On the relationship between financial performance and position of businesses in supply chain networks

A. Seiler, C. Papanagnou, P. Scarf*

Salford Business School, University of Salford, Manchester M5 4WT, UK
**corresponding author, email: p.a.scarf@salford.ac.uk*

Abstract: We investigate how the network position of organisations in an extended supply chain network impacts their financial performance. The paper argues that performance measurement tools should incorporate a network (external, connectedness) perspective in addition to an internal financial perspective. We merge local networks of companies in a supply chain into a single, extended network in which the transactional value-flows on arcs are known. Network position characteristics of focal companies are determined using social network analysis. The impact of these characteristics on financial performance is studied using regression analysis. In the context of our case study, there is some evidence that profitability is related to connectedness and market share. In this way, the paper describes how organisations might enrich their performance measurement tools with connectedness metrics.
Keywords: Supply chain management; social network analysis; performance measurement.

1 Introduction

Many organisations, to be more effective and efficient, link with other organisations to form supply chains. The nature and extent of the linkages in these supply chains are expected to impact upon business dynamics and organisational performance (Wagner *et al.*, 2012; Um and Kim, 2018). Global manufacturing operations mean that networks formed of supply chains are typically large and complicated. Furthermore, organisations realise that, in the future, competition to attract more end-customers will be transferred to the supply chain level, pitting one supply chain against another. Verganti and Pisano (2008) state that "it is not about the decision whether to collaborate, but the need to understand and to take informed decisions". Also, it is increasingly recognised that "if a supply chain is properly managed, its whole value can be greater than the sum of its parts" (Shi and Yu, 2013). Thus, it is important to understand competitive advantage by establishing a set of metrics that can measure and evaluate the performance of the entire supply chain, and thereby guide strategic interventions (Gunasekaran *et al.*, 2004; Chae, 2009). These modern, global realities together with a need for new concepts in performance analysis has led to increased research into supply chain performance measurement (Gopal and Thakkar, 2012; Balfaqih *et al.*, 2016; Maestrini *et al.*, 2017).

In general, performance measurement systems are associated with reference models that contain a standard description of management processes, a framework of relationships among the standard processes, and standard metrics to measure process performance (Ittner *et al.*, 2003). However,

organisations often neglect the use of performance measurement tools, basing their management and analysis on experience and intuition (Simchi-Levi *et al*., 2004), or even, fail to implement effective tools or extract maximum value from their performance measurement data (Hudson *et al.*, 1999).

A broad categorisation of performance measures is obtained by classifying the different measures into financial and non-financial, both often referred to as synthetic process indicators (Merchant and Van der Stede, 2007). Many organisations, when typically monitoring their broad set of activities and processes, use financial performance measures. When these processes are linked to external entities, the focus needs to extend beyond the boundary of companies, constructing inter-organisational management and network accounting systems (Chenhall, 2005). These systems should better support a single organisation (called a focal company) working within a network. They should also better support the management and performance of the entire network, by monitoring the ability of the network itself to leverage network output. Indeed, when Melnyk *et al.* (2014) consider whether performance measurement is fit for the future, they find that practitioners are often struggling to manage in volatile environments. While performance measurement applied within the boundaries of the focal company has evolved from design and implementation (Bourne *et al.*, 2000; Neely *et al.*, 2001) to application and review (Henri, 2006; Braz *et al.*, 2011), the external view has fallen behind. Thus, the literature on performance measurement describes performance measurement across organisational boundaries as a challenge (Brewer and Speh, 2001; Chan and Qi, 2003; Folan and Browne, 2005; Li *et al*., 2005; Shepherd and Günter, 2006; Acar *et al.*, 2009; Hernández-Espallardo *et al.*, 2010; Maestrini *et al.*, 2017).

Consequently, it is no longer sufficient to analyse performance only from the narrow perspective of the focal company and only in financial terms (i.e. returns), ignoring aspects such as cooperation and socialisation among firms (Franco-Santos *et al.*, 2012; Um and Kim, 2018). In our paper, therefore, we present interdisciplinary research that uses social network analysis to investigate the linkage between organisations in supply chain networks and their performance. In so doing, we evaluate influences on the performance of an organisation by measuring key position variables that are derived from social network theory and that reflect the entire network structure and its relationships. Our focus is small and medium enterprises (SMEs) in the German automotive plastics processing industry.

We study a single, complete supply chain network of fifteen focal companies and their suppliers and customers. A software tool created by us merges the supply chain data of the focal companies into the single, extended supply chain network which has no clear boundaries. Our approach is more holistic than the standard analysis of dyadic connections of company-specific supply chains. We collect data on the network position of the focal companies by detecting and interpreting patterns of links among all stakeholders within the network. Also, our network is more than binary because we collect data on transactional value flows on the network arcs (links between the focal companies). We evaluate the financial performance of these companies using business reports drawn from the business register of the German Federal Gazette and data available from commercial providers of digital business information such as Bisnode. In our network, we study 448 companies in all, the fifteen focal companies and their 433 suppliers and customers. Connections between the companies are evaluated on the basis of two different weighting schemes: cash flows (for products or materials) and product-type flows (number of distinct product-types).

This paper is important because we quantify the effect of network position upon financial performance of organisations in a visible network using real-time transactional data that distinguishes upstream and downstream linkages. Maestrini *et al*. (2018) recently identified the need for such a study. Other studies similar to ours either do not make the network visible (Li *et al*., 2013), treat networks separately by overlooking possible interactions (Kim *et al.*, 2011), use questionnaire data to quantify the network (Gronum *et al.*, 2012) or study binary networks (Schilling and Phelps, 2007). On visualisation, as Basole *et al*. (2016) state, this is challenging because "complete or even comprehensive supply network data are generally not available", if they are "the information can often be overwhelming to the end user if not presented appropriately", and therefore "supply network visualization hardly happens". Furthermore, Nooy *et al*. (2011) state that visualization is important to trace and understand patterns of ties intuitively.

Our purpose is to provide an evidential basis for the enhancement of standard performance measures with metrics that quantify the connectedness of an organisation in its supply chain network. We also address the need for further research into external aspects of performance measurement, as "most studies addressing these aspects are either discussed theoretically or investigated by means of

context-specific implementation of a particular supply chain performance measurement system framework" (Maestrini *et al.*, 2017).

The structure of the paper is as follows. In the next section, we position our study and its contribution within the existing literature. Then, in section 3 we describe our methodology and present our research questions, specifying well-defined and testable hypotheses relating to these. Section 4 describes the supply chain network of interest in detail. In section 5, the results of our analysis are presented, and we make conclusions and discuss avenues for further research in section 6.

2 Literature review

A supply chain is a collection of firms that interact with each other in the procurement, manufacture and use of resources to provide goods and services (Harland *et al.*, 2001). A supply chain can be represented by a directed graph, a mathematical entity with nodes (the firms), arcs (links between the firms), and flows on the arcs (cash or resource flows between firms). A directed graph is a network (West, 2001) (although a network need not be a directed graph). Social network analysis examines the inter-connectedness of social entities (Granovetter, 1973; Burt, 1976; Burt, 1992), such as persons (e.g. Kumar *et al.*, 2006; Gardy *et al.*, 2011), clans (e.g. Mokken, 1979), journals (e.g. Garfield, 1972), and organisations (e.g. Mizruchi, 1996). It is therefore natural to use social network analysis to study supply chains (Carter *et al.*, 2007, Borgatti and Li, 2009, Bellamy and Basole, 2013), and the purpose of such analyses are many-fold: to understand network structure (e.g. Lomi and Pattison, 2006; Yu *et al.*, 2008; Nuss *et al.*, 2016); to study network evolution (e.g. Choi *et al.*, 2001); to determine if cooperation is better than competition (e.g. Jarillo and Stevenson, 1991); to determine if connectedness encourages innovation (e.g. Schilling and Phelps, 2007; Gronum *et al.*, 2012; Fox *et al.*, 2013; Bellamy *et al.*, 2014); to study knowledge transfer networks and improve their performance (e.g. Bond *et al.*, 2008); and to study the formation of manufacturing joint-ventures (e.g. Carnovale and Yeniyurt, 2014).

