitive advantage. Specifically to understand customer/market requirements and work with trading partners to create order winning products and services. Following the work of Wu et al. (2006), we conceptualise SCC as a multidimensional construct that encompasses four dimensions: information exchange, coordination, interfirm activity integration, and supply chain responsiveness. Each of the four dimensions reflects an ability to collaboratively perform cross-functional, e.g., collaboration across product/service design, purchasing, production, sales/marketing, and distribution functions, and inter-organisational activities, e.g., strategic information sharing and coordination between a focal firm and its supply chain partners, that are required in the supply chain process (Wong et al., 2011; Wu et al., 2006; Zhao et al., 2011).

Information exchange refers to the ability of a firm to strategically share knowledge/information about product and process with its supply chain partners in an effective and efficient manner (Wu et al., 2006). Prior research has revealed information exchange to be an important supply chain capability. Fully developed, it can enable a firm to achieve effective and efficient flows of products and services, information (Shore and Venkatachalam, 2003), and pull away from competitors (McAfee and Brynjolfsson, 2008). For example, such integration has been shown to help the firm develop production plans and deliver products and services on time (Droge et al., 2012; Flynn et al., 2010).

Interfirm coordination entails the ability of a firm to coordinate transaction-related supply chain activities (e.g., procurement, sales, and delivery) with customers and suppliers (Wu et al., 2006). In a dynamic market, one of the key issues of SCM is to find suitable mechanisms to coordinate the logistical processes among supply chain partners (Zimmer, 2002). Coordination among supply chain partners is one of the most fundamental capabilities helping firms reduce transaction costs and lead times, improve flexibility to cope with high demand uncertainty, increase efficiency of product development, and increase operational efficiency (Horvath, 2001; Wu et al., 2006).

Activity integration entails building strategic relationships with supply chain partners (Yu et al., 2013; Wu et al., 2006). Specifically, it involves strategic collaboration between a focal firm and its customers and suppliers in managing boundary spanning business activities, including collaboration in purchasing, planning and forecasting, and joint product development (Flynn et al., 2010; Wong et al., 2011; Yu et al., 2013). Activity integration creates opportunities for leveraging the knowledge embedded in collaborative processes thus enabling greater cost reduction, value creation, and improved delivery performance (Wong et al., 2011).

Supply chain responsiveness is defined as the extent to which supply chain members respond to changes in the environment (Williams et al., 2013; Wu et al., 2006). In today's increasingly dynamic business environment, supply chain responsiveness has become a highly prized capability (Wang and Wei, 2007; Williams et al., 2013). Supply chain responsiveness is a vital capability that is reflected in the ways in which supply chain managers change production and delivery quantities and product mix in response to shifts in demand and supply. These changes are likely to lead to improved performance outcomes such as a lower production cost, higher customer satisfaction, faster delivery, and improved on time performance (Williams et al., 2013; Wong et al., 2011).

2.4. SCC and financial performance

The RBV positions organisational capabilities as important for achieving competitive advantage (Song et al., 2007). Researchers widely accept, based upon empirical studies, the RBV's contention that a firm's resource capabilities influence its performance (e.g., Nath et al., 2010; Song et al., 2007; Yu et al., 2014). However, very few empirical studies have investigated the linkage between SCC and financial performance and none as comprehensively. One notable exception is the work of Wu et al. (2006) that employed a second-order factor consisting of an aggregate of the four dimensions of SCC examined herein to investigate the effect on marketing and financial performance. In the present study, we extend their analysis by examining the impacts of each dimension of SCC, e.g., information exchange, coordination, interfirm activity integration, and responsiveness, on financial performance. By disaggregating SCC into its constituent parts and examining the effect of each dimension on performance, this study contributes to the building of a deeper understanding of the nature of the relationship between SCC and financial performance. Further, it serves as a point of replication in a new context of the few instances where a single dimension of SCC had been tested in relation to financial performance. Given the foregoing arguments and the theoretical perspective of RBV, we offer the following set of hypotheses:

H2. (a) information exchange; (b) coordination; (c) activity integration, and (d) responsiveness have significant positive effect on financial performance.

Using the RBV as a theoretical lens (Amundson, 1998), we develop a conceptual framework that proposes DDSC and SCC as important organisational capabilities for the firms to achieve sustained competitive advantages (i.e., financial performance). The research model is presented in Fig. 1.

