# Do network capabilities improve corporate financial performance? Evidence from financial supply chains

**Abstract**

**Purpose:** This study bridges the gap in the literature on supply chain finance (SCF) by exploring the relationship between network capabilities and corporate financial performance (CFP) in financial supply chains (FSCs).

**Methodology:** We adopt panel data regression to analyse the joint investment activities among 1359 manufacturing firms and 289 financial service providers in China to explore how network capabilities, both network power and network centrality, improve CFP in the FSCs.

**Findings:** Under the FSCs environments, network centrality (i.e., eigenvector centrality, closeness centrality, betweenness centrality) raises CFP (ROA, ROE, Tobin's Q), and network power (node degree, clustering coefficient) also improves CFP. However, node strength from the network power stream has a negative effect on Tobin's Q, indicating that when the partner of a firm has an extremely strong influence in FSCs, this weakens the bargaining ability and flexibility of focal firm, thus reducing its long-term financial performance.

**Originality:** This study answers the call for more empirical research on SCF to provide a broader sample set of financial supply chain management (FSCM) from joint investment activities. This is one of the earliest studies to shed light on a new perspective—how network capabilities improve CFP in the FSCs.

**Practical implications:** The joint investment activities among industrial chain partners and financial service providers help managers understand the advanced financing solutions generated by internal and external network organisations as well as be aware of network capabilities impact CFP in FSCs.

**Keywords:** Supply chain finance solutions; Financial supply chain; Corporate financial performance; Network organisation; Investment activities

**Article classification:** Research paper

# 1 Introduction

The attention paid to supply chain finance (SCF) has increased in practice and academia since the global financial crisis of 2007–2008 (Wetzel and Hofmann, 2019). Taken as a whole, the perspectives of SCF are mainly drawn from two aspects: the 'financial-oriented' perspective and the 'supply chain-oriented' or 'buyer-driven' perspective (Caniato *et al.*, 2016). The 'financial-oriented' perspective regards SCF as a set of financing solutions, financing from payables or receivables, which can be divided into pre-shipment, in-transit, and post-shipment financing; and financial institutions are vital in this perspective (Moretto *et al.*, 2019). The 'supply chain-oriented' perspective regards SCF as a set of solutions that optimises inventory in the supply chain to increase cash availability or reduce financing costs; again, financial institutions are important but not mandatory (Caniato *et al.*, 2019). Therefore, no matter from the perspective of 'financial-oriented' or 'supply chain-oriented', financial institutions and financing solutions are essential parts of SCF solutions.

Financial flows and advanced financing technologies in SCF solutions have received increased attention in recent years, especially in the process of digital transformation (Wetzel and Hofmann, 2019). With the development of digital transformation technologies, many advanced supply chain-based and industrial chain-based financing solutions have emerged in supply chain management, thereby promoting the rapid development of 'financial-oriented' SCF. In other words, the financial supply chain (FSC) is becoming more important in SCF solutions (Xu *et al.*, 2018). Table 1 summarises some typical modes of financing the FSC. These typical financing solutions promote close connections among suppliers, customers, and service providers (i.e. financial institutions) using multiple financing modes to integrate material, financial, and information flows in FSC practices (Hofmann *et al.*, 2019). Therefore, studies of financial flows and financial services in the digital transformation era within the scope of the FSC have become increasingly important.

Insert Table 1 here

In response to the increasing importance of financial flows and financial services, 20–25% of enterprises already adopt advanced technologies to manage their supply chain and industrial chain partners (Gornall and Strebulaev, 2018). In this study, these methods are considered to be the FSC, namely, defined herein as, *optimised planning, managing, and controlling of the financial flows among supply chain, industrial chain and financial service partners to efficiently facilitate material and information flows in the process of supply chain management based on a certain product* (Wuttke *et al.*, 2013). In contrast to SCF methods, which typically follow the principle of optimising the cash flow across industrial chain, supply chain, and financial service participants, the FSC emphasises these methods form product-based financial technologies and financing schemes. Therefore, in FSCs, close collaboration is required between the financial and supply chain managers in an enterpsrise, and extensive collaboration is also encouraged beyond the firm's borders with service providers (e.g. financial institutions), suppliers, customers, and upstream and downstream enterprises. Our research sheds light on the SCF literature by investigating how to handle the constraint of financial liquidity using the typical FSC ways of joint investment activities among industrial chain and financial service partners.

We focus on joint investment activities among industrial chain partners, which is one type of financing modes in the FSCs, which have become increasingly popular in the resource-intensive manufacturing industry and differ from joint venture activities, a well-researched financing solution. A joint venture is a business entity created by two or more parties that involves the creation of a new separate organisational entity (Pfeffer and Nowak, 1976). However, joint investment activities do not necessarily involve the creation of a separate organisational entity, which allows for the flexible use of financing instruments among partners for an enterprise to obtain financial flows (e.g. equity investment, securities transaction, entrusted investment, and portfolio investment) among supply chain and industrial chain partners (Chang *et al.*, 2012;

Chakuu *et al.*, 2019). To a certain extent, joint ventures constitute a specific type of joint investment activities. In the context of joint investment activities among industrial chain and financial service partners, the advanced financing instruments are the financial flows, the materials among industrial chain levels are the material flows, and the financing information both from financial flows and from material flows are the information flows, allowing us to provide a robust snapshot of the FSCs.

Previous research has explored the relationship between network capabilities and corporate financial performance (CFP) in the SCF solutions based on the theories of resource dependence and network organisation (Hillman *et al.*, 2009; Carnovale *et al.*, 2019). Since enterprises should continuously transform themselves by reshaping resource configurations to establish their advantage, Hillman *et al.* (2009) suggest that network capabilities as an organisational resource affect the operation strategies of the enterprise based on resource dependence theory. This theory usually describes the organisational behaviour among suppliers, customers, and focal enterprises in the network environment based on interdependence effects and restricted effects (Carnovale *et al.*, 2019). This research adopts resource dependence theory (i.e. resource abilities and resource channels) to capture the network capabilities (i.e. network power and network centrality) of enterprises to access organisational resources. Specifically, two themes of network capabilities that may impact CFP emerge: (1) network power, which identifies the abilities of enterprises in the FSCs, and (2) network centrality, which quantifies the channels of enterprises in FSCs.

To explore how network capabilities improve CFP in FSCs, our research is the first to construct network structural characteristics by considering an important but understudied financing solution of joint investment activities among industrial chain and financial service partners. We choose joint investment activities among enterprises in the computers, communications, and other electronics equipment Manufacturing Industry in China (termed MI hereafter) because of its vast production networks, and resource-intensive manufacturing processes, and multiple industrial chain-based financing solutions. We also consider joint investment activities between the MI and Financial Industry (FI) because the financial flows provided by financial institutions can effectively promote material flows and information flows. Therefore, in this study, joint investment activities mainly comprise of vertical financing among MI industrial chain partners and horizontal financing between MI and FI partners. We then construct the FSC networks for each year using joint investment data, generating symmetric matrices for each year between 2012 and 2017 and obtaining a dynamic panel dataset of FSC network structures over these six years. We finally estimate the potential effects using panel data regression to test several theoretical hypotheses.

Our research contributes to the SCF literature in at least threefold. First, we explore an important but understudied financing solution of SCF, namely, joint investment activities among industrial chain and financial service partners in FSCs. Rather than only focusing on vertical investment in a single industrial chain in the vein of Carnovale *et al.* (2019), we also investigate the horizontal investment between MI and FI partners, boarding the financing channels both vertically and horizontally. Second, in FSCs, our research is the first to provide a nuanced understanding of network capabilities and theoretically explain how they improve CFP. Our findings add to the FSC literature by evidencing that network centrality (i.e. eigenvector centrality (EC), closeness centrality (CL), and betweenness centrality (BC)) and network power (node degree (ND), node strength (NS) and the clustering coefficient (CC)) positively contribute to CFP. Third, the operation strategies and financing solutions evolved from our findings would be helpful for SCF stakeholders, especially from the perspective of FSC management. For instance, the financial and supply chain managers in a firm should understand that product-based financing solutions are required; Further, they should realise the importance of network relationships rather than solely focusing on linear financing relationships to broaden financing channels both horizontally and vertically; they should be aware that of the network capabilities have a significant impact on CFP in the FSCs.