In particular, Kim *et al.,* (2011) and Kao *et al.* (2017) ask whether connectedness impacts upon performance and technical efficiency. This is the concern of our paper. It is anticipated that the position of a firm in a network and the structure of the network (its architecture) together influence performance (Basole *et al.*, 2018; Yan *et al.*, 2015; Caniato *et al.,* 2013). In our paper, in addition, we consider the flows

on the links, the values of transactions between the connected firms, and so we go beyond the study of the impact of binary connections (Petróczi *et al*., 2007) on performance, and discriminate strong ties from weak ties.

Traditionally, performance measurement in supply chain management does not adopt a network perspective. It rather looks internally at the firm (Franco-Santos *et al.,* 2012; Melnyk *et al.,* 2014), with little attention paid to external connectedness to other firms. Estampe *et al*. (2013) proposed a supply chain maturity grid ranging from level 1 (internal function geared towards the own organisation only) to level 5 (complete embeddedness in a network of supply chains). To assess level 5, the question is: what network characteristics one would propose as potential performance measures. Related to this is the question: what networks characteristics are important with respect to performance (Beamon, 1998). For example, one might consider if asymmetry influences performance (Michalski, 2018).

Connecting a traditional performance measure to connectedness depends on the nature of the performance measure, whether financial (e.g. Christopher, 1998), or non-financial e.g. innovative output (Schilling and Phelps, 2007; Gronum *et al.*, 2012; Fox *et al.*, 2013; Bellamy *et al.*, 2014), or qualitative e.g. customer satisfaction (Beamon, 1998). In our paper, we relate financial performance to network characteristics. Christopher (1998) argues that liquidity, profitability and productivity (efficiency) are three key areas where supply chain management can affect the financial performance of an organisation. Liquidity is often associated with the viability of enterprises (Johnson and Templar, 2011; Needles *et al*, 2014; Martínez-Ferrero and Frías-Aceituno, 2015). There is evidence that profitability is associated with financial sustainability and growth of an organisation (Sengupta *et al.,* 2006; Flynn *et al*., 2010; Wagner *et al.,* 2012), and that efficient organisations have succeeded to compete even in turbulent markets by utilising better their total assets and resources (Chan and Qi, 2003; Bhagwat and Sharma, 2007; Pellinen *et al*., 2016). Thus, it seems comprehensive to choose financial performance measures that capture liquidity, profitability and efficiency, and so we adopt measures relating to these.

Returning to the matter of externalising performance measurement, the challenge is collecting supply-chain network data. If one wants to look beyond the focal company when measuring performance then one needs data beyond the focal company (Gunasekaran *et al.,* 2004). These data are

difficult to collect because they lie with other organisations. The process of data collection for a network is necessary to make the network visible (Nooy *et al.,* 2011), but it is not sufficient (Gronum *et al.,* 2012).

Making a supply chain network visible is a serious challenge (Borgatti, 2009). There are many problems. The first is that a particular firm—the focal company—will likely know only about their own connections. These connections form a sub-network called the ego-network of the focal company. Thus, knowledge of the complete network requires knowledge of which firms belong to the network (what are the nodes), who is connected to whom (the arcs), and what are the flows of goods, services and cash between them (the value-flows). The second challenge concerns the extent of the network. "Everything is connected to everything else" (Barabási, 2003). Thus, it is necessary for the network to be bounded for it to be visible. Thirdly, there are degrees of visibility. Thus, the firms and the connections may be known (binary network), but value-flows may not. The network we study in this paper is an extended but bounded network with known value-flows.

Network extension (defining the boundary of the visible network) and data collection go hand-in-hand. Thus, the researcher can extend the network if the relevant data can be collected. This brings us to the topic of data collection. Data may be collected either directly or indirectly. Direct data collection uses questionnaires or interviews and typically results in qualitative data (Li *et al.,* 2013; Gronum *et al.,* 2012) and is analogous to primary data collection in social research. Indirect data is analogous to secondary data, typically not collected for the purpose of visualising a corporate network of relationships.

Indirect data may be binary (Schilling and Phelps, 2007) or may be the values of flows (e.g. of materials, products, cash, information, between firms). The latter are transactional data, and they are the most desirable and their collection is the most challenging (Nooy *et al.*, 2011). The desirability is the result of their perceived objectivity.

Thus, in summary, to relate the external (network perspective) to the internal (performance measurement of the firm), it is necessary to analyse a fully-visible (known transactional value-flows), extended network of multiple firms. To our knowledge, no such analyses exist in the literature. Our purpose in this paper is to present such an analysis, with value flows representing strength of ties. In this manner, we take a "bird's eye" view of a supply chain network that goes beyond ego-networks.

Furthermore, we address the lack of a study that integrates "the insights gained from conceptual, empirical, and modelling/simulation work on supply chain system architecture" (Bellamy and Basole, 2013). Following Papakiriakopoulos and Pramatari (2010), the inclusion of the network characteristics into a performance measurement system creates new opportunities for performance improvement, strategic rethinking, and recommendations for action.

3 Methodology

Our purpose is to inform the debate on adoption of an external, network-positional perspective in performance measurement in an organisation. We do this by testing the influence of the network characteristics, strength of links, node centrality and link diversity, of organisations upon their financial performance . We focus on these particular network characteristics (strength of links, centrality and diversity) because they correspond to those underlying principles (flows, architecture, roles) of network theory that social network theorists argue are most important (Lin 2017; Brintrup *et al.*, 2015; Borgatti and Lopez-Kidwell, 2011; Lin, 1999; Borgatti and Everett, 1992; Burt, 1976; Granovetter, 1973).

Our analysis considers a sample of businesses, labelled the *focal companies*, operating in the German automotive plastics processing industry. To describe our methodology, we first set out our research questions. We then formulate these as specific hypotheses. Next, we define measures of financial performance (Table 1) and network position (Table 2 and Table 3) with which we test these hypotheses. Finally, we describe data collection on the supply chain network of interest and how the values of our measures are calculated.

3.1 Research questions and hypotheses

The application of social network analysis can help to explain benefits of embeddedness within a network of structurally interdependent nodes. Such benefits mean access to knowledge, as well as resources and information, ultimately resulting in organisational advantages (Granovetter, 1973). On this notion of embeddedness, a strong relationship with partners across the network is expressed by trust and has advantages in terms of information sharing, co-investment and fast, constructive feedback.

Strong relationships are often claimed to lead to better performance (Putnik *et al*., 2016; Bordons *et al*., 2015; Li *et al.*, 2013; Danese and Romano, 2012; Wiengarten *et al.*, 2010; Singh and Power, 2009). Links of various strengths characterise the position of an organisation within a supply chain network. Thus, our first research question asks:

RQ1: Does the performance of an organisation depend on the strength of its links within the supply chain network?

We characterise each relationship between a focal company and its business partners by cash flow related to procurement or sales. To draw conclusions about the impact of the strength of the links on the financial performance, social network analysis allows us to calculate (directed) aggregated strength. Thus, we calculate aggregated strength as the proportion of such cash flows between focal companies and their mutually shared business partners. Table 3 provides the definition. Our precise hypothesis is then:

H1: The higher is the aggregated strength of links of an organisation in the supply chain network, the better is the performance of that organisation.

In this way, we argue then that strength relates to flows.

Turning now to centrality, and the underlying principle of network architecture, a central position in the network ought to strengthen the negotiating position with partners (Lin 2017; Schilling and Phelps, 2007; Lin, 1999; Cook *et al*. 1983) and thus having an impact on performance (Basole *et al.*, 2018; Yan *et al.*, 2015; Kim *et al.*, 2011). Therefore, our second research question asks:

RQ2: Does the performance of an organisation depend on the centrality of that organisation within the supply chain network?