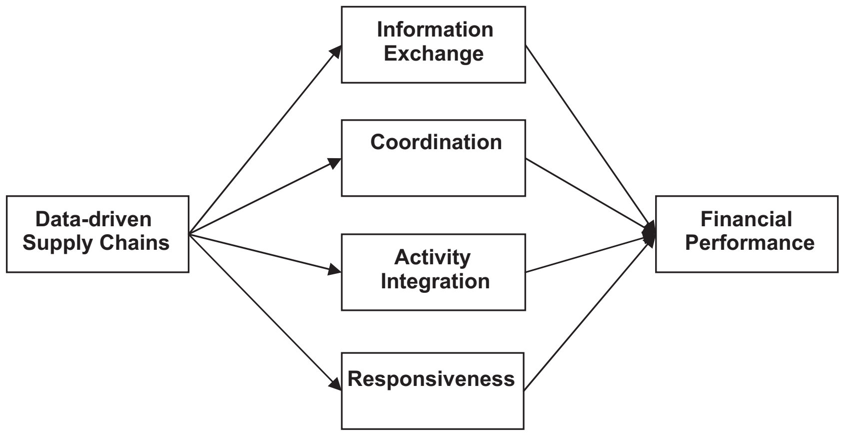

Fig. 1. Conceptual framework.

3. Research method and data

3.1. Sample and data collection

The data for this study were gathered from manufacturers in China. With regard to the sample pool, we strategically chose five regions that represent different stages of economic development in China, including Pearl River Delta, Yangtze River Delta, Bohai Sea Economic Area, Central China, and Southwest China (Zhao et al., 2006). Our sample covered all major geographical regions in China. We used the China Enterprises Directory as the starting point for identifying potential participants. To obtain a representative sample, we randomly selected 1500 manufacturing firms from China Enterprises Directory in the five regions. We contacted the key informants by telephone and email before sending out the questionnaires to obtain their preliminary agreement to take part in the study. In order to ensure that the respondents were sufficiently knowledgeable to answer the questions, we identified a key informant in each randomly selected manufacturer who held a position such as CEO, president, director, or general manager. When contacting these top executives, we suggested that the relevant senior function or departmental managers should answer different sections of the questionnaire (Li et al., 2008). The measurement items of a theoretical construct were sometimes answered by several functions or departments. For example, the construct of SCC involved the opinions not only from CEO or president, but also from operations and supply chain managers. This approach has the benefit of providing an overall perspective from the top executives and an expert perspective from the relevant functional area of the firm (Li et al., 2008). Most of the informants had been in their current position for more than five years. Thus, based on position and tenure it is reasonable to expect that the informants could offer deep insights into the functional activities and be knowledgeable about the content of the inquiry. The questionnaires with a cover letter explaining the main purpose of the study and assuring confidentiality were sent to 1230 firms that agreed to participate and provide information for this research. After several reminders, a total of 337 questionnaires were received. Eight returned questionnaires were discarded because of significant missing data, which leads to 329 completed and useable questionnaires. The effective response rate was 26.75%. Table 1 provides a summary of demographic characteristics of respondents. As shown in Table 1, data were obtained from respondents in a wide variety of manufacturing firms, and the respondents represent a wide variety of backgrounds.

3.2. Variables and measurement

The measurement items used in this study were mainly adapted from the literature. Due to the unique characteristics of the Chinese manufacturing industry (Li et al., 2008), we modified in minor ways the existing measurement scales in order to account for language and cultural differences. All items for DDSC, SCC, and financial performance were measured using a seven-point Likert scale since reliability tends to increase as the number of scale points increases from two-point to seven-point (Lissitz and Green, 1975; Preston and Colman, 2000). Table 2 reports the measurement scales used in this study.

In the case of DDSC where there was no reliable and valid existing measurement instrument, we developed new items by reviewing literature and consulting with academic and industrial experts. First, to formulate the DDSC construct as a reflective factor we turned to experts and knowledgeable academicians for guidance as to content, e.g., Manyika et al. (2011) and Sanders (2014). Second, we developed the new measure based on our understanding of the constructs and our observations during company visits and field interviews with the top executives. Third, after the measurement items were developed, practitioners from five randomly selected manufacturers reviewed and evaluated the items in order to pre-assess the reliability and validity of the scales. We measured *data-driven supply chains* using four items: build consistent interoperable and cross-functional department databases, aggregate customer data and make them widely available to improve service

Table 1
Demographic characteristics of respondents (n = 329).

	Number of firms	Percent (%)
Industries		
Automobile	113	34.3
Chemicals and petrochemicals	50	15.2
Electronics and electrical	26	7.9
Fabricated metal product	8	2.4
Food, beverage and alcohol	9	2.7
Rubber and plastics	13	4.0
Textiles and apparel	110	33.4
Number of employees		
1–100	56	17.0
101–200	36	10.9
201–500	65	19.8
501–1000	27	8.2
1001–3000	54	16.4
>3000	91	27.7
Firm age (years)		
≤10	103	31.3
11–20	104	31.6
21–30	35	10.6
>30	87	26.4
Respondent location (geographical regions)		
Pearl River Delta[a]	17	5.2
Yangtze River Delta	33	10.0
Bohai Sea Economic Area	22	6.6
Central China	27	8.2
Southwest China	230	69.9
Years in current position		
≤5	136	41.3
6–10	101	30.7
>10	92	28.0

Note:
[a] It includes one firm in Taiwan and one firm in Hong Kong.

level, implement advanced demand forecasting and supply planning across suppliers, and implement lean manufacturing and model production virtually (e.g., digital factory). Respondents were asked to respond using a seven-point scale, from 1 "strongly disagree" to 7 "strongly agree".