The rest of this paper is structured as follows. Section 2 reviews related works on SFC, the FSC, resource dependence theory, and network organisation theory and connects these with CFP in the FSCs. Section 3 presents theoretical analysis and proposes research hypotheses. Section 4 describes empirical study using panel data regression models and discuses several interesting findings. Section 5 discusses the theoretical and managerial implications. Conclusions are presented in Section 6.

## 2 Literature review

### *2.1 Research background*

#### *2.1.1 SCF and the FSC*

Scholars have defined SCF from multiple perspectives. One of the most cited definitions is that by Vanpoucke (2009), stating that SCF covers 'optimizing the inter-financial resources as well as the integration of financing processes with customers, suppliers, and service providers, to increase the value of all participating enterprises'. In this study, SCF covers three dimensions: the supply chain, finance, and technology. First, the supply chain dimension emphasises the importance of collaboration with supply chain and industrial chain participants (Caniato *et al*., 2016). Second, the financial dimension emphasises the use of advanced financing tools for financial flows to improve cash flow management (Wuttke *et al.,* 2013). Third, the technology dimension emphasises the adoption of information technology (IT) to promote the application of SCF solutions (Gelsomino *et al.,* 2016). Thus, *SCF is a supply chain-based or industrial chain-based financing solution using advanced IT and financing instruments to improve the financial flow management of participating enterprises, emphasising collaboration across a product-based supply chain and industrial chain partners, such as focal firms, service providers (e.g. financial institutions), suppliers, and customers* (*Caniato et al., 2016; Lam et al., 2019).*

Owing to the emergence of multiple participants and tiers in SCF solutions, the traditional linear relationships among participants should been transformed into a network organisation and the network capabilities of participants should be considered. Seiler *et al.* (2020) explore how the network position of the enterprise in an extended supply chain network affects its financial performance, arguing that the performance measurement tools in SCF solutions should consider the network position. Martin and Hofmann (2017) argue that financial service providers are compulsory actors in SCF solutions that can better provide the resources of organisational members and add value to organisational members in SCF practices. Ali *et al.* (2019) indicate that the strong tie of firms significantly enhances firm performance and suggest that firms should share more information in their supply chain network to allow partners to improve their operational capabilities. Carnovale *et al.* (2019) argue that firms can take advantage of network characteristics to resource access, which can increase CFP.

The links between the FSC and SCF mainly rest on the financial and the supply chain perspectives. On the side of the financial perspective, financial flows are one of the main pillars of the FSC. Studies of FSC discuss how to plan, manage, and control the financial flows among supply chain and industrial chain participants to improve CFP. Accordingly, one of the core elements of SCF is to manage product, information and financial flows in a coordinated manner, making the FSC an important part of SCF. On the side of the supply chain perspective, the management of financial flows is a vital aspect of supply chain management, particularly in the trade finance and diverse financing processes. The typical financing modes in FSC practices such as supply chain contracts, platform financing, trade credit, buyer credit, and banking transactions have also received attention in SCF. Hence, both the FSC and SCF belong to the scope of supply chain management, but the FSC focuses on coordinating financial flows and financial transactions through advanced financial technology and financial services. Hence, it is an important part of SCF that focuses on financial flows and advanced financial services to promote the effective integration of material, information, and financial flows among supply chain and industrial chain participants (Gupta and Dutta, 2011).

Studies of FSC mainly examine the following five aspects. First, the definition of the FSC. According to Blackman *et al.* (2013), that FSC comprises network organisations that coordinate financial transactions via financial processes and enable goods flows and financial services between the trading partners in a product supply chain. Second, the interaction between the FSC and product supply chain, suggesting it is a reciprocal relationship between the product and financial processes within a supply chain or industrial chain (Wuttke *et al.,* 2013). Third, the business ecosystem of FSC, which is involved in the coordination of the financial transactions among upstream enterprises, downstream enterprises, and their financial partners (Gupta and Dutta, 2011). Fourth, the integration of information flows through IT, such as the integration of transactional data from within the enterprise, e-commerce systems, industrial chain partners, and financial service providers (Fairchild, 2005). Finally, FSC performance, such as financial performance, non-financial performance, operational performance, and strategic performance (Xu *et al.,* 2018).

The FSC has important characteristics in the digital era. Advanced and diversified financial instruments and financing schemes should be encouraged, because digitisation and innovative financing solutions are becoming increasingly important, and new financial instruments and advanced financing solutions provide an unprecedented opportunity for firms to increase their financial management capability and operating efficiency, especially in resource-intensive manufacturing processes. Further, organisational characterises should be considered because the FSC involves many stakeholders (e.g. suppliers, customers, financial institutions, platform providers, supply chain participants, and industrial chain participants). Hence, organisational characterises should be considered when seeking FSC practices. Further, financial network structure should be considered because the business ecosystem of the FSC comprises multiple tiers among supply chain and industrial chain partners. As such, the FSC is changing from a single linear relationship to a network organisation. These characteristics are understudied, and little research has discussed the role of organisational characteristics, namely, network capabilities, in FSCs, especially based on a real trading set. We thus aim to address this important gap by investigating the relationship between network capabilities and CFP in FSCs.

### *2.1.2 Network organisation theory*

Prior researches have defined a network organisation as a combination of relationships that a business maintains with its partners to access information, resources, and markets (Gulati, 1999). Network organisation theory was developed by Chang *et al.* (2012), who argue that ‘firms do not operate in isolation’, emphasising the importance of interaction among enterprises throughout the business ecosystem. In supply chain management, this ecosystem has developed as a supply chain network. Specifically, supply chain networks mainly emphasise network power and network centrality to identify the connectedness or cohesiveness of the enterprises in the network (Wuttke *et al.*, 2013). Therefore, in FSCs, network structures of enterprises are generated through multiple tiers among supply chain partners, industrial chain partners, and financial service providers through specific activities (e.g. asset investment, joint investment, complementary resources), and these partners are also connected with their own network environments.

Many scholars have studied supply chain management from the perspective of network organisation theory. For example, Zaheer and Bell (2005) investigate the supply chain network based on the views of organisational strategy, arguing that enterprises with superior network structures can better exploit their internal capabilities to improve financial performance. Chang *et al.* (2012) develop strategies for the supply chain network in the following areas: relation-specific assets, knowledge-sharing routines, complementary resources and capabilities, and network position. Song *et al.* (2019) investigate the role of the firm’s position in enhancing access to resources throughout the entire network, emphasising the importance of utilising network resources in the supply chain. Therefore, existing research indicates that the network organisation, as a kind of resource, provides a theoretical basis for analysing how the network structural characteristics of the FSC affect CFP.

### *2.1.3 Resource dependence theory*

As one of the main ways to access resources, network capabilities are thus considered to be an important source of organisational resources, thereby affecting CFP based on resource dependence theory (Basole *et al.*, 2018). Resource dependence theory, a fundamental perspective for understanding organisational cooperation and other cooperative relationships (e.g. joint investment activities, strategic alliances, buyer–supplier relationships), is mainly composed of two basic factors: resource interdependence and resource constraints. Resource interdependence indicates that the normal operation of a firm relies on the resources provided by other firms, and this resource interdependence occurs in the network organisation when a firm needs external resources to implement an activity, as shown by Pfeffer and Nowak (1976). Resource constraints refer to the effects of interdependence, namely, a firm is faced with constraints based on how interdependent the it is in relation to other network participants, and is bound by conditions as a result (Hillman *et al.*, 2009).

Many scholars of supply chain management have studied how network capabilities affect firm's operating performance based on resource dependence theory. For example, Vanpoucke *et al.* (2009) argue that the degree of dependence of focal firms and supply chain partners is positively related to the power of those partners to achieve goals, but negatively related to resource availability. Hillman *et al.* (2009) find that firms acquire network resources through cooperation with other firms, indicating that small and medium-sized enterprises can obtain more benefits than larger firms. Ma *et al.* (2020) argue that for firms that operate in a network organisation, their operating efficiency depends on resource dependence and resource constraints. In general, the operating capacities of an enterprise in a network organisation depend on its power to take actions and the centrality of the network structure (Yang *et al.*, 2019). Therefore, existing research indicates that resource dependence theory provides a theoretical basis for analysing how network capabilities affect CFP in FSCs.