Social network analysis provides a variety of centrality measures. Following Robins (2015, p. 182), it is best to at least focus the measurement of centrality on (undirected) degree centrality and (directed) betweenness centrality. By looking at the definitions provided in Table 3, it is apparent that, in our given case of short network paths between nodes, these two centrality measures may correlate. Therefore, we first focus on degree centrality and test the following hypothesis:

H2-1: The higher is the degree centrality of an organisation in the network, the better is the performance of that organisation.

Bonacich power generalises the notion of (undirected) centrality to accommodate circumstances in which being connected to well-connected nodes brings positive ($\beta > 0$, see Table 3) or negative ($\beta < 0$) consequences (Bonacich, 1987). Since we expect the shape of the environment of the focal companies to affect financial performance, we test the following hypothesis:

H2-2: The higher is the Bonacich power ($\beta > 0$) of an organisation in the network, the better is the performance of that organisation.

Finally, a network position that is characterised by diverse links ought to reduce dependency because alternatives are available. Thus, diverse links which relate to the underlying principle of roles, may facilitate collaboration and information-sharing (Inkpen, 1996) and also strength in negotiations with business partners. We study diversity based on the product-type flows of focal companies. Therefore, the third research question asks:

RQ3: Does the performance of an organisation depend on the diversity of product-type flows of that organisation in the supply chain network?

In order to assess diversity of product-type flows, we apply the concept of hubs and authorities developed by Borgatti and Li (2009). By formulating the following hypotheses, this concept allows us to evaluate the diversity both on the procurement side, as well as on the sales side of focal companies:

H3-1: The higher is the share of product-type flows from an organisation to its customers in the supply chain network (hubs), the better is the performance of that organisation.

H3-2: The higher is the share of product-type flows to an organisation from suppliers in the supply chain network (authorities), the better is the performance of that organisation.

A focal company gets a high-value of *HUB* for delivering to customers that have many focal companies as suppliers. Further, a focal company gets a high-value of *AUTH* for being supplied by suppliers that have many focal companies as customers. The underlying idea is that the more an organisation is linked to hubs and authorities, the more diverse are its relationships due to flows of different product-types within the network.

Also in relation to diversity, we anticipate that organisations that are able to satisfy the needs of different markets, e.g. via a large product variety, should be more successful. Consequently, our final research question asks:

RQ4: Does the performance of an organisation depend on diversity in its affiliation to different complementary sectors of industry besides the focal industry?

Looking for structural uniformity, we create classes of industries that refer to aspects of network role theory (Borgatti and Everett, 1992). Nodes that are structurally similar to each other are reduced to classes that share an affiliation in the same industry. Assuming links to various markets, the vulnerability to fluctuations in demand ought to be reduced and exogenous influences may have less drastic consequences (Klibi *et al.*, 2010). Thus, based on the number of different complementary industries *IND* we test the precise hypothesis:

H4: The higher the number of complementary sectors of industry besides the focal industry to which an organisation is connected, the better is the performance of that organisation.

3.2 Definition of financial and network position variables

To evaluate financial performance comprehensively, and in accord with our review of the literature, we chose measures of profitability, liquidity and efficiency (Table 1). The notation in Table 2 defines entities that are used in the definitions of the network position measures or variables in Table 3.

Table 1. Notation and definition of financial performance variables

Revenue per employee, *RE*	$RE =$	$\frac{revenue}{number\ of\ empl.}$	a profitability measure somewhat independent of company-size
Operating profit, *OP*	$OP =$	$profit\ after\ tax + tax + interest + depreciation$	an (unadjusted) measure of profitability
Return on Assets, *ROA*	$ROA =$	$\frac{profit\ before\ tax}{total\ assets}$	a profitability measure relative to capital assets rather than human capital (*RE*)
Asset turnover, *AT*	$AT =$	$\frac{revenue}{total\ assets}$	a measure of the efficiency with which a company deploys its assets.
Dynamic debt ratio, *DDR*	$DDR =$	$\frac{debt}{cash\ flow}$	a measure of liquidity

Table 2. Notation used in the definition of network position variables

$G_{\mathrm{D}}(V, A)$	The directed graph that is the set V of nodes (companies) and the set A of arcs (cash flows). The companies are the focal companies, their suppliers, and their customers.
v	$v = \lvert V \rvert$, the number of nodes in $G_{\mathrm{D}}(V, A)$ (the number of companies in the network).
u	The number of focal companies, $u < v$.
w	The number of industries in which the focal companies trade.
x_{ij}	Defined on $G_{\mathrm{D}}(V, A)$, $x_{ij} \geq 0$ for all *i* and *j* is the weight of the arc from node *i* to node *j* (monetary value of the procurement by company *i* from company *j*). In terms of the supply chain network we study, this is the cash flow from a company to its supplier to pay for materials or the cash flow from a customer to a company to pay for manufactured product. Note: in the network we consider, a company may act as both a customer and a supplier.
X	The $v \times v$ matrix (x_{ij}) of cash flows, called the *cash flow matrix.*
$G_{\mathrm{U}}(V, E)$	The undirected graph that is the set V of nodes (companies) and the set E of edges (links).
y_{ij}	Defined on $G_{\mathrm{U}}(V, E)$, for all *i* and *j*, $y_{ij} = 1$ if company *i* trades with company *j* and $y_{ij} = 0$ otherwise; y_{ij} indicates the presence or absence of an edge (link) in $G_{\mathrm{U}}(V, E)$.
Y	The symmetric $v \times v$ matrix (y_{ij}), called the *adjacency matrix.*
$H_{\mathrm{D}}(W, B)$	The directed graph that is the set W of nodes (the *u* focal companies and *w* industries in which they operate) and the set B of arcs (from a focal company to an industry if the focal company operates in that industry). This network simplifies the network $G_{\mathrm{D}}(V, A)$ by aggregating, into industries, the trade between focal companies and their suppliers and customers.
r_{ij}	Defined on $H_{\mathrm{D}}(W, B)$, $r_{ij} = 1$ if company *i* operates in industry *j*, $r_{ij} = 0$ otherwise.
R	The $u \times w$ matrix (r_{ij}), called the *affiliation matrix*.
p_{ij}	Defined on $G_{\mathrm{D}}(V, A)$, p_{ij} is the number of different types of product procured by company *i* from company *j* in V. The product-types procured by *i* from *j* each have a corresponding cash flow that sum to x_{ij}.
P	The $v \times v$ matrix (p_{ij}), called the *product-mix matrix*
g_{ij}	Defined on $G_{\mathrm{D}}(V, A)$, g_{ij} is the number of arcs in the shortest path from node *i* to node *j*
G	The $v \times v$ matrix (g_{ij}), called the *geodesic distance matrix.*
h_{ijk}	Defined on $G_{\mathrm{D}}(V, A)$, the shortest path from node *i* to node *k* that passes through node *j*.

Table 3. Definition of network position variables

Aggregated strength, *AS*	$AS_i = \sum_j \frac{x_{ij}}{\sum_k x_{kj}} + \sum_j \frac{x_{ji}}{\sum_k x_{jk}}$	The (directed) aggregated share of cash flows from and to company *i*.
Degree centrality, *C*	$C_i = \sum_j y_{ij}$	Total number of companies with links to company *i.* An undirected measure.
Betweenness centrality, *BC*	$BC_j = \sum_{i<k} h_{ijk}/g_{ik}$	How often company *j* lies on the shortest path between any two other companies (Borgatti *et al.,* 2013, p. 174). A directed measure.
Eigenvector centrality, *EC*	The *i*th component e_i of $\boldsymbol{e}$, the solution of the linear equations $\mathbf{Y}\boldsymbol{e} = \lambda\boldsymbol{e}$ for which λ is maximum.	An (undirected) centrality measure in which connections (links) to well-connected nodes score more highly, in relative terms, than connections to less well-connected nodes.
Bonacich power, *BP*	$BP_i(\beta) = \sum_j (\alpha - \beta C_j) y_{ij}$	A more general measure of (undirected) centrality than *C* and *EC*.
Hubs, *HUB*	$HUB_i = \sum_j \frac{p_{ij}}{\sum_k p_{kj}}$	Similar to (directed) aggregated strength, but with the proportion of product-types sold that is aggregated, and the more diverse the product-types a company provides upstream to customers recognised as hubs in the supply chain, the higher its *HUB* score.
Authorities, *AUTH*	$AUTH_i = \sum_j \frac{p_{ji}}{\sum_k p_{jk}}$	The complement of *HUB*, so that the more product-types a company procures from the downstream supply chain suppliers recognised as authorities, the higher its *AUTH* score. A directed measure.
Industries, *IND*	$IND_i = \sum_j r_{ij}$	The number of different industries to which company *i* is connected. A directed measure.