Following the research of Wu et al. (2006), we conceptualised *SCC* as a multidimensional construct that includes information exchange, coordination, activity integration, and supply chain responsiveness. The measures for SCC were adapted from Wu et al. (2006). A total of 17 items were developed for four components of SCC. All these items were measured using a seven-point scale from 1 (strongly disagree) to 7 (strongly agree).

Financial performance was measured using four perceptual measures, including growth in sales, growth in return on investment, return on assets (ROA), and growth in ROA following Narasimhan and Kim (2002). In accordance with previous studies (e.g., Flynn et al., 2010; Narasimhan and Kim, 2002; Wu et al., 2006; Yu et al., 2013), our respondents were asked to assess their performance relative to the performance of main competitors over the last three years. The indicators were measured using a seven-point Likert scale (ranging from 1 "much worse than your major competitors" to 7 "much better than your major competitors").

Firm size and *industry type* were used as control variables in our model. We controlled for firm size by using the number of employees as a proxy because larger firms may have more resources for managing supply chain activities, and thus may achieve higher business performance than small firms (Yu et al., 2013). The type of industry was controlled because firms in the different manufacturing industries may develop different levels of SCC (Devaraj et al., 2007; Yu, 2015).

3.3. Questionnaire design and pre-test

Following previous guidance, e.g., Flynn et al. (2010) and Zhao et al. (2011), the English version of the questionnaire was first developed and then translated into Chinese, and then back-translated to ensure conceptual equivalence. The back-translated English version was also checked against the original English version. A number of questions were reworded to improve the accuracy of the translation and relevance to business practices in China. Even though the scales were used prior and demonstrated to be valid, we took extra steps before administering the survey. In order to assess the content validity of the measurement scales, we consulted three academic experts, who were selected on the basis of their research and consult-

Table 2
CFA results.

Measurement items	Factor loadings	t-values	α	CR	AVE
1. Data-driven supply chains			0.887	0.889	0.666
Build consistent interoperable, cross-functional department databases to enable concurrent engineering, rapid experimentation and simulation, and co-creation	0.816	–			
Aggregate customer data and make them widely available to improve service level, capture cross- and up-selling opportunities, and enable design-to-value	0.850	17.539			
Implement advanced demand forecasting and supply planning across suppliers	0.831	17.021			
Implement lean manufacturing and model production virtually (such as digital factory) to create process transparency, develop dashboards, and visualize bottlenecks	0.766	15.288			
2. Information exchange			0.940	0.941	0.799
Our company exchanges more information with our partners than our competitors do with their partners	0.900	–			
Information flows more freely between our company and our partners than between our competitors and their partners	0.886	24.162			
Our company benefits more from information exchange with our partners than do our competitors from their partners	0.914	26.036			
Our information exchange with our partners is superior to the information exchanged by our competitors with their partners	0.874	23.458			
3. Coordination			0.944	0.945	0.774
Our company is more efficient in coordination activities with our partners than are our competitors with theirs	0.845	–			
Our company conducts transaction follow-up activities more efficiently with our partners than do our competitors with theirs	0.894	21.648			
Our company spends less time coordinating transactions with our partners than our competitors with theirs	0.899	21.899			
Our company has reduced coordination costs more than our competitors	0.871	20.666			
Our company can conduct the coordination activities at less cost than our competitors	0.889	21.424			
4. Activity integration			0.935	0.937	0.788
Our company develops strategic plans in collaboration with our partners	0.914	–			
Our company collaborates actively in forecasting and planning with our partners	0.926	28.368			
Our company projects and plans future demand collaboratively with our partners	0.886	25.210			
Our company always forecasts and plans activities collaboratively with our partners	0.822	21.185			
5. Responsiveness			0.917	0.919	0.740
Compared to our competitors, our supply chain responds more quickly and effectively to changing customer and supplier needs	0.844	–			
Compared to our competitors, our supply chain develops and markets new products more quickly and effectively	0.833	18.861			
In most markets, our supply chain is competing effectively	0.906	21.793			
The relationship with our partner has increased our supply chain responsiveness to market changes through collaboration	0.855	19.706			
6. Financial performance			0.941	0.945	0.814
Growth in sales	0.737	–			
Growth in return on investment	0.954	18.351			
Return on assets (ROA)	0.932	17.883			
Growth in ROA	0.966	18.601			

Model fit statistics: $\chi^2 = 701.773$, $p = 0.000$; df = 260; $\chi^2/df = 2.699$; RMSEA = 0.072; CFI = 0.949; IFI = 0.949; GFI = 0.855; SRMR = 0.039

ing activities. Further, we conducted a pilot test with five randomly selected manufacturers using semi-structured interviews. Based on the feedback, redundant and ambiguous items were eliminated or modified.