### *2.2 Research gap*

Considering the digital transformation technologies empowering SCF solutions, advanced financing solutions and IT are becoming more important. As an important branch of SCF, the FSC focuses on financial flows and financial services to design, manage, and control the financial transactions among supply chain partners, industrial chain partners, and service providers to facilitate material flows and information flows in the product-based supply chain and industrial chain. Therefore, this research focuses on a classic financing mode in FSCs, namely, joint investment activities among industrial chain partners and financial services providers, which have become increasingly popular in vast production networks and differ from other well-researched financing solutions in the manufacturing industry. Although previous studies of the FSC mainly focuses on its definition, the interaction between FSC and product supply chains, business ecosystems, the integration of information flows through IT, and its performance, the FSC as a financial network organisation that coordinates financial flows with trading partners in a product-based supply chain and industrial chain and the role of its network structure on CFP have been ignored, especially studies using Chinese empirical data. Therefore, juxtaposed on the theories of network organisation and resource dependence, our research explores the extent to which network capabilities affect CFP in FSCs. It is the first study to construct two kinds of network characteristics, namely, network power and network centrality, to estimate the potential effect on CFP in terms of return on assets (ROA), return on equity (ROE), and Tobin's Q (TBQ). Our research thus extends the FSC literature on how network capabilities improve CFP by examining joint investment activities among industrial chain partners and financial service providers.

## 3 Research hypotheses

### *3.1 Hypothesis framework*

In the previous section, we discussed the related but juxtaposed theories of network organisation and resource dependence to understand the FSC through the financing modes of joint investment activities among industrial chain partners and financial service providers. In this study, the product-based financing modes are constructed by horizontal investment among the MI and financial service providers and by vertical investment among industrial chain levels. Hence, this study extends the scope of FSC practices to the network organisation environment, suggesting that network capabilities of enterprises should be considered when they seek to improve their financial performance. Consequently, to explore the role that the network capabilities play in enhancing CFP, we should obtain variables for a firm's network structural characteristics and CFP. Inspired by Chen (2018), this study uses ROA, ROE and TBQ to measure CFP. The rationales for using these variables is straightforward: ROA indicates the efficiency of a firm's management in generating income from resources; ROE measures the efficiency of a firm in generating earnings from shareholder capital; and TBQ measures the efficiency between market value and working capital (Kaldor, 1966). For network capabilities in FSCs, this research focuses on two types of network structures. The first is network power, which measures the influence of a firm in the network and posits that the connectedness is inherent and governs the mutual behaviour between network participants (Dahl, 1957); here ND, NS, and CC are used as agents. The second is network centrality, which identifies the importance of a firm in the whole network and considers the cohesiveness (i.e. density) of an enterprise throughout that network (Borgatti, 2005); here, EC, CL, and BC are used. In addition, the integration effect between network power and network centrality is crucial to CFP. Table 2 represents the definitions for these variables.

Insert Table 2 here

### *3.2 Hypothesis development*

#### *3.2.1 Network power and CFP*

The concept of network power has been long studied in the supply chain management literatures (Chakuu *et al.*, 2019). Under the FSCs, the network power of a firm is derived from the attractiveness of its own resources and freedom to obtain financial resources from other organisations. Thus, power is the capability of the firm to create financing relationships among industrial chain partners and financial partners, to broaden its ability to obtain financial resources in the FSCs (Provan *et al.*, 1980). Specifically, in FSCs, network power is mainly composed of the amount of contact with other enterprises, weight of transactions with other partners, and embeddedness with other partners in the FSC network organisation (Kim *et al.*, 2011).

Therefore, this study expects a positive correlation between network power and corporate revenue, ROA. When an enterprise with a higher level degree enters the FSCs, it can flexibly choose its FSC partners because it has more enterprises from which to select, which may increase its revenue. Enterprises that improve network power can better manage their suppliers and financial service providers, which may significantly improve their ability to obtain financial resources (Olsen *et al.*, 2014). Similarly, as embeddedness increases, the bargaining power of an enterprise also rises, thereby reducing its purchasing cost of the enterprise and increasing the revenue of enterprises in FCS practices. Therefore, we make predictions based on the following hypotheses:

H1: Network power has a positive effect on ROA.

H1a: Network power (ND) has a positive effect on ROA.

H1b: Network power (NS) has a positive effect on ROA.

H1c: Network power (CC) has a positive effect on ROA.

In addition to increasing corporate revenue, we also expect network power to have a positive impact on corporate profits, ROE. According to the theory of resource dependence, firms seek to increase control through various types of organisational resources, so as to improve their profit performance (Hillman *et al.*, 2009). Therefore, in FSC practices, we expect firms with high network power, to have higher profit as well as revenue. Therefore, we make predictions based on the following hypotheses:

H2: Network power has a positive effect on ROE.

H2a: Network power (ND) has a positive effect on ROE.

H2b: Network power (NS) has a positive effect on ROE.

H2c: Network power (CC) has a positive effect on ROE.

In addition, increasing the network power of enterprises can improve their access to resources and enhance their financing ability in the FSCs. These advantages improve not only their short-term financial performance in terms of revenue and profit, but also their long-term performance in terms of TBQ (Drees and Heugens, 2013). Therefore, with an increase in network power, firms can access more financial resources, which improves their management of financial flows in FSC practices. Therefore, we predict that long-term performance (TBQ) also increases. Hence,

H3: Network power has a positive effect on TBQ.

H3a: Network power (ND) has a positive effect on TBQ.

H3b: Network power (NS) has a positive effect on TBQ.

H3c: Network power (CC) has a positive effect on TBQ.

### *3.2.2 Network centrality and CFP*

Although network power is crucial in explaining CFP in the FSCs, network centrality should also be explored in detail. In FSCs, network centrality can be regarded as the basis for promoting the channels of organisational resources, making it crucial for explaining CFP (Pugliese *et al.,* 2014). Specifically, in FSCs, network centrality is mainly composed of the shortest path to reach two other firms, the shortest distance to reach all other firms, and the prestige score for a firm in the whole network organisation (Kim *et al.,* 2011). We also expect that network centrality can improve ROA. To achieve the best revenue performance, enterprises should design the resources of the entire FSC, so that those with a higher concentration can access more of the available resources and generate more diverse channels, all of which help improve ROA (Caniato *et al.,* 2016). Thus, we make predictions based on the following hypotheses:

H4: Network centrality has a positive effect on ROA.

H4a: Network centrality (BC) has a positive effect on ROA.

H4b: Network centrality (EC) has a positive effect on ROA.

H4c: Network centrality (CL) has a positive effect on ROA.

Next, we expect that the increase in network centrality has a positive impact on corporate profits, ROE. In FSCs, enterprises that increase their network centrality also increase access to resources and reduce dependence on a single firm, which directly affects CFP such as corporate profits. In addition, enterprises that increase network centrality through diverse channels create opportunities for cooperation between finance partners both from industrial chains and from financial institutions, which can directly increase ROE (Kale and Shahrur, 2007). Thus, we make predictions based on the following hypotheses:

H5: Network centrality has a positive effect on ROE.

H5a: Network centrality (BC) has a positive effect on ROE.

H5b: Network centrality (EC) has a positive effect on ROE.

H5c: Network centrality (CL) has a positive effect on ROE.

Network centrality is considered to be a key organisational resource, as it can directly result in competitive advantage for enterprises in FSCs. As improving network centrality is directly related to the diversity of organisational connections among financial service and industrial chain partners, it directly influences TBQ performance (Gupta and Dutta, 2011). Generally, these competitive advantages improve not only financial performance in terms of revenue and profits, but also the performance of TBQ. Therefore, we make predictions based on the following hypotheses:

H6: Network centrality has a positive effect on TBQ.

H6a: Network centrality (BC) has a positive effect on TBQ.

H6b: Network centrality (EC) has a positive effect on TBQ.

H6c: Network centrality (CL) has a positive effect on TBQ.