Further, in Table 3, we briefly indicate the nature of each measure. We make some additional detailed comments in relation to Bonacich power here. Bonacich power (*BP*) is a more flexible measure of centrality than degree centrality (*C*) and eigenvector centrality (*EC*) and it generalises these measures. Choosing β is a matter of the analyst (Borgatti *et al.*, 2013). If $\beta = 0$, then *BP* is equivalent to *C*. Further if $\beta = 1/\lambda_{max}$ (where λ_{max} is defined in Table 3 under eigenvector centrality), *BP* is equivalent to *EC*. A value

$\beta > 0$ implies positive effects for being connected to those who are themselves well-connected. When it may be advantageous to be connected to those who are themselves not well-connected then $\beta < 0$ is appropriate, wherein power derives from being connected to the powerless, and to the contrary, having many powerful partners can reduce one's own power. Finally, we note that β acts as a weight on the centrality score of the neighbours of a node, whereby a small absolute value of β gives more weight to local network structure than distant network structure, and vice versa. The parameter α is a scaling parameter that is typically chosen so that *BP* does not depend on the size, *v*, of the network. In fact, all the centrality measures that we use are rescaled in this way.

3.3 Testing the hypotheses

We test the hypotheses in five steps, which we describe in detail below. These five steps are: (i) processing of ego-network data, (ii) network creation, (iii) evaluation of business reports and the supply chain network, (iv) statistical analysis, and (v) interpretation of this analysis in such a way that motivates the enrichment of existing performance measurement metrics.

In the first step, real enterprise transactional data on each ego-network of each focal company is processed. Each ego-network consists of a focal company, its customers and suppliers and the relationships originating from cash flows between each focal company and its suppliers and customers. As we create network data in an indirect way, we do not "rely on the often inaccurate recollections of respondents" (Nooy *et al.*, 2011, p. 26) when assessing relationships via questionnaires. We develop a software tool that allows us to process the cash flows (procurement and sales) using the structured query language SQL.

In the second step, we merge the different ego-networks of the focal companies. As all focal companies are comparable, operating in one particular industry, we make the supply chain network visible. To achieve this, we inspect the individual supply chain networks for common business partners between different focal companies and highlight the connections. The output is a network $G_{\mathrm{D}}(V, A)$ with v = 448 nodes. This network is our first subject of inspection. The second subject concerns the business reports of focal companies. Network flow data and financial data are matched for the same fiscal year.

In the third step, we measure network position characteristics. We analyse the network position of focal companies in the supply chain network using social network analysis software Gephi (https://gephi.org), UCINET (https://sites.google.com/site/ucinetsoftware/home), and Pajek (http://pajek.imfm.si/doku.php). The Gephi tool is useful for representing the network. Pajek and UCINET, on the other hand, have greater flexibility for calculating centrality measures. We evaluate for each focal company: (i) *strength of the links*; (ii) *degree centrality*; (iii) *Bonacich power*; (iv) *betweenness centrality*, (v) *hubs*; (vi) *authorities*; and (vii) *the number of complementary industries*. These measures, defined in Table 3, are the independent variables (*IVs*) of our statistical analysis. Standardised measures are used in the statistical analysis. The dependent variables (*DVs*) measure the financial performance of the focal companies. We obtain the *DVs* by quantitative analysis of business reports. We evaluate: (i) *revenue per employee*; (ii) *operating profit*; (iii) *return on assets*; (iv) *asset turnover*; *and* (v) *dynamic debt ratio*.

Using these five different financial performance measures, we ensure that financial performance is not only evaluated in the sense of profitability (revenue per employee, return on assets, operating profit) but also in the sense of liquidity (operating profit, dynamic debt ratio) and efficiency (asset turnover, return on assets). Although there are possible overlaps in the categorisation of these different financial performance measures, we use them to explain financial performance comprehensively (Deyhle, 2008). As we require general financial performance measures that are suitable to compare different organisations in one particular industry, alternative approaches such as activity-based costing cannot be applied.

In the fourth step, we analyse the statistical association between network position properties and financial performance measures, having initially imputed missing values of financial variables and checked for the presence of influential data points. A initial correlation analysis indicates the financial performance measures most related to network position properties. Then, using multiple linear regression, we not only investigate the combined effect of the network position variables (predictors) on the financial performance measures (response), but also control our findings for the company size (number of employees E). Significance of the different selected predictors is determined using a t-test for the partial coefficients. To find evidence for network position characteristics influencing financial

performance, we test our hypotheses (section 3.1). The inclusion of network position variables in the multiple linear regression models is based on a backwards elimination procedure.

Finally, in the fifth step, we interpret our analyses and the outcome of the tests of our hypotheses. In so doing, we focus on how existing performance metrics might be enriched through the use of connectedness measures, and how such measures might be implemented in practice.

4 The network and its associated measures

In accordance with our methodology, we create the extended supply chain network $G_{\mathrm{D}}(V, A)$, using a software tool created by us to merge the revenue (sales) and procurement data of the sample of focal companies studied. To meet ethics requirements, we label rather than name the focal companies. However, we go beyond the analysis of each individual network and highlight common business partners of different focal companies. Thus, before encoding the names of companies, we verify each dataset for proper naming. Otherwise, the network generation would not be able to identify common nodes between different focal companies.

Figure 1 shows the network $G_{\mathrm{D}}(V, A)$ with the 15 focal companies and their customers and suppliers, 448 companies (nodes) in all. The plot shows that the network is more than a collection of simple, hierarchical three-tier networks. This is because intra-tier links exist between the focal companies.

In our analysis, we assume an equilibrium (of exchange of goods for cash) in the connections between companies. Thus, the relationships up- and downstream in the supply chain are assumed to be equally important. We generally do not distinguish connectivity up- and downstream in the supply chain. Only in terms of diversity do we differentiate between hubs (customer side) and authorities (supplier side).