3.4. Non-response bias and common-method bias

Using the extrapolation approach suggested by Armstrong and Overton (1977), we first assessed non-response bias by testing for differences between early and late respondents by two demographic characteristics, sales and number of employees. A *t*-test was performed to compare the characteristics of early and late respondents in terms of sales and number of employees. The *t*-test results reveal no significant statistical difference ($p < 0.05$) among the category means for number of employees and sales, which suggests that non-response bias is not likely to be a concern in this study. Furthermore, a chi-square test was also conducted to check non-response bias (Cao and Zhang, 2011; Chavez et al., 2012). A total of ten measures used in the questionnaire were randomly selected to compare early and late respondents using the chi-square test. The results show that all the significance values of the 10 selected measures were well above 0.10, indicating that received questionnaires from respondents represent an unbiased sample. Thus, we conclude that non-response bias is unlikely in our study.

Because we obtained data from a single respondent per firm using the self-reported questionnaire, common method bias might be an issue (Podsakoff et al., 2003). Appropriate arrangements for the order of questionnaire items can reduce respondents' consistent motive to a certain extent, which decreases the common method bias in self-reporting (Podsakoff et al., 2003). As such, when designing the questionnaire, we adopted different instructions for different scales, and the adjacent variables in the conceptual model were put in distinct sections (Zhao et al., 2011). Furthermore, as noted above, our respondents were familiar with the constructs since they were in senior operations and supply chain management positions. To test for possible common method bias, confirmatory factor analysis (CFA) was applied to Harman's single-factor model (Flynn et al., 2010; Podsakoff et al., 2003). The model fit indices (χ^2 = 3374.543, df = 275, RMSEA = 0.185, CFI = 0.641, IFI = 0.642, and SRMR = 0.107) were unacceptable and significantly worse than those of the measurement model. This result indicates that a single factor model is not acceptable and that common method bias is unlikely. Furthermore, we used a latent factor to capture the common variance among all observed variables in the measurement model (Podsakoff et al., 2003; Zhao et al., 2011). The resulting model fit indices were not significantly different from those of the measurement model, and the model with a latent factor marginally improved the fits (CFI by 0.012 and IFI by 0.013). Also, the item loadings for their factors are still significant in spite of the inclusion of a common latent factor. Based on our examination, we conclude that common method bias is not a serious concern in this study.

4. Data analysis and results

We used the two-step procedure (Anderson and Gerbing, 1988) to test the proposed conceptual model and to analyse the survey data we performed structural equation modelling (SEM) using AMOS 23. The overall model fit was tested using the comparative fit index (CFI), the incremental fit index (IFI), the goodness-of-fit index (GFI), the standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), and normed chi-square (i.e., χ^2/df) (Byrne, 2009; Hair et al., 2006; Hu and Bentler, 1999). An RMSEA between 0 and 0.05 indicates a good fit, and between 0.05 and 0.10 is acceptable (Hair et al., 2006; MacCallum et al., 1996). CFI and IFI values greater than 0.90 are generally considered to indicate a good fit, and more liberal cut-off values (between 0.80 and 0.90) should be used for normed fit indices such as GFI (Hair et al., 2006; Segars and Grover, 1993; Sharma et al., 2005). A SRMR value less than 0.08 is considered a good fit (Hair et al., 2006; Hu and Bentler, 1999). The normed chi-square estimates the relative efficiency of competing models, and it should not exceed 5.0 (Bentler, 1989; Marsh and Hocevar, 1985).

4.1. Measurement model

4.1.1. Content validity analysis

Before data collection begins, it is essential to evaluate content validity of measurement items (Haynes et al., 1995). Content validity was established through a comprehensive analysis of relevant supply chain management and big data literature, careful synthesis and critical evaluation of existing theoretical constructs, and as noted previously, an iterative construct review and a pilot test by academic and industrial experts (Cao and Zhang, 2011; Garver and Mentzer, 1999; Zhao et al., 2011). Following the approach suggested by previous research, e.g., Garver and Mentzer (1999), Gerbing and Anderson (1988) and O'Leary-Kelly and Vokurka (1998), we then performed a series of analyses to assess the unidimensionality, reliability and validity (discriminant, convergent, and criterion) of the six theoretical constructs, including DDSC, the four dimensions of SCC, and financial performance.

4.1.2. Unidimensionality analysis

We assessed the unidimensionality of the theoretical constructs using CFA (Gerbing and Anderson, 1988). As shown in Table 2, the CFA results indicate that the measurement model in this study is found to have acceptable fit indices (Byrne, 2009; Hair et al., 2006; Hu and Bentler, 1999). The measurement model fits are good, with the CFI and IFI well above the recommended threshold of 0.90, and the SRMR less than 0.08 (Hu and Bentler, 1999). Thus, we conclude that unidimensionality of the constructs is confirmed.