### *3.2.3 Total effect of both network power and network centrality on CFP*

In addition to considering the structural characteristics that form both network power and network centrality, we also consider their total effect in FSC practices. The network power (connectedness) of enterprises facilitates the access to resources and the network centrality (cohesiveness) of enterprises represents the channels for accessing to those resources; therefore, both abilities and channels can be used to increase CFP in FSC practices (Lechner and Leyronas, 2007). For the firm, improving financial performance depends on connectedness (abilities), but this cannot be separated from cohesiveness (channels) when designing FSC solutions (Hearnshaw and Wilson, 2013). Carnovale *et al.* (2016) argue that the stronger connectedness and the closer cohesiveness, the stronger is the firm's capacity to access finance resources, which raises CFP. Therefore, we make predictions based on the following hypotheses:

H7: Both network power and network centrality affect CFP.

H7a: Both network power and network centrality affect ROA.

H7b: Both network power and network centrality affect ROE.

H7c: Both network power and network centrality affect TBQ.

## 4 Empirical study

### *4.1 Sample selection and data collection*

The main research question focuses on the role of network capabilities in improving CFP in FSCs. To answer this, we source our variables from three data sources: (1) the measures of network capabilities in FSCs mainly comprise ND, NS, CC, EC, CL, and BC; (2) the measures of CFP comprise ROA, ROE, and TBQ; (3) and the key control variables are enterprise scale (ES), the asset/liability ratio (AL), the fixed assets ratio (RA), firm age (AGE), ownership concentration (OC), board size (BS), and regional macro-economy (RE), following by Lu and Shang (2017) and Lee *et al.* (2017).

To describe the network structural characteristics in FSCs, the CSMAR database (http://www.gtarsc.com) is used. Specifically, we select the listed firms with joint investment activities from the MI and the FI in the A-share market. The CSMAR database provides transaction reports on joint investments between partners, and these are mainly comprise equity investments, securities transactions, entrusted investments, and portfolio investments. We choose joint investment activities among MI industrial chain partners because of the vast production networks and resource-intensive manufacturing processes that generate many industrial chain-based financing solutions. We also consider joint investment activities between the MI and FI because the financial flows provided by financial institutions can promote material flows and information flows in the FSCs, especially in the resource-intensive manufacturing industry. Joint investment activities between two financial institutions are not considered in this study because they lack the basic material flows in FSCs. The joint investment network constructed in this study is different from that of Carnovale *et al.* (2019), who only choose the automotive industry because of its vast production networks. However, we add financial institutions into the joint investment networks to broaden the financing solutions for the FSC, both vertically and horizontally, to integrate financial, material and information flows extensively into the vast production networks and intensive manufacturing processes.

Next, to obtain the dynamic panel dataset for the network structural characteristics in FSCs, this study first generates symmetric matrices for each year in 2012–2017 as follows. Each matrix is comprised of $n$ rows and $n$ columns (i.e. a matrix of size $n \times n$, hence the symmetric label) where each firm is represented in a distinct row and column of the matrix. In the original sample, there are $240 \times 240$ in 2012, $258 \times 258$ in 2013, $258 \times 258$ in 2014, $269 \times 269$ in 2015, $294 \times 294$ in 2016, and $329 \times 329$ in 2017. Therefore, there are 1648 firms (1359 MI firms and 289 FI firms), generating six adjacency matrices. We label these matrices $A_t$, where $t$ represents the year. Each element, $a_{ij}$, of the matrix (for year $t$) is assigned a value of either zero or one (thus it is binary in construction), where a value of one indicates firms $i$ and $j$ (in year $t$), and the joint investment amount as a weight of the link between firms $i$ and $j$. Thus, we have a dynamic panel dataset of the network structure over six years.

Next, to gather information on CFP, this study uses the Wind database (http://www.wind.com.cn/), which provides financial information disclosed by firms. We cross-reference this dataset against the firms in the joint investment network using their ticker symbols, to obtain the complete data. Collectively, the matrices referenced above define the network structure of the FSC, and thus all the network-related independent variables are calculated, for each year, using these matrices. After calculating all the network variables, removing observations that lacked complete financial information, and adding the relevant control variables, this study eventually retains 703 observations with complete information.

### *4.2 Operationalisation of the variables*

#### *4.2.1 Dependent variables*

Three dependent variables used in this study are ROA, ROE, and TBQ. The first dependent variable, ROA, shows the percentage of how profitable a firm's assets are in generating revenue (Burton *et al.*, 2002). The second dependent variable is ROE, which is a metric of how firms use equity to generate profits (Arditti, 1967). Finally, we examine corporate TBQ, which is the relationship between the market value of shares and the capital employed by corporations (Kaldor, 1966). For specific mathematical formulae refer to Table 2 and the descriptive statistics of dependent variables in Table 3.

Insert Table 3 here

#### *4.2.2 Independent variables*

To operationalise the network capabilities of enterprises in the FSC environments, we use network power and network centrality separately. The first group of network measures captures the network power of one enterprise: (1) the number of links to other firms (ND); (2) the weights of the links to other firms (NS); and (3) the embeddedness of the links to other firms (CC). The second group of network measures captures network centrality: (1) the shortest distance between two other firms (BC); (2) the shortest distance to reach all other firms (CL); and (3) the prestige score in the whole network (EC). For specific mathematical formulae refer to Table 2, and the descriptive statistics of independent variables in Table 3.

*4.2.3 Control variables*

To capture any unobserved heterogeneity in the relationship between network capabilities and CFP, we consider some key control variables. First, existing research has shown that the ES, namely, the logarithmic transformation of a firm's total assets, reflects all resources easily convertible into cash. We also control for any experiential effects by including AGE, the firm's OC (the shareholding ratio of the largest shareholder), the firm's BS (number of directors), RE (the logarithmic transformation of the annual GDP of the province in which the firm is registered), and AL. In addition, since all the dependent variables are financial and time-varying, we expect the possibility of significant autocorrelation and endogeneity. Thus, in all the empirical models, the one-year lags of the dependent variable are included as independent variables ($t-1$). Finally, the descriptive statistics of the control variables in Table 3, and Table 4 shows the correlation results.

Insert Table 4 here

*4.3 Models and results*

*4.3.1 Existence of network power*

To capture any unobserved heterogeneity in the relationship between network capabilities and CFP in FSCs, this study makes these variables the control variables and their respective effects are tested in Models 1–3 (the baseline models). To check the potential effect of network power on CFP, we use ROA, ROE and TBQ as the independent variables and create the panel data regression modes in Models 4–6:

$$ROA_{i,t} = \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{1}$$

$$ROE_{i,t} = \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{2}$$

$$TBQ_{i,t} = \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{3}$$

$$ROA_{i,t} = \beta_1 ND_{i,t} + \beta_2 NS_{i,t} + \beta_3 CC_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{4}$$

$$ROE_{i,t} = \beta_4 ND_{i,t} + \beta_5 NS_{i,t} + \beta_6 CC_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{5}$$

$$TBQ_{i,t} = \beta_7 ND_{i,t} + \beta_8 NS_{i,t} + \beta_9 CC_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t}\ , \tag{6}$$

where the subscript $i$ denotes the $i^{th}$ firm, and the subscript $t$ denotes time; $\boldsymbol{z}_i$ is the set of control variables including ES, AL, RA, AGE, OC, BS, and RE; $u_i$ is the set of individual-specific and time-invariant effects that are fixed over time; and $v_{i,t}$ is a time-varying random component. The independent variables are as follows: $ROA_{i,t}$ stands for the ROA of the $i^{th}$ firm at time $t$; $ROE_{i,t}$ stands for the ROE of the $i^{th}$ firm at time $t$; and $TBQ_{i,t}$ stands for the Tobin's Q of the $i^{th}$ firm at time $t$. The dependent variables of network power are as follows: $ND_{i,t}$ is the ND of the $i^{th}$ firm at time $t$; $NS_{i,t}$ is the NS of the $i^{th}$ firm at time $t$; and $CC_{i,t}$ is the CC of the $i^{th}$ firm at time $t$. We then use the random effect estimator to test our hypotheses and adopt Lam (2018) approach to address the possible autocorrelation of errors in our estimation. The regression results of the potential effect of network power are shown in Table 5.