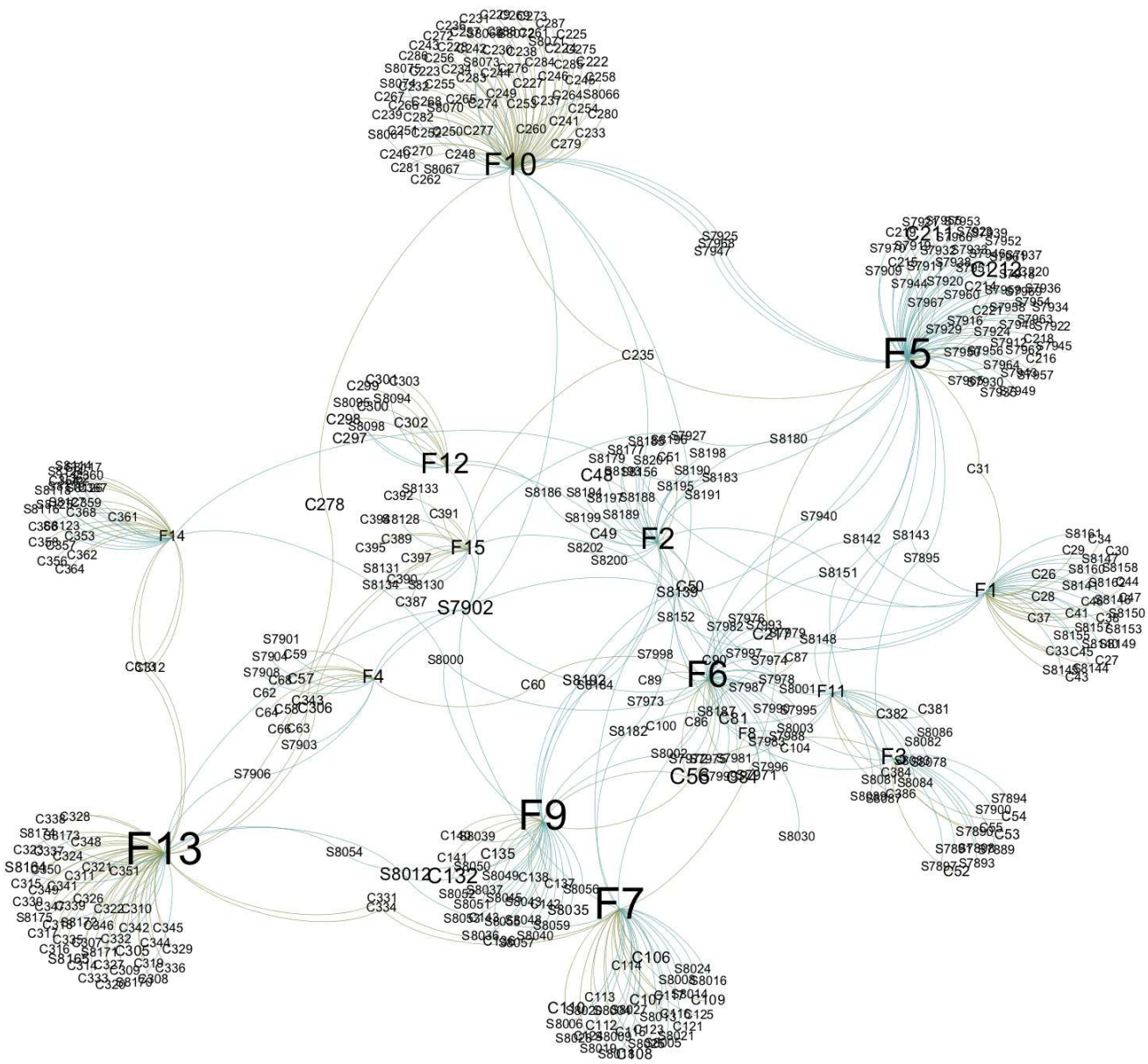


Figure 1. The directed graph, $G_D(V, A)$, of the network in our study, with v = 448 companies of which u = 15 are focal companies (coded F<num>). Suppliers (coded S<num>), and customers coded C<num>. Where companies are both suppliers and customers the designation of supplier or customer is determined by the direction of the arc representing the cash flow. The font of the node label is proportional to the total cash flow, $\Sigma_j x_{ij}$, to the company j at that node.

As an aside, we briefly investigate the topology of the network by comparing its degree distribution to that of a randomly-generated network whose degree distribution follows a power law (see Figure 2). Barabási and Albert (1999) generate such networks through preferential attachment. Thadakamalla *et al*. (2004) and Zhao *et al.* (2011) anticipate that a supply chain network is scale-free so that it has a power-law degree distribution. A cumulative plot shows the proportion of all vertices characterised by a particular degree or higher. Although we observe some resemblance between these two plots, the network topology here departs from a power-law degree distribution and tends to be more like an exponential degree distribution. Brintrup *et al.* (2016) make a similar observation.

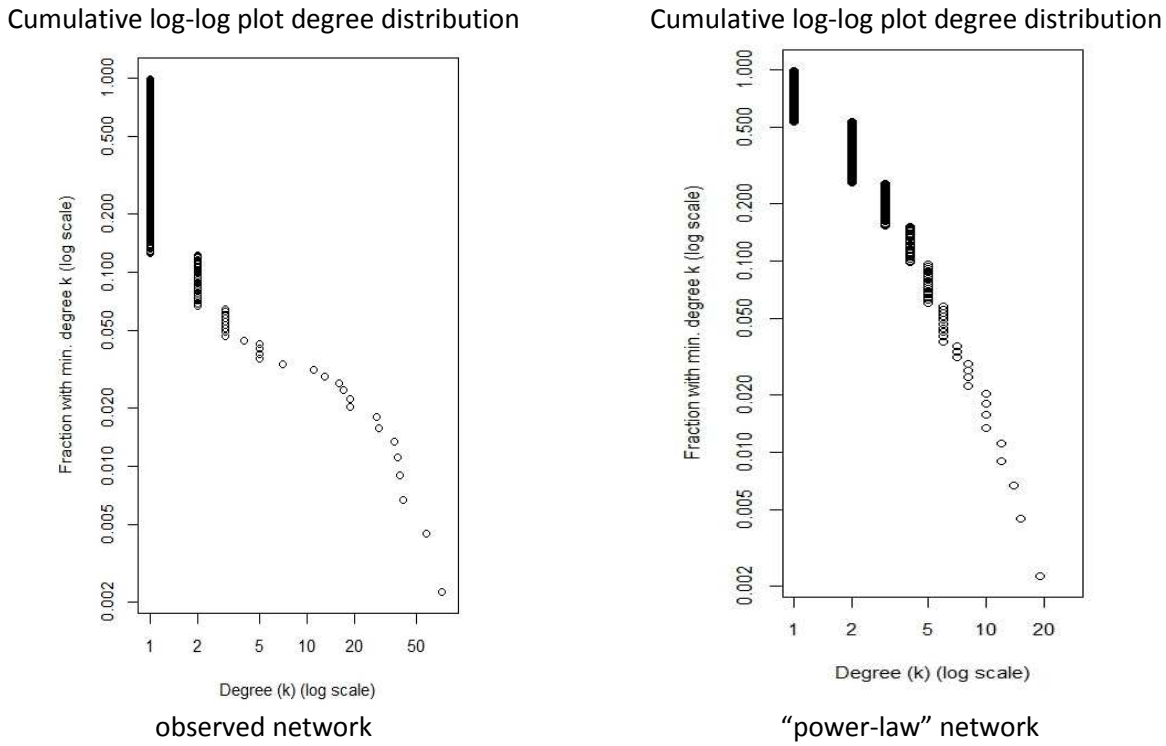


Figure 2*:* Comparison of the degree distribution of the observed network $G_D(V, A)$ with the degree distribution of a randomly-generated network with a power-law degree-distribution.

In the statistical analysis that follows in section 5, we focus on the results of the focal companies because we do not possess financial information for the other 433 companies in the network. Thus, to test our hypotheses, we collect characteristics on network position of our sample of 15 focal companies. Our sample embodies typical manufacturing companies from the plastics processing industry. These companies are small and medium-sized enterprises that operate in the automotive plastics supply chain

in Germany. These 448 companies represent approximately a 1% convenience sample of the whole population of automotive plastics in Germany. The data describe the 2012 financial year (Jan. 2012 - Dec. 2012). Access to the supply chain data of these companies was facilitated through a software supplier common to the focal companies. The data are otherwise unbiased. Nevertheless, because of the small sample size in our study, we must rule out that few (one or two) companies dominate the others in terms of values of the *IV*s or the *DV*s. Therefore, we do exhaustive tests for outliers, and where we find some evidence, we moderate our claims. In this way, we consider whether the prerequisites for applying our statistical procedures are met. Limited resources and inaccessibility of data for reasons of confidentiality would make it very difficult to collect a *random* sample of a large size from this industry or one similar. Nonetheless, we anticipate that important insight will be gained using our methodology on our data, and we are, to our knowledge, the first to perform a quantitative network analysis on company performance to this level of detail.

The values of the measures of interest for the 15 focal companies are shown in Table 4. Social network analysis software (here UNICET v6.560) implements the required algorithms to calculate the network position variables. In the calculation of Bonacich power (*BP*), as discussed in the methodology, we have to pay attention to the value of β. By default, UCINET set $\beta = 0.108 = 0.995/\lambda_{max}$, and we use this value initially. All values are normalised automatically by UNICET. The testing of our hypotheses is invariant to these scaling factors.