4.1.3. Reliability analysis

Once the unidimensionality of the measurement scales was demonstrated, the next step was to assess scale reliability before performing any further validation analysis (Gerbing and Anderson 1988). Cronbach's alpha and composite reliability (CR) were used to examine the reliabilities among the items within each factor. Table 2 shows that the Cronbach alpha and CR of all the constructs are above the widely recognized rule of thumb of 0.70 (Hair et al., 2006; Nunnally, 1978; O'Leary-Kelly and Vokurka, 1998). Thus, we conclude that our theoretical constructs exhibit adequate reliability.

4.1.4. Convergent validity analysis

Once both the unidimensionality and reliability of the measurement scales are deemed acceptable, it is fundamental to establish convergent and discriminant validity using the measurement model in SEM (Garver and Mentzer, 1999). We conducted a CFA using the maximum likelihood approach to evaluate the convergent validity of each measurement scale (O'Leary-Kelly and Vokurka, 1998). As shown in Table 2, the item loadings for each factor are greater than 0.70 and significant at the 0.001 level based on t-values, which suggests convergent validity of the theoretical constructs (Hair et al., 2006). Furthermore, the CFA results reported in Table 2 also reveal that the standardized coefficients for all items greatly exceed

Table 3
Descriptive statistics.

	Mean	S.D.	1	2	3	4	5	6
1. Data-driven supply chains	4.359	1.297	0.816[a]					
2. Information exchange	4.751	1.218	0.493**	0.894				
3. Coordination	4.744	1.194	0.594**	0.728**	0.880			
4. Activity integration	4.645	1.280	0.614**	0.661**	0.763**	0.888		
5. Responsiveness	4.663	1.273	0.600**	0.683**	0.771**	0.799**	0.860	
6. Financial performance	4.376	1.362	0.527**	0.405**	0.462**	0.397**	0.468**	0.902

Note:
[a] Square root of AVE is on the diagonal.
** Correlation is significant at the 0.01 level (2-tailed).

twice their standard errors and that the t-values are all larger than 2, which further demonstrates convergent validity (Hair et al., 2006). Additionally, the average variance extracted (AVE) of each construct greatly exceeds the recommended critical value of 0.50 recommended by Fornell and Larcker (1981), which indicates strong convergent validity. Based on these results, it can be concluded that our constructs express sufficient convergent validity.

4.1.5. Discriminant validity analysis

Discriminant validity was examined by comparing the correlation between the construct and the square root of AVE. Discriminant validity is indicated if the AVE for each multi item construct is greater than the shared variance between constructs (Fornell and Larcker, 1981). Table 3 reports the means, standard deviations, square root of AVE, and correlations of the theoretical constructs. As shown in the table, the square root of AVE of all the constructs is greater than the correlation between any pair of them, which provides evidence of discriminant validity (Fornell and Larcker, 1981). In addition, discriminant validity was further evaluated through inter-factor correlation (Anderson and Gerbing, 1988). While a weak correlation can be expected, a strong correlation between factors indicates that they are measuring the same construct (Anderson et al., 2002). Table 3 indicates that the inter-construct correlation is less than the recommended cut-off value of 0.85 (Brown, 2006). Thus, discriminant validity is further confirmed (Bagozzi et al., 1991).

4.1.6. Criterion-related validity analysis

The level of criterion-related validity is indicated by the size of the correlation between the scores on a test instrument (predictor) and an outcome variable (the criterion) (Flynn et al., 1990; Nunnally, 1978). Consistent with existing guidelines (e.g., Hair et al., 2006) and previous research in establishing criterion-related validity, e.g., Devaraj et al. (2007) and Sila (2007), we used Pearson's correlation coefficient to test the relationships between the constructs (data-driven supply chains and SCC) and the outcome variable (financial performance). Table 3 shows that all of the predictor scales have statistically significant positive correlations with financial performance. Based on the results of the bivariate correlation analysis, we conclude that our theoretical constructs exhibit acceptable levels of criterion-related validity (Hair et al., 2006; Nunnally, 1978).

4.2. Structural model

SEM with AMOS 23 was used to test the hypotheses proposed in the conceptual model (see Fig. 1). The results of the hypothesis test are reported Table 4 and Fig. 2. The overall fit indices of the structural model were good (Hu and Bentler, 1999). Although firm size and industry type were included in the analyses as control variables, we find no statistically significant effect of firm size and industry types on financial performance. The inclusion of additional control variables in the research model lends credibility to our results given that after controlling for firm size and type of industry we still observed

Table 4
The results of hypothesis test using SEM.