Insert Table 5 here

For the baseline models, the regression results of Eqs. (1)–(3) are presented in columns 2–4 of Table 5, and due to the limited space, we do not analyse these results in detail. The regression results of the potential influence of network power on CFP are presented in columns 5–7 of Table 5. First, hypothesis 1 (a–c) dealt specifically with the effect of network power on ROA, and the corresponding regression results of Eq. (4) are presented in column 5 of Table 5: the coefficient of ND is positive but not statistically significant at the 10% level, which does not support H1a; the coefficient of NS is positive and statistically significant at the 5% level, which supports H1b; and the coefficient of CC is positive and statistically significant at the 5% level, which supports H1c; Finally, the goodness-of-fit index of Eq. (4) is 0.1770, which is greater than the fitting index of Eq. (1) at 0.0990, indicating that network power does increase ROA overall.

Hypothesis 2 (a–c) dealt with the impact of network power on ROE, and the corresponding regression results of Eq. (5) are presented in column 6 of Table 5. The coefficient of ND is positive and statistically significant at the 10% level; thus, H2a is supported. The coefficient of NS is positive but not statistically significant at the level of 10%, which does not support H2b. Finally, the coefficient of CC is positive and statistically significant at the 10% level, which supports H2c. The goodness-of-fit index of Eq. (5) is 0.1060, which is greater than the goodness-of-fit of Eq. (2) at 0.0650, indicating that network power is also increase ROE on the whole.

Finally, Hypothesis 3 (a–c) dealt with the impact of network power on TBQ, and the corresponding regression results of Eq. (6) are presented in column 7 of Table 5. The coefficient of ND is negative but not statistically significant at the 10% level, which does not support H3a; the coefficient of NS is negative but statistically significant at the 5% level, which does not support H3b; and the coefficient of CC is positive and statistically significant at the 1% level, which supports H3c. Finally, the goodness-of-fit index of Eq. (6) is 0.1410, which is greater than the goodness-of-fit index of Eq. (3) at 0.1010, indicating that network power increases TBQ overall.

*4.3.2 Existence of network centrality*

To check the potential effect of network centrality on firms' financial performance, we use BC, EC, and CL as the dependent variables and create the panel data regression models in Models 7–9:

$$ROA_{i,t} = \beta_{10} BC_{i,t} + \beta_{11} EC_{i,t} + \beta_{12} CL_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{7}$$

$$ROE_{i,t} = \beta_{13} BC_{i,t} + \beta_{14} EC_{i,t} + \beta_{15} CL_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t} \tag{8}$$

$$TBQ_{i,t} = \beta_{16} BC_{i,t} + \beta_{17} EC_{i,t} + \beta_{18} CL_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t}\,, \tag{9}$$

where the subscript $i$ denotes the $i^{th}$ firm and the subscript $t$ denotes time. The dependent variables are $ROA_{i,t}$, $ROE_{i,t}$, and $TBQ_{i,t}$ and the independent variables are as follows: $BC_{i,t}$ is the BC of the $i^{th}$ firm at time $t$, $EC_{i,t}$ is the EC of the $i^{th}$ firm at time $t$, and $CL_{i,t}$ is the CL of the $i^{th}$ firm at time $t$. The set of control variables, $\boldsymbol{z}_i$, includes ES, AL, RA, AGE, OC, BS and RE. $u_i$ is the set of individual-specific and time-invariant effects that are fixed over time and $v_{i,t}$ is a time-varying random component. We then use the random effect estimator to test our hypotheses and adopt Lam (2018) approach to address the possible autocorrelation of errors in our estimation. The regression results for check the potential effect of network centrality are shown in Table 6.

Insert Table 6 here

The regression results of the potential influence of network centrality on CFP are presented in columns 5–7 of Table 6. First, Hypothesis 4 (a–c) dealt with the impact of network centrality on ROA (see column 5). The coefficient of BC is positive but not statistically significant at the 10% level, which does not support H4a; the coefficient of EC is positive and statistically significant at the 5% level, which supports H4b; and the coefficient of CL is positive and statistically significant at the 10% level, which supports H4c; finally, the goodness-of-fit index of Eq. (7) is 0.1227, which is greater than the goodness-of-fit index of Eq. (1) at 0.0990, indicating that network centrality increase ROA overall.

Hypothesis 5 (a–c) dealt with the impact of network centrality on ROE, and the corresponding regression results of Eq. (8) are presented in column 6 of Table 6. The coefficient of BC is negative and not statistically significant at the 10% level, which does not support H5a; the coefficient of EC is positive and statistically significant at the 5% level, which supports H5b; and the coefficient of CL is positive and statistically significant at the 10% level, which supports H5c. Finally, the goodness-of-fit index of Eq. (8) is 0.1240, which is greater than the goodness-of-fit index of Eq. (2) at 0.0650, indicating that network centrality increases ROE overall.

Finally, Hypothesis 6 (a–c) dealt with the impact of network centrality on TBQ, and the corresponding regression results of Eq. (9) are presented in column 7 of Table 6. The coefficient of BC is positive and statistically significant at the 10% level, which supports H6a; the coefficient of EC is positive and statistically significant at the 1% level, which supports H6b; and the coefficient of CL is positive but not statistically significant at the 10% level, which does not support H6c. Finally, the goodness-of-fit index of Eq. (9) is 0.1304, which is greater than the goodness-of-fit index of Eq. (3) at 0.1010, indicating that network centrality increases corporate TBQ on the whole.

*4.3.3 Total existence of both network power and network centrality*

To check the total effect from both network power and network centrality on CFP in FSCs, we use ND, NS, CC, BC, EC, and CL as the dependent variables and create the panel data regression models in Models 10–12:

$$ROA_{i,t} = \beta_{19} ND_{i,t} + \beta_{20} NS_{i,t} + \beta_{21} CC_{i,t} + \beta_{22} BC_{i,t} + \beta_{23} EC_{i,t} + \beta_{24} CL_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t} \quad (10)$$

$$ROE_{i,t} = \beta_{25} ND_{i,t} + \beta_{26} NS_{i,t} + \beta_{27} CC_{i,t} + \beta_{28} BC_{i,t} + \beta_{29} EC_{i,t} + \beta_{30} CL_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t} \quad (11)$$

$$TBQ_{i,t} = \beta_{31} ND_{i,t} + \beta_{32} NS_{i,t} + \beta_{33} CC_{i,t} + \beta_{34} BC_{i,t} + \beta_{35} EC_{i,t} + \beta_{36} CL_{i,t} + \boldsymbol{\lambda z}_i + u_i + v_{i,t}, \quad (12)$$

where the subscript $i$ denotes the $i^{th}$ firm and the subscript $t$ denotes time. The dependent variables are $ROA_{i,t}$, $ROE_{i,t}$ and $TBQ_{i,t}$; the independent variables are $ND_{i,t}$, $NS_{i,t}$, $CC_{i,t}$, $BC_{i,t}$, $EC_{i,t}$, $CL_{i,t}$; $\boldsymbol{z}_i$ is the set of control variables that includes ES, AL, RA, AGE, OC, BS and RE; $u_i$ is the set of individual-specific and time-invariant effects that are fixed over time, and $v_{i,t}$ is a time-varying random component. We again use the random effect estimator to test our hypotheses and adopt Lam (2018) approach to address the possible autocorrelation of errors in our estimation. The regression results of the potential effect of network centrality are shown in Table 7.

Insert Table 7 here

The regression results of the effect of both network power and network centrality on CFP are presented in columns 5–7 of Table 7. First, Hypothesis 7a dealt with the juxtaposition of network power and network centrality against ROA, and the corresponding regression results of Eq. (10) are presented in column 5 of Table 7. The coefficient of ND is positive but not statistically significant at the 10% level, the coefficient of NS is positive and statistically significant at the 5% level, the coefficient of CC is positive but not statistically significant at the 10% level, the coefficient of BC is positive and statistically significant at the 10% level, the coefficient of EC is positive and statistically significant at the 10% level, and the coefficient CL is positive but not statistically significant at the 10% level; consequently, H7a is partly supported. The goodness-of-fit index of Eq. (10) is 0.1815, which is greater than the goodness-of-fit index of Eq. (1) at 0.0990, indicating that the juxtaposition of network power and network centrality is significantly helpful for increasing ROA overall.