When presenting the financial measures, where appropriate, cash flows are given in millions of monetary units (mmu) and revenue per employee in thousands of monetary units (tmu). Missing values of financial measures (for FOCs 8, 9 and 14) resulted from inaccessibility or imperfect fulfilment of accounting policies. Therefore, to perform our analysis comprehensively, we do multiple imputation. That is, we impute the missing values to form an imputed dataset, defined as the conjunction of the observed data points and the imputed data points. Then, the statistical analysis that relates network characteristics to financial performance is repeated for each of five imputed datasets to ensure its robustness (van Buuren and Groothuis-Oudshoorn, 2011). The imputation step uses predictive mean matching, in which plausible values are each drawn from a distribution for a missing value conditioned on the multivariate distribution of the observed values.

Table 4. Values of all dependent variables (*DV*) and independent variables (*IV*). Imputed data (5 values) are shown in italics; where values are imputed, summary measures are calculated using the mean of the imputed values.

		Dependent variables *DV*					Independent variables *IV*						
Comp.	*E*	*RE* (tmu)	*OP* (mmu)	*ROA* (%)	*AT*	*DDR*	*AS*	*C*	*BP* β=0.108	*BC*	*HUB*	*AUTH*	*IND*
FOC1	135	141.07	0.53	-3.45	2.43	9.96	1.41	0.085	49.18	0.142	0.00	1.29	0
FOC2	218	139.20	2.48	4.63	1.89	6.66	3.99	0.065	14.15	0.099	0.79	2.79	0
FOC3	103	192.08	1.80	20.21	3.05	2.29	1.19	0.038	19.81	0.057	0.06	0.65	2
FOC4	80	198.98	2.33	31.97	2.19	0.46	0.95	0.036	16.72	0.061	0.47	0.92	3
FOC5	380	163.94	9.52	7.69	1.34	3.65	5.10	0.161	185.05	0.271	0.20	7.22	1
FOC6	230	189.58	1.20	3.66	2.51	14.75	4.89	0.092	46.44	0.165	1.55	4.49	1
FOC7	415	155.37	5.67	6.57	2.05	5.62	3.35	0.087	36.02	0.168	0.80	1.17	2
FOC8	50	160.54	*2.48*	*44.55*	*2.70*	*6.90*	1.27	0.011	10.52	0.007	0.66	0.64	0
			1.61	*44.55*	*0.77*	*2.29*							
			0.53	*4.63*	*2.19*	*0.45*							
			2.48	*10.6*	*2.51*	*2.29*							
			0.53	*4.63*	*1.34*	*6.66*							
FOC9	270	151.60	*1.20*	*-4.68*	*1.89*	*5.62*	3.15	0.081	24.72	0.148	0.47	3.60	1
			1.80	*31.97*	*0.77*	*2.01*							
			0.53	*7.69*	*2.51*	*5.62*							
			0.53	*7.69*	*2.51*	*0.46*							
			1.20	*-0.43*	*1.97*	*6.90*							
FOC10	250	196.66	14.87	44.55	1.97	0.45	3.40	0.174	236.81	0.314	0.00	1.27	0
FOC11	60	161.08	0.35	-0.43	2.70	12.27	1.17	0.043	28.67	0.062	0.00	1.44	1
FOC12	126	142.13	3.40	-4.68	0.77	6.90	1.54	0.029	7.04	0.049	0.00	1.03	0
FOC13	261	244.91	7.47	10.60	1.99	2.01	6.79	0.130	35.04	0.219	3.19	1.61	0
FOC14	47	142.25	*2.33*	*20.21*	2.51	*2.01*	1.07	0.063	12.07	0.112	0.84	0.50	2
			1.61	*44.55*		*12.27*							
			1.61	*4.63*		*12.27*							
			1.80	*3.66*		*12.27*							
			1.20	*4.63*		*1.08*							
FOC15	86	171.87	1.61	6.26	1.52	1.08	1.74	0.043	26.20	0.075	0.97	0.38	0
Median		161.08	1.80	7.69	1.99	4.12	1.74	0.065	26.20	0.112	0.47	1.27	1
Mean		170.08	3.70	11.56	2.05	5.46	2.73	0.076	49.90	0.130	0.67	1.93	0.87
St. dev.		29.43	4.06	13.42	0.57	4.33	1.82	0.048	67.28	0.087	0.83	1.88	0.99

We expect further insights whether companies are sales or procurement oriented. Based on $G_D(V, A)$, the product-mix matrix **P**, defined in Table 2, allows one to distinguish diversity in product flows up- and downstream the supply chain.

Although all focal companies of our egocentric network study are manufacturing companies in the same industry, these companies may produce for other industrial sectors. We classify the industries of focal companies based on the WZ2008 classification (Statistisches Bundesamt, 2008). Then in the

distinct affiliation network $H_D(W, B)$ we connect focal companies to their industries and create classes of structural isomorphism. This network is shown in Figure 3.

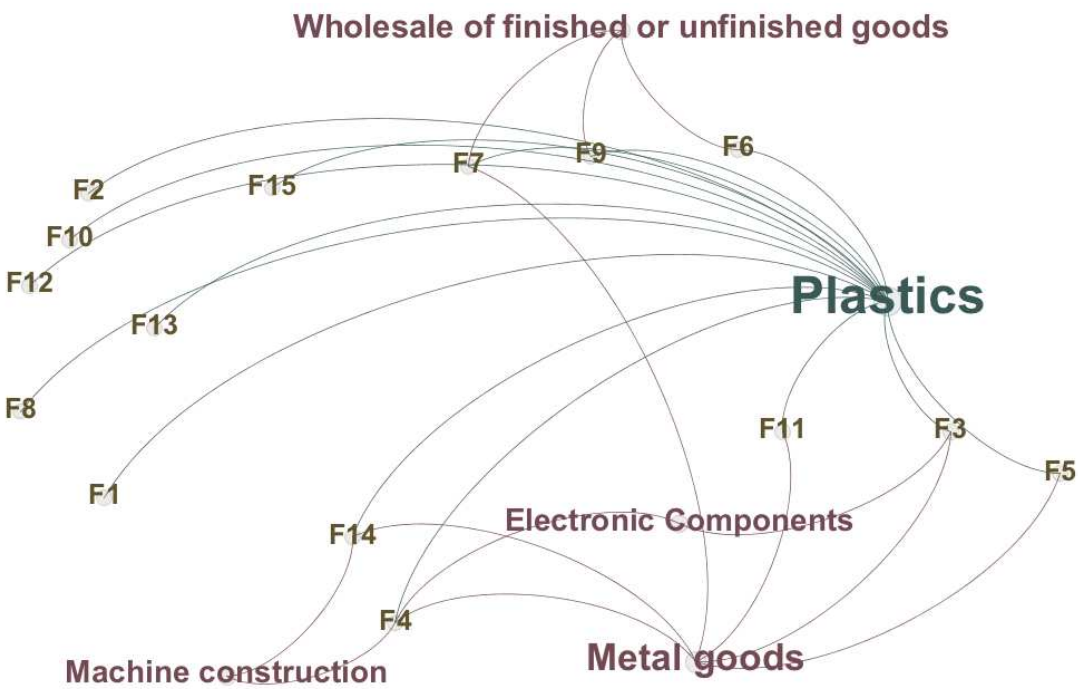


Figure 3. The Directed Graph HD(W ,B) of the network in our study with w = 5 industries and u = 15 focal companies (coded F<num>). Arcs from a focal company to an industry indicate affiliation of the focal company with that industry.