Structural paths	Standardised coefficient	t-values	Hypothesis test
Data-driven supply chains → Information exchange	0.765***	11.687	H1a: Supported
Data-driven supply chains → Coordination	0.880***	12.458	H1b: Supported
Data-driven supply chains → Activity integration	0.878***	13.157	H1c: Supported
Data-driven supply chains → Responsiveness	0.900***	12.608	H1d: Supported
Information exchange → Financial performance	0.029	0.380	H2a: Not supported
Coordination → Financial performance	0.226*	2.258	H2b: Supported
Activity Integration → Financial performance	−0.138	-1.384	H2c: Not supported
Responsiveness → Financial performance	0.415***	3.741	H2d: Supported

Model fit statistics: χ^2 = 1162.164, p = 0.000; df = 313; χ^2/df = 3.713; RMSEA = 0.091; CFI = 0.903; IFI = 0.903; GFI = 0.768; SRMR = 0.066.
*** $p < 0.001$.
* $p < 0.05$.

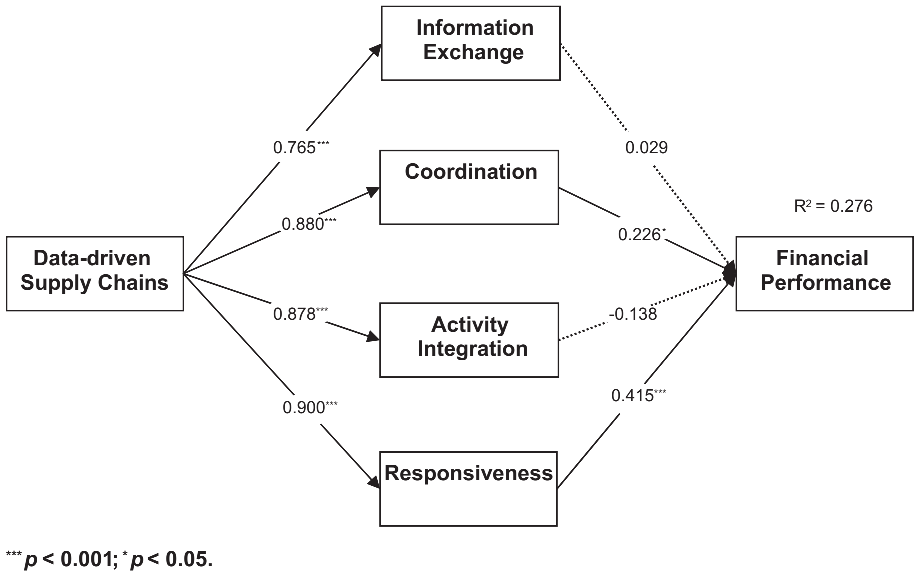

Fig. 2. Model with results.

significant positive relationships between the theoretical constructs. The results shown in Table 4 support H1a-d that DDSC positively affects all four dimensions of SCC. The structural model also shows that coordination ($\beta = 0.226$, $p < 0.05$) and responsiveness ($\beta = 0.415$, $p < 0.001$) are significantly and positively associated with financial performance, which lends strong support for H2b and H2d. However, no significant relationships were found between information exchange and financial performance and between activity integration and financial performance. Hence, H2a and H2c are rejected.

5. Discussion and implications

Drawing upon the RBV, this study explored the relatively new topic of DDSC. There are a variety of implications and insights that flow from this research. We will begin the discussion with theoretical implications and then transition to managerial implications.

5.1. Theoretical implications

To the best of our knowledge, this is the first attempt to empirically investigate the relationship between DDSC, each dimension of SCC, and financial performance. While articles in practitioner outlets and consultancy reports, e.g., Libert (2013) and Manyika et al. (2011), are becoming more prevalent, their content is mostly descriptive, and thus there has been a lack of rigorous scientific investigation into the topic of big data applications in supply chain operations (Schoenherr and Speier-Pero, 2015). The development of big data for supply chain management research and practice has been relatively slow (Chae, 2015; Hazen et al., 2014). Further, findings from this study are consistent with the fundamental principles of the RBV, which suggests that the basis for competitive advantage in firms lies primarily in the application of bundles of valuable resources at the firm's disposal (Barney, 1991; Wernerfelt, 1984). The empirical evidence offered in this study reveals that DDSC and SSC are valuable firm resources and capabilities, thus providing important theoretical insights into future research directions for big data and supply chain management scholars. This study deepens our understanding on how supply chains can be managed in data-rich environments.

Our first theoretical insight reveals that the role of DDSC has been illuminated as a precursor to SCC. Specifically, our study found that DDSC has a significant positive effect on all four dimensions of SCC, including information exchange, coordination, interfirm activity integration, and supply chain responsiveness. The manufacturing sector was an early and intensive user of data to drive supply chain operations process, adopting information technology (e.g., ERP and RFID) to purchase, design, produce, and deliver products since the dawn of the computer era (Manyika et al., 2011). The volatility of demands from customers and suppliers has always been a critical issue for manufacturing firms to increase supply chain flexibility and responsiveness. According to the RBV, DDSC has the capability of transforming the decision making process by allowing enhanced visibility of supply chain operations enabling firms to increase supply chain integration and coordination (McAfee and Brynjolfsson, 2012; O'dwyer and Renner, 2011). DDSC leads to new frontiers in supply chain transparency, visibility and process automation, thus enabling multiple supply chain partners to seamlessly interact in the joint design, production, delivery and service of complex customer orders.