Hypothesis 7b dealt with the effect of both network power and network centrality on ROE, and the corresponding regression results of Eq. (11) are presented in column 6 of Table 7. The coefficient of ND is positive but not statistically significant at the 10% level, the coefficient of NS is positive and statistically significant at the 5% level, the coefficient of CC is positive and statistically significant at the 10% level, the coefficient of BC is negative but not statistically significant at the 10% level, the coefficient of EC is negative but not statistically significant at the 10% level, and the coefficient of CL is positive but not statistically significant at the 10% level; consequently, H7b is partly supported. The goodness-of-fit index of Eq. (11) is 0.1362, which is greater than the goodness-of-fit index of Eq. (2) at 0.0650, indicating that the integration of network power and network centrality is significantly helpful for increasing ROE on the whole.

Finally, Hypothesis 7c dealt with the effect of the juxtaposition of network power and network centrality on TBQ, and the corresponding regression results of Eq. (12) are presented in column 7 of Table 7. The coefficient of ND is negative but not statistically significant at the 10% level, the coefficient of NS is positive but not statistically significant at the 10% level, the coefficient of CC is positive and statistically significant at the 5% level, the coefficient of BC is positive and statistically significant at the 10% level, the coefficient of EC is negative but not statistically significant at the 10% level, and the coefficient of CL is negative and statistically significant at the 5% level; thus, H7c is partly supported. The goodness-of-fit index of Eq. (12) is 0.1704, which is greater than the goodness-of-fit index of Eq. (3) at 0.1010, indicating that the juxtaposition of network power and network centrality is significantly helpful for increasing corporate TBQ on the whole. A summary of the results of all the hypotheses is presented in Table 8.

Insert Table 8 here

*4.3.4 Robustness check*

To test the robustness of the above results on how network capabilities improve CFP in the FSCs, we consider the baseline models in Models 1–3 as scenario S0; for scenario S1, we add the network structural characteristics including network power and network centrality into Models 10–12. We then adopt the Diebold and Mariano (2002) test to compare S1 with S0 for ROA, ROE, and TBQ, respectively. The parameter 'alternative' for the R function 'dm.test' is set to be 'greater'. For this multiple testing, we let $H_0^{(1)}, H_0^{(2)}, \cdots, H_0^{(m)}$ be a family of null hypotheses indicating that the performance levels of S0 and S1 are equivalent. The alternative hypothesis $H_1^{(i)}$ indicates that S1 is statistically superior to S0 in each scenario for $i = 1, 2, \cdots, m.$ We then use a Bootstrap sampling strategy to obtain 422 ( $703 \times 3/5$ ) sub-observations in each time period, where $m = 50$ (Xu *et al.*, 2019). Finally, we obtain the p-values across the scenarios using the adjusted R-squared; the p-value calculated using the Diebold–Mariano test for ROA is 0.031, the p-value for ROE is 0.044, and the p-value for TBQ is 0.039. The results of all the Diebold–Mariano tests are statistically significant at the 5% level. Thus, we reject the null hypotheses and accept the alternative hypothesis in all the scenarios. In summary, under FSCs, the conclusion that network capabilities are an important resource for improving CFP is supported.

## 5 Discussion

*5.1 Theoretical implications*

First, our research is the first to provide a nuanced understanding of how network capabilities improve CFP and theoretically explain why network capabilities as organisational resources affect the CFP in FSCs. Although previous research on SCF has discussed how network structural characteristics affect CFP, (e.g. Carnovale *et al.* (2019) consider EC and network density, and Ali *et al.* (2019) consider strong ties and bridge ties in supply chain networks), our research is the first to expand the analysis into FSCs, an important branch of SCF. Moreover, compared with previous SCF studies based on the network organisation, such as Seiler *et al.* (2020), our research offers a broader view of the SCF network organisation by detailed evidencing that network structural characteristics affect CFP based on both network centrality (EC, CL, and BC) and network power (ND, NS, and CC). Therefore, our research adds to the FSC literature, an importance branch of SCF, by finding that enterprises with strong network capabilities can obtain better financial resources in FSCs.

Second, our research boards the financing channels using joint investment activities (both vertically and horizontally), which is an important but understudied financing solution of the FSC. We explore joint investment activities among MI industrial chain participants because of its vast production networks and multitude of industrial chain-based financing schemes are generated. Rather than focusing on vertical investment in a single industrial chain akin to Carnovale *et al.* (2019), we also investigate horizontal investment among MI and FI partners because the financial flows provided by financial institutions can promote material flows and information flows in the resource-intensive manufacturing industry, such as MI. In addition, little research has considered such financing solutions in SCF (i.e. studies of the FSC from the network organisation perspective); hence, this financing scheme also contributes to the financing solutions of SCF. Although a large number of pervious researchers have discussed the financing solutions of SCF, studies are usually based on a single supply chain as Xu *et al.* (2018), a single industrial chain as Carnovale *et al.* (2019), or a single financial service providers in Ma *et al.* (2020). By contrast, our research considers two types of financing channels at the same time: vertical financing from industrial chain participants and horizontal financing from financial service providers.

Third, this study responds to the calls by Hearnshaw and Wilson (2013) and Xu *et al.*

(2018) for more empirical studies of SCF that can provide a broader sample set of FSC solutions based on real joint investment activities among Chinese MI and FI enterprises. Our research sample includes both manufacturing enterprises and financial institutions in FSCs as well as considers their industrial chain cooperation based on financial flows. This is different from previous case studies of the FSC. For example, Blackman *et al.* (2013) detailed discuss the global FSC strategy for a specific enterprise, Motorola. On the contrary, our research uses a large trading sample of 1648 Chinese firms (1359 MI firms and 289 FI firms), providing evidence that the network structural characteristics impact CFP in the FSCs. Moreover, since numerous enterprises are seeking for FSC solutions globally, this particular empirical study form Mainland China has implications for emerging economies.

### *5.2 Managerial implications*

With the digital transformation empowering SCF, advanced IT and diversified financial instruments provide new opportunities for SCF solutions, especially for its importance branch FSC. This study is the first to explore joint investment activities among MI industrial chain participants and its financial service providers in FSCs. Differing from traditional financial solutions that typically follow the principle of optimising the financial flows of a single firm, we extends this scope into all industrial chain, supply chain and financial service participants using advanced IT and diversified financial instruments. Therefore, first, we strongly recommend close collaboration between the financial managers and supply chain managers in an enterprise to efficiently facilitate material flows and financial flows in a product-based supply chain and industrial chain. At the same time, extensive collaboration is also encouraged beyond the borders of the enterprise, namely, with service providers (e.g. financial institutions), upstream enterprises, and downstream enterprises, by designing the financial risk of the business ecosystem.

Second, managers should realise the importance of network relationships rather than solely focusing on linear characterises in the FSCs, to broaden financing channels for

FSC solutions and improve CFP. They should also be aware that network capabilities significantly impact CFP in FSCs. Our research indicates that network relationships can broaden the financing channels for resource-intensive manufacturing enterprises and that network capabilities can improve CFP. Therefore, managers should consider how first-degree supply base connections and extended networks affect financial performance. To maximise CFP, managers should strive towards a robust and diverse supply base (i.e. a larger network structure) where their organisational resources play a central role.

Finally, managers should establish this awareness about the duality of organisational resources in the FSC solutions, namely, the interdependence and the constraints of resources. When managers seek SCF or/and FSC solutions, they should realise the importance of diversified financing channels because large suppliers, consumers, and financial institutions can bring network advantages for focal firms, but the risk of resource constraints also exists. We find that network structural characteristics positively impact CFP in most cases, but that NS has a direct negative effect on TBQ because one partner has an extremely strong influence in FSCs, this weakens the bargaining ability and flexibility of the focal firm in FSCs, thus lowering long-term CFP, such as TBQ.