5 Analysis

Using the imputed datasets, we study the association between each *DV* and the *IV*s using correlation analysis (section 5.2), and to test our hypotheses we analyse in section 5.3 the influence of several network related *IVs* simultaneously on each financial *DV* using the multiple linear regression model:

$$DV = b_0 IV_1 + \cdots + b_r IV_r + \text{error} \tag{1}$$

where error$\sim N(0, \sigma^2)$ independent. This step is repeated for each of the five imputed datasets. The set of variables in this analysis is denoted *S1*. For *BP*, we present the results for $\beta = 0.108 = 0.995/\lambda_{\max}$.

Prior to these two steps (correlation and regression), we also look for potential outliers and influential data points. In these ways (multiple imputation and outlier analysis), we aim to ensure that our analysis is robust. Where we find outliers or data points (focal companies) with large influence, we

present findings robustly. Further, although our variable selection procedure reduces the risk of multi-collinearity, we also test and discuss multi-collinearity.

5.1 Outlier Analysis

The Grubbs test is a standard test for the presence of an outlier, and we apply this test while noting that the appropriate response to outlier identification is a matter of debate (Barnett and Lewis, 1994). We also present box and whisker plots (Figure 4) with FOCs that are outliers indicated. It is clear that FOC10 is outlying for both *OP* and *BP*. There are also outliers in *AUTH* (FOC5), and *HUB* (FOC13).

5.2 Results of correlation analysis

The matrix scatter plot in Figure 5 shows each variable of interest plotted against every other. In particular, the large influence of FOC5 and FOC10 in the *OP-BP* relationship can be identified visually. Table 5 shows the corresponding Pearson correlation coefficients and *p*-values for a significance test in each case. We calculate the correlations for each imputed dataset, and present the maximum and minimum correlation (across the five values) in each case. This shows significant results for three (*RE, OP, ROA*) of the five dependent variables that are robust to the missingness of some data.

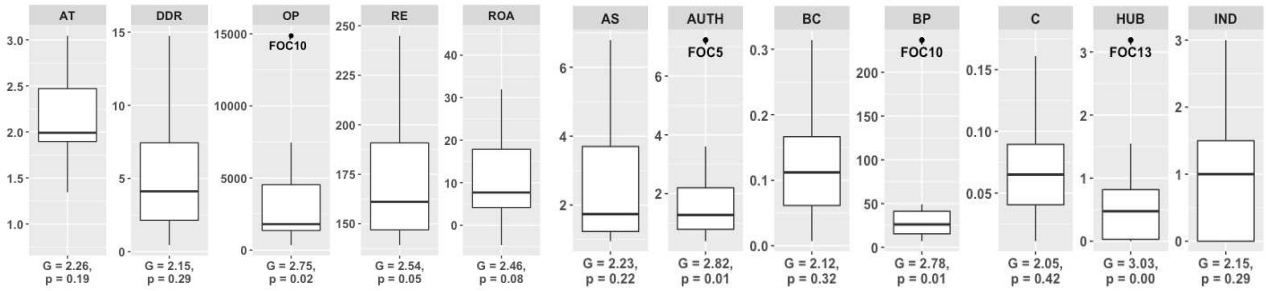


Figure 4. Box and whisker plots of all the variables in *S1*, and with the Grubbs statistic *G* and corresponding *p*-value shown.

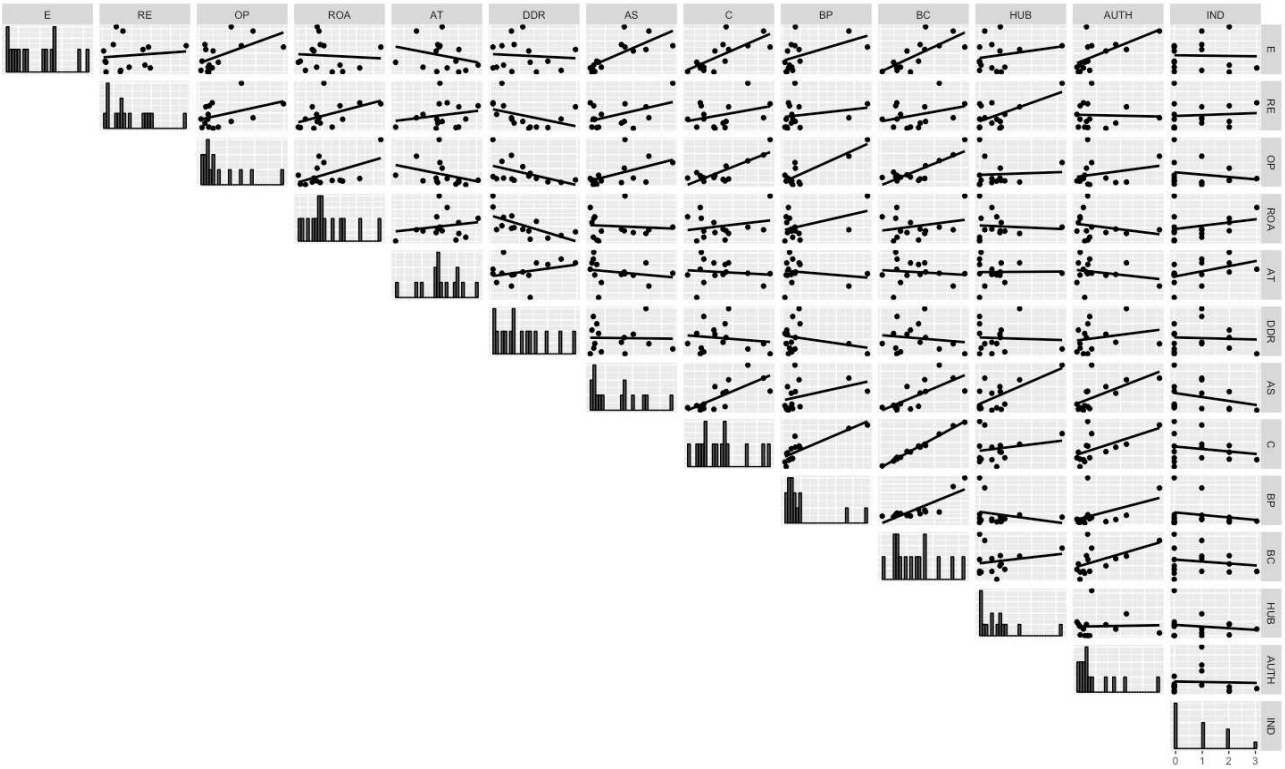


Figure 5. Matrix scatter plot and histograms of all variables in S1**.** Where values are missing and therefore imputed, values are presented are the mean of the five imputed values.

5.3 Results for multiple linear regressions

For each imputed dataset, starting with the full model, we optimise the models using backwards elimination. The number of explanatory (independent) variables is reduced as long as the adjusted coefficient of determination barely differs. The reduction of independent variables also reduces the risk of multi-collinearity. However, we additionally calculate the variance inflation factor *vif* (Fox, 2016) to justify our final model. The overall significance of the final, optimised model is determined by an overall F-test for each *DV* (Table 6). Table 7 and 8 show the summarised results of the two most relevant regressions (*OP* and *RE*) for the final models. There we show results with and without the inclusion of *BP* because of the outlier (FOC10) and the apparent large influence of FOCs 5 and 10 in *OP* v *BP*. In Table 8, we also show the final model for each imputed dataset. In each case, we present the regression coefficients, corresponding *p*-value and the variance inflation factor.

Table 5. Pearson correlation coefficients of all associations in S1. Double entries are maximum and minimum correlation over the imputed datasets. Single entries indicate absence of missing data.