As a second contribution, we found that coordination and supply chain responsiveness are significantly and positively related to financial performance. In particular, the model explains 27.6% of the variance in financial performance. These findings shed light on the importance of DDSC capabilities to financial performance. Our findings are generally consistent with those of Wu et al. (2006), who examined the mediating role of SCC and found that SCC serve as a catalyst in transforming IT-related resources into higher value for firms, e.g., marketing and financial performance. Our findings are also consistent with the fundamental principles of the RBV (Amit and Schoemaker, 1993; Wernerfelt, 1984). In a data-rich environment, supply chain coordination and responsiveness represent a firm's abilities to effectively combine internal and external resources using information-based business processes to fulfil customer requirements (Amit and Schoemaker, 1993; Wu et al., 2006). The findings of the significant positive effects of coordination and responsiveness on financial performance provide evidence of the benefits for cooperating closely with supply chain partners such as customers and suppliers. A potential rationale for this is that building collaborative relationships with supply chain partners helps manufacturers reduce mistakes and waste in activities across partner firms through interfirm coordination (Chavez et al., 2015). Another potential rational is that supply chain responsiveness helps manufacturers better understand customer requirements and better respond to customer demand, thus allowing the manufacturer to add more value at lower cost to customers.

However, we found no significance in the relationship between information exchange and financial performance, and activity integration and financial performance. A possible interpretation for the lack of significance in the relationship between information exchange and financial performance is that the correlation between both constructs may not be linear. Sum et al. (1995) found empirical evidence that when information sharing improves through programs such as material requirements planning (MRP) it will do so only to a certain threshold level, and any benefits will not increase proportionately once that threshold is reached. In other words, significant changes in information sharing beyond a certain limit will not make a major difference to performance improvement. Alternatively, agency theory provides another interpretation indicating that the accuracy of information can be distorted by suppliers, who can start acting as competitors following their own interests (Eisenhardt, 1989; Rossetti and Choi, 2005; Swink et al., 2007). In other words, it is the accuracy and quality of information shared, rather that the amount, which may be generating competitive advantage (Chavez et al., 2015). With regard to the lack of significance in the relationship between activity integration and financial performance, an interpretation suggests that too much of external integration can be harmful for organizations (Chavez et al., 2012; Swink et al., 2007). This is compatible with the law of diminishing synergies, which anticipates a curvilinear relationship between partnerships and manufacturing performance (Das et al., 2006). According to Das et al. (2006, p. 576), supply chain partnerships can be a "double-edge strategy with indiscriminate application resulting in performance degradation". Alternatively, contingency theory provides another interpretation suggesting that there should be a fit between practices and the environment, which determines performance improvement (Ginsberg and Venkatraman, 1985). For instance, it is well supported that companies operating in certain industry environments, e.g. fast-paced industries, are likely to encounter problems when dealing with well-established and long-term supply chain relationships (Chavez et al., 2012; Das et al., 2006; Guimaraes et al., 2002). According to Guimaraes et al. (2002), unless supply chain partners can keep up with the characteristics of the industry at which companies operate, they are likely to inhibit the buyer's ability to react accordingly.

5.2. Managerial implications

The findings of this study have important managerial implications and insights for manufacturers building DDSC. In a data-rich environment, manufacturers have unprecedented amounts of data, much of which is never put to use (Kwon et al., 2014; Manyika et al., 2011; Sanders, 2014). Further, it has been suggested that information overload can adversely impact managerial decision-making process (Mendelson, 2000). Our research suggests that a focus on SCC, particularly projects related to coordination and responsiveness will drive greater financial performance. There is much discussion among academics and practitioners about big data applications in supply chain operations, and the opportunities and challenges of DDSC. The important question is whether using big data in supply chain processes is just hype or if it has a real effect in enabling performance improvement (Chae et al., 2014). Our study reveals that the effect of DDSC on SCC is positive and significant. As such this study suggests that managers employing big data in supply chain contexts will be rewarded with greater supply chain capability and improved financial performance. Maximising supply chain responsiveness and managing multiple supply chain configurations have become the new imperatives for today's supply chain executives. Managers should understand that DDSC are central to solving problems and identifying opportunities in supply chains.

To survive in today's data-rich environments, it is important for managers to recognize the relationship between DDSC and SCC in improving financial performance. Further, managers need to realize that different dimensions of SCC, including coordination, activity integration, information exchange, and supply chain responsiveness, will have differential effects on financial performance. Manufacturing managers have limited resources and must choose the most effective deployment of these resources to build DDSC capabilities for performance improvement.