## 6 Conclusion

This is one of the earliest papers to explore how network capabilities improve CFP in the context of FSCs, and our findings have significant implications for both FSC and SCF solutions. In this study, we consider FSC solutions by selecting MI and FI firms with joint investment activities listed on the A-share market, which provides a robust snapshot of FSCs (the integration among financial, material and information flows). We measure network capabilities by using network power to describe connectedness, and network centrality to capture cohesiveness, to explore how network structural characterises improve CFP. The empirical results indicate that network capabilities can effectively improve CFP in FSCs overall, but that NS has a direct negative effect on TBQ. These findings and insights are important for both academics and practitioners.

With the digital transformation empowering SCF solutions, our study contributes to the literature on FSC management in at least threefold. (1) Joint investment activities as a financing solution have been expanded into the FSCs. Considering the vast production networks and multiple industrial chain-based financing schemes in the resource-intensive manufacturing industry, we first choose vertical investment among MI industrial chain participants as well as investigate horizontal investment among MI and FI partners because the financial flows provided by financial institutions can promote material flows and information flows for MI enterprises. Therefore, our research broadens financing solutions both vertically and horizontally, which provides a robust snapshot of FSCs. (2) Network capabilities can improve CFP by providing empirical evidence on a new real trading sample in the FSCs. The empirical results show that network capabilities have a positive and significant impact on CFP in most cases, but that NS has a direct negative effect on TBQ. Third, theoretical contributions and practical insights into SCF solutions are presented in detail. By juxtaposing the theories of network organisation and resource dependence, this study presents specific insights for FSC participants. Taken together, it puts forward a new perspective on managing network power and centrality in FSCs to improve CFP.

Our research has several limitations. While we discuss the unobserved heterogeneity in the relationship between network structure and CFP in the FSCs, further research should explore the various mechanisms through which these works. Future research could also test the marginal effects of these structural characteristics on corporate financial performance within FSC environments (Caniato *et al.,* 2018). Additionally, considering that digitisation can promote the exactly match of online and offline transaction data, other digitised transaction data should be explored in FSC solutions to reduce investment risk for banks using digital assets. Finally, the way in which network power and network centrality were measured in this study differs from those in previous works, and so future research could explore this theme using different structural characteristics.

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Table 1 The typical financing modes in FSC practices.

| Practices | Explanations | Sources |
|---|---|---|
| Bank credit | Financing provided from a bank involving working capital and pre-export finance. | Caniato et al. (2016) |
| Buyer credit | Financing provided to finance suppliers (e.g. advance payments or deposits). | Thangam (2012) |
| Trade credit | The credit extended (i.e., a short-term delay in payments) by a seller to its buyers for the purchase of goods. | Chen (2015) |
| Open account credit | Buying enterprise obtains credit from suppliers without formally offering security or involving third-party security. | Wuttke et al. (2013) |
| Reverse factoring | A financial arrangement where a corporation facilitates early payment of its trade credit obligations to suppliers. | Van der Vliet et al. (2015) |
| Supply chain contracts | Retailer share the market uncertainty with its supplier to optimal quantity for joint profit maximization by using diverse coordination contracts (i.e., buybacks, quantity discounts, revenue-sharing, quantity flexibility contracts, and capacity reservation contracts). | Lee and Rhee (2010) |
| Equity financing | Financing provided from financial institutions, supply chain and industrial chain partners by equity (i.e., equity investments, securities transactions, entrusted investments, and portfolio investments). | Carnovale et al. (2019) |
| Inventory financing | Buyer provides loan to supplier to finance work in progress. | Chakuu et al. (2020) |
| Platforms financing | Portals with a key role of a large company, offering its suppliers to transfer the invoices to the investors accredited in the platform. | Vannoni (2020) |

Table 2 List of network metrics

| Metric | Definition | Formula |
|---|---|---|
| ND | ND is the number of links that firm has with other firms in the network. The adjacent matrix when a link exists between firms and and otherwise. It captures the network power of a firm from the perspective of link number. | |
| NS | NS is the sum of all neighbouring link weights in the network. is the number of neighbours of firm and is the weight from firm to NS reflects the network power of a firm from the perspective of weight. | |
| CC | CC is the portion of actual links ( ) between the firm ( ) within its neighbourhoods divided by the maximal possible links . The CC reflects the network power of a firm from the embeddedness with its neighbours. | |
| BC | BC indicates that firm is located on the shortest path connecting other firms in the network. is the sum of the number of all the shortest paths between firms and and is the number of the shortest paths that pass through firm BC reflects the centrality by quantifying the number of times a firm acts as a bridge along the shortest distance between two other firms. | |
| CL | CL is the inverse of the average shortest path length from one firm to all other firms in the network. CL reflects the shortest distance to reach all other firms. | |
| EC | EC is a measure of the influence of a firm in a network. is the set of the neighbours of firm is a constant, and is the adjacency matrix. EC reflects the centrality of a firm according to prestige scores, such as Google’s PageRank. | |
| ROA | ROA is a metric that indicates how profitable a firm’s assets are in generating revenue. | |
| ROE | ROE is a metric of how well a firm utilises its equity to generate profits. | |
| TBQ | TBQ is the relation of the market value of shares to the capital employed by corporations, where is net consumption out of capital, is the savings of workers, *g* is the growth rate, is income, is capital, is savings out of capital and is the fraction of new securities issued by firms. | |

Table 3 Descriptive statistics of the dependent variables

| Variable | N | Min | Max | Mean | Skewness | SD |
|---|---|---|---|---|---|---|
| ROA | 702 | -3.994 | 0.393 | 0.030 | -21.473 | 0.163 |
| ROE | 702 | -46.517 | 1.255 | 0.001 | -26.206 | 1.765 |
| TBQ | 702 | 0.805 | 126.952 | 2.608 | 19.843 | 5.270 |
| ND | 702 | 1 | 71 | 5.859 | 6.922 | 5.496 |
| NS | 702 | 2 | 25.927 | 3.872 | 4.791 | 2.280 |
| CC | 702 | 0 | 0.099 | 0.040 | 0.357 | 0.028 |
| EC | 702 | 0 | 0.438 | 0.027 | 3.721 | 0.065 |
| CL | 702 | 0 | 130 | 23.353 | 5.312 | 17.304 |
| BC | 702 | 0 | 10 | 4.001 | 5.256 | 1270.426 |
| ES | 702 | 17.388 | 30.893 | 22.970 | 1.516 | 2.370 |
| AL | 702 | 0.020 | 0.950 | 0.454 | 0.346 | 0.250 |
| RA | 702 | 0.001 | 0.790 | 0.149 | 1.032 | 0.135 |
| AGE | 702 | 2 | 27 | 10.454 | 0.552 | 6.547 |
| OC | 702 | 5.280 | 88.550 | 31.787 | 1.015 | 14.240 |
| BS | 702 | 5.000 | 18 | 10.595 | -0.383 | 0.608 |
| RE | 702 | 8.640 | 11.485 | 10.596 | 0.608 | -0.383 |

**Note(s)**: the values of observations (N), the minimum (Min) and maximum (Max), the mean (Mean), as well as the skewness (Skewness) and standard deviation (SD).

Table 4 Correlation results

| Variable | ROA | ROE | TBQ | DE | NS | CC | EC | CL | BC | ES | AL | RA | AGE | OC | BS | RE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ROA | 1 | | | | | | | | | | | | | | | |
| ROE | 0.753* | 1 | | | | | | | | | | | | | | |
| TBQ | 0.231 | 0.321 | 1 | | | | | | | | | | | | | |
| ND | 0.009 | 0.023 | 0.057 | 1 | | | | | | | | | | | | |
| NS | -0.022 | 0.009 | 0.059 | 0.943 | 1 | | | | | | | | | | | |
| CC | 0.059 | -0.024 | 0.033 | 0.048 | 0.055 | 1 | | | | | | | | | | |
| EC | 0.001 | 0.013 | 0.057 | 0.479 | 0.550 | 0.019 | 1 | | | | | | | | | |
| CL | 0.021 | 0.013 | 0.013 | -0.060 | -0.001 | 0.100 | -0.065 | 1 | | | | | | | | |
| BC | 0.006 | 0.021 | 0.051 | 0.733 | 0.746 | -0.065 | 0.516 | -0.062 | 1 | | | | | | | |
| ES | 0.030* | 0.098 | -0.236 | 0.516 | 0.566 | 0.038 | 0.416 | -0.041 | 0.400 | 1 | | | | | | |
| AL | -0.179 | -0.067 | -0.084 | 0.339* | 0.382 | 0.129 | 0.217 | 0.039 | 0.240 | 0.753* | 1 | | | | | |
| RA | 0.006 | 0.029* | -0.016 | -0.254 | -0.281 | 0.012 | -0.193 | -0.006 | -0.179 | -0.394 | -0.269 | 1 | | | | |
| AGE | -0.059 | -0.056 | 0.064 | 0.033 | 0.038 | 0.075 | -0.052 | -0.006 | 0.004 | 0.069 | 0.145* | -0.050 | 1 | | | |
| OC | 0.095 | 0.057 | -0.061* | 0.050 | 0.093 | 0.061 | 0.139 | 0.035 | 0.072 | 0.155* | 0.031 | -0.118 | -0.143 | 1 | | |
| BS | -0.062 | -0.017 | -0.068 | 0.453 | 0.485 | 0.174 | 0.257 | -0.055 | 0.297 | 0.687 | 0.543 | -0.290 | -0.015 | -0.009 | 1 | |
| RE | 0.048 | 0.029 | -0.012* | -0.066 | -0.097 | -0.276 | -0.066 | 0.022 | -0.051 | -0.199 | -0.164 | 0.207 | -0.215 | -0.096 | -0.177 | 1 |

**Note(s)**: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Main estimation results for network power

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) |
|---|---|---|---|---|---|---|
| Constants | -0.6366*** | -6.8676*** | 28.0264*** | -0.6922*** | -7.6829*** | 13.7038*** |
| Control variables | | | | | | |
| ES | 0.0321*** | 0.3511** | -1.2552** | 0.03487*** | 0.3848*** | -1.4291*** |
| AL | -0.2921** | -2.2112** | 4.1799* | -0.2977** | -5.669*** | 4.7926** |
| RA | 0.0355** | 1.0703* | -4.8934 | 0.0283 | 0.9744* | -4.3699** |
| AGE | -0.0003* | -0.0099 | 0.0551 | -0.0003 | -0.0097 | 0.0552* |
| OC | 0.0005 | -0.0002 | 0.0054 | 0.0005 | 0.0002 | 0.0076 |
| BS | -0.0079* | -0.0994** | 0.3581** | -0.0070* | -0.0986** | 0.3726** |
| RE | 0.0109 | 0.0613 | -0.1627* | 0.0122 | 0.0898 | -0.3959 |
| Independent variables | | | | | | |
| ND | | | | 0.0030 | 0.0420* | -0.0299 |
| NS | | | | 0.0120** | 0.1466 | -0.2861* |
| CC | | | | 0.0899** | 2.4269* | 7.7079*** |
| Fit indices | | | | | | |
| Adjusted $R^2$ | 0.0990 | 0.0650 | 0.1010 | 0.1770 | 0.1060 | 0.1410 |

**Note(s)**: ****p* < 0.01; ***p* < 0.05; **p* < 0.10.

Table 6 Main estimation results for network centrality

| | Model (1) | Model (2) | Model (3) | Model (7) | Model (8) | Model (9) |
|---|---|---|---|---|---|---|
| Constants | -0.6366*** | -6.8676*** | 28.0264*** | -0.7077*** | -7.6171*** | 10.6734*** |
| Control variables | | | | | | |
| ES | 0.0321*** | 0.3511** | -1.2552** | 0.0356*** | 0.3887*** | -1.3834*** |
| AL | -0.2921** | -2.2112** | 4.1799* | -0.3074*** | -2.3528*** | 4.6388*** |
| RA | 0.0355** | 1.0703* | -4.8934 | 0.0287 | 1.0167* | -4.7235** |
| AGE | -0.0003* | -0.0099 | 0.0551 | -0.0004 | -0.0110 | 0.0581* |
| OC | 0.0005 | -0.0002 | 0.0054 | 0.0005 | 0.0001 | 0.0047 |
| BS | -0.0079* | -0.0994** | 0.3581** | -0.0079* | -0.1006** | 0.3588*** |
| RE | 0.0109 | 0.0613 | -0.1627* | 0.0110 | 0.06377 | -0.1758 |
| Independent variables | | | | | | |
| BC | | | | 0.1922 | -2.0161 | 5.5569* |
| EC | | | | 0.0004** | 0.0023** | 0.0613*** |
| CL | | | | 0.0010* | 0.0090* | 0.0041 |
| Fit indices | | | | | | |
| Adjusted $R^2$ | 0.0990 | 0.0650 | 0.1010 | 0.1227 | 0.1240 | 0.1304 |

**Note(s)**: ****p* < 0.01; ***p* < 0.05; **p* < 0.10.

Table 7 Main estimation results for total existence of both network power and network centrality

| | Model (1) | Model (2) | Model (3) | Model (10) | Model (11) | Model (12) |
|---|---|---|---|---|---|---|
| Constants | -0.6366*** | -6.8676*** | 28.0264*** | -0.7218*** | -8.0217*** | 9.7353*** |
| Control variables | | | | | | |
| ES | 0.0321*** | 0.3511** | -1.2552** | 0.0366** | 0.4030* | -1.4813*** |
| AL | -0.2921** | -2.2112** | 4.1799* | -0.3084*** | -2.3927*** | 5.0476** |
| RA | 0.0355** | 1.0703* | -4.8934 | 0.0228 | 0.9416* | -4.2883 |
| AGE | -0.0003* | -0.0099 | 0.0551 | -0.0003 | -0.0107 | 0.0583* |
| OC | 0.0005 | -0.0002 | 0.0054 | 0.0005 | 0.0002 | 0.0073 |
| BS | -0.0079* | -0.0994** | 0.3581** | -0.0075* | -0.1022** | 0.3842*** |
| RE | 0.0109 | 0.0613 | -0.1627* | 0.0118 | 0.0878 | -0.3962 |
| Independent variables | | | | | | |
| ND | | | | 0.0031 | 0.0395 | -0.0140 |
| NS | | | | 0.0117** | 0.1272** | 0.2224 |
| CC | | | | 0.0816 | 2.4145* | 8.0864** |
| BC | | | | 0.1503* | -1.6599 | 5.1207* |
| EC | | | | 0.0005* | 0.0030* | -0.0057 |
| CL | | | | 0.0003 | 0.0002 | -0.0100** |
| Fit indices | | | | | | |
| Adjusted $R^2$ | 0.0990 | 0.0650 | 0.1010 | 0.1815 | 0.1362 | 0.1704 |

**Note(s)**: ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table 8 Summary of findings

| Hypotheses | Results |
|---|---|
| H1a: Network power (ND) has a positive effect on ROA. | Not supported |
| H1b: Network power (NS) has a positive effect on ROA. | Supported |
| H1c: Network power (CC) has a positive effect on ROA. | Supported |
| H2a: Network power (ND) has a positive effect on ROE. | Supported |
| H2b: Network power (NS) has a positive effect on ROE. | Not supported |
| H2c: Network power (CC) has a positive effect on ROE. | Supported |
| H3a: Network power (ND) has a positive effect on TBQ. | Not supported |
| H3b: Network power (NS) has a positive effect on TBQ. | Not supported |
| H3c: Network power (CC) has a positive effect on TBQ. | Supported |
| H4a: Network centrality (BC) has a positive effect on ROA. | Not supported |
| H4b: Network centrality (EC) has a positive effect on ROA. | Supported |
| H4c: Network centrality (CL) has a positive effect on ROA. | Supported |
| H5a: Network centrality (BC) has a positive effect on ROE. | Not supported |
| H5b: Network centrality (EC) has a positive effect on ROE. | Supported |
| H5c: Network centrality (CL) has a positive effect on ROE. | Supported |
| H6a: Network centrality (BC) has a positive effect on TBQ. | Supported |
| H6b: Network centrality (EC) has a positive effect on TBQ. | Supported |
| H6c: Network centrality (CL) has a positive effect on TBQ. | Not supported |
| H7a: Both network power and centrality have a positive effect on ROA. | Partly supported |
| H7b: Both network power and centrality have a positive effect on ROE. | Partly supported |
| H7c: Both network power and centrality have a positive effect on TBQ. | Partly supported |