	OP	*ROA*	*AT*	*DDR*	*AS*	*C*	*BP*	*BC*	*HUB*	*AUTH*	*IND*
RE	0.39 0.41	0.15 0.58**	0.13 0.26	-0.42 -0.33	0.47*	0.34	0.21	0.33	0.61**	-0.04	0.08
OP		0.23 0.63**	-0.40 -0.14	-0.48* -0.41	0.50* 0.53**	0.80*** 0.83***	0.86*** 0.87***	0.80*** 0.84***	0.06 0.06	0.22 0.26	-0.20 -0.17
ROA			-0.12 0.34	-0.62** -0.39	-0.22 0.04	0.03 0.37	0.18 0.55**	0.04 0.39	-0.09 -0.04	-0.32 -0.13	0.15 0.28
AT				0.16 0.42	-0.28 -0.10	-0.24 0.05	-0.24 -0.03	-0.25 0.04	-0.00 0.04	-0.28 -0.16	0.36 0.50*
DDR					-0.07 0.05	-0.18 -0.08	-0.25 -0.23	-0.19 -0.07	-0.08 -0.02	0.11 0.30	-0.21 0.07
AS						0.73***	0.38	0.71***	0.67***	0.62**	-0.28
C							0.84***	1.00***	0.20	0.55**	-0.19
BP								0.84***	-0.22	0.45*	-0.19
BC									0.19	0.52**	-0.16
HUB										0.03	-0.14
AUTH											-0.04

(*** significant at 1%, ** 5%, * 10%)

5.4 ***Discussion of results***

The results of the multiple linear regressions show two out of five models are significant (*RE* and *OP*) in a manner that is robust to outliers and the imputation of missing data. In order to address possible multi-collinearity, we adjust the *RE* model by removing *BC* (cut-off: vif > 3.5). Regarding the *OP* model (with BP) we identify some multi-collinearity for the reason of *AS*. This suggests some possible overlap between strength of links *AS* and *BP*. Thus, we also adjust the "with-*BP*" models by removing *AS* (cut-off: vif > 3.5). Table 7 and 8 now show reasonably stable estimates. As both models (*RE* and *OP*) are indicative of the profitability aspect of performance, we answer our research questions in this light.

- RQ1: the answer yes is tentatively supported because H1 is confirmed by the significance of the coefficient of *AS* in the *RE* model (Tables 7).
- RQ2: the answer yes is tentatively supported because H2-1 is confirmed by the significance of the coefficient of *C* in the *OP* model (5/5 imputed datasets) (Table 8), and noting that while the coefficient

of *BP* in the *RE* and the *OP* models is significant (Tables 7 and 8) confirmation of H2-2 is reserved because of the large influence of FOC5 and the outlier FOC10.

- RQ3: the answer yes is not supported because both H3-1 (*HUB*) and H3-2 (*AUTH*) are not accepted, the latter because of the sign of the coefficient and noting that FOC5 is an outlier in *AUTH*.
- RQ4: the answer yes is tentatively supported because H4 is confirmed by the significance of the coefficient of *IND* in the *RE* model.

Table 6. Multiple regression models F-statistic

	RE	*OP*	*ROA*	*AT*	*DDR*
R^2	0.79	0.92	0.73	0.34	0.43
F	2.85*	8.71***	2.04	0.39	0.57
p	0.10	0.00	0.20	0.89	0.77

(*** significant at 1%, ** 5%, * 10%)

Table 7. Regression coefficients for the final, optimised model for RE with and without inclusion of *BP*

	With *BP*			Without *BP*		
	Coeff.	*p*	vif	Coeff.	*p*	*vif*
Intercept	137.5			136.3		
AS	23.52	0.00	3.22	19.84	0.01	3.45
C				227.87	0.25	2.56
BP	0.19	0.06	1.47			
BC						
HUB						
AUTH	-9.57	0.03	1.93	-8.11	0.07	1.83
IND	15.75	0.02	1.29	13.59	0.06	1.23
E	-0.20	0.02	3.16	-0.19	0.06	3.26

Table 8 Regression coefficients for the optimised model for OP for each imputed dataset (ID) and with and without inclusion of *BP*

	ID1			ID2			ID3			ID4			ID5		
	Coeff.	*p*	vif	Coeff.	*p*	vif	Coeff.	*p*	vif	Coeff.	*p*	vif	Coeff.	*p*	vif
Inter.	128.7			-144.4			-346.4			33.0					
AS															
C															
BP	55.8	.00	1.58	54.67	.00	1.58	56.6	.00	1.58	56.8	.00	1.58	55.48	.00	1.58
BC															
HUB	1065.0	.08	1.23	971.54	.09	1.23	1037.6	.08	1.23	1088.0	.07	1.23	972.3	.09	1.23
AUTH	-816.5	.02	1.73	-795.5	.02	1.73	-840.0	.01	1.73	-838.1	.02	1.73	-816.5	.01	1.73
IND															
E	9.8	.08	2.06	11.38	.04	2.06	11.3	.04	2.06	9.8	.08	2.06	12.08	.03	2.06
	Without *BP*														
Inter.	-830.6			-1056			-1341			-914			-1350		
AS															
C	84573	.00	1.50	85850	.00	1.51	89174	.00	1.51	84945	.00	1.51	88569	.00	1.51
BP															
BC															
HUB	-618.5	.43	1.05	-660.4	.39	1.05	-668.0	.38	1.05	-617.7	.46	1.05	-684.6	.36	1.05
AUTH	-702.7	.10	1.44	-656.0	.11	1.44	-717.2	.08	1.45	-715.2	.11	1.45	-674.0	.10	1.44
IND															
E															

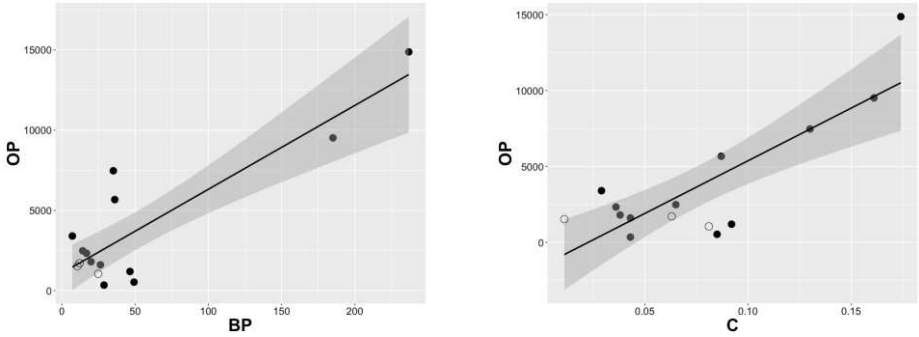
Comparing the two models of *RE* and *OP*, one might recommend *OP* as the best fitting. The adjusted R^2 indicates that 61% of the variability in *RE* is explained by *AS, BP, AUTH, IND* and *E*, compared to 85% in *OP* explained by *BP, HUB, AUTH* and *E*. However, in this regard we should acknowledge the strong influence of two data points (FOCs 5 and 10) on the results for *BP*. Therefore, for the companies in the network we study, those companies that are the most connected to well-connected nodes (*BP*) have the highest financial performance (Figure 6a). However, we do not claim our analysis supports this association in general. Instead, we claim our analysis provides some evidence to support the general conclusion that profitability is positively associated connectedness (undirected centrality, *C*) (Figure 6b). Thus, we regard the models

$$\mathrm{E}(RE) = 136 + 19.8AS + 228C - 8.11\,AUTH + 13.6IND - 0.19E, \quad (2)$$

$$\mathrm{E}(OP) = (-1.10 + 86.62C - 0.65\,HUB - 0.69\,AUTH) \times 10^3, \quad (3)$$

as robust models of network oriented performance. For model (2), adjusted R^2 = 0.50, and for model (3) adjusted R^2 = 0.71. The coefficients in (3) are estimated using the mean of the imputed datasets.

We must however be cautious about making strong conclusions about effect of network characteristics on financial performance in general because the financial measures that represent liquidity and efficiency (*DDR* and *AT*) showed no association with network characteristics at all.



(a) (b)

Figure 6. Scatter plots for *OP* v *BP* and *OP* v *C.* Open dots are the means of imputed values.

The results then indicate that it is advantageous to be central, but we cannot claim generally that this advantage stems from connections to well-connected companies. Nonetheless, in our sample those connected to the well-connected perform best, so that performance improvement may stem not only from having many business partners, but also by identifying and focusing on relationships with well-connected ones. Therefore our results suggest that network embeddedness