Our results indicate that coordination and supply chain responsiveness are significantly and positively associated with financial performance. The findings imply that developing capabilities, such as coordination among supply chain partners and quick response to shifts in market demand, can help managers manage supply chains more effectively and achieve better financial performance. Because the fundamental nature of business competition has shifted from that of competition between individual firms to competition between entire supply chains, in order to build supply chain capabilities, firms need to identify, utilize, and analyse data to facilitate the supply chain process.

Our results indicate that information exchange and activity integration are not positively associated with financial performance. The implication is that managers should realise that activity integration and information exchange have inherent limitations. Strategic integration activities are not cost free. Personal time, communication media, and information systems are required to collect and assimilate knowledge from supply chain partners (Swink et al., 2007). Firms do not consistently gain superior performance from information and knowledge sharing and integration with their customers and suppliers. Instead, sharing precise, accurate and timely information can be the real source of competitive advantage (Chavez et al., 2015). In addition, information exchange and activity integration with supply chain members (such as suppliers and customers) can be replicated by competitors, who also have access to the same suppliers and customers.

6. Conclusions

While practitioner outlets and consultancy reports suggest that using big data in supply chain management has the potential to generate competitive advantage, empirical studies are scarce. Our study contributes positively to theory by strongly supporting the value of DDSC to SCC. Next, our research also implies that there is a positive effect of SCC (coordination and responsiveness) on financial performance. Furthermore, our study expands the RBV of the firm by explaining the relationship between DDSC and SCC with the aim of improving financial performance.

While this research has made significant contributions to research and practice, there are limitations that need to be considered when interpreting the study findings. One important limitation is the cross-sectional nature of the data. It has been suggested that instead of a single research design, multiple research techniques may be required to have a holistic understanding of the supply chain management phenomena (Boyer and Swink, 2008). Research in supply chain management is frequently survey-based (Malhotra and Grover, 1998), but other less common techniques such as ethnography, action research, and other atypical research approaches could be used (Boyer and Swink, 2008). This argument does not necessarily suggest that "more is better" in research, but that multiple techniques can be of great benefit if triangulation is achieved through their combination. Future research should seek to utilize multiple methods to examine a broader perspective of the field. This study could not find support for the relationship between information exchange and financial performance, and activity integration and financial performance. The contingency view offers a possible explanation for the lack of significance. Studies have called for further investigation of the contingency framework, naming a variety of moderating variables such as company size, company position in the supply chain, supply chain length, channel structure and the length of the buyer–supplier relationships (Germain et al., 2008; Sousa and Voss, 2008). Future research should consider these and other variables as possible moderators in order to extend the link between SCC and performance, and explore further the contingency perspective in the area. In addition, in the present study we developed a construct to measure DDSC. Future research is encouraged to test the new construct in different cultural settings in order to prove its validity and reliability.

Appendix A. Questionnaire

1. Data-driven supply chains. Please indicate the degree to which you agree to the following statements relating to your company's big data analytics (1 = strongly disagree; 7 = strongly agree)

- Our company builds consistent interoperable, cross-functional department databases to enable concurrent engineering, rapid experimentation and simulation, and co-creation
- Our company aggregates customer data and make them widely available to improve service level, capture cross- and upselling opportunities, and enable design-to-value
- Our company implements advanced demand forecasting and supply planning across suppliers
- Our company implements lean manufacturing and model production virtually (such as digital factory) to create process transparency, develop dashboards, and visualize bottlenecks

2. Supply chain capability. Please indicate the degree to which you agree to the following statements relating to your company's supply chain capability. (1 = strongly disagree; 7 = strongly agree)

Information exchange

- Our company exchanges more information with our partners than our competitors do with their partners
- Information flows more freely between our company and our partners than between our competitors and their partners
- Our company benefits more from information exchange with our partners than do our competitors from their partners
- Our information exchange with our partners is superior to the information exchanged by our competitors with their partners

Coordination

- Our company is more efficient in coordination activities with our partners than are our competitors with theirs

- Our company conducts transaction follow-up activities more efficiently with our partners than do our competitors with theirs
- Our company spends less time coordinating transactions with our partners than our competitors with theirs
- Our company has reduced coordination costs more than our competitors
- Our company can conduct the coordination activities at less cost than our competitors

Activity integration

- Our company develops strategic plans in collaboration with our partners
- Our company collaborates actively in forecasting and planning with our partners
- Our company projects and plans future demand collaboratively with our partners
- Our company always forecasts and plans activities collaboratively with our partners

Responsiveness

- Compared to our competitors, our supply chain responds more quickly and effectively to changing customer and supplier needs
- Compared to our competitors, our supply chain develops and markets new products more quickly and effectively
- In most markets, our supply chain is competing effectively
- The relationship with our partner has increased our supply chain responsiveness to market changes through collaboration

3. Financial performance. Please provide an estimate of and evaluate in the scale below how your firm compares to your major industrial competitors over the last three years (1 = much worse than your major competitors; 7 = much better than your major competitors).

- Growth in sales.
- Growth in return on investment.
- Return on assets (ROA).
- Growth in ROA.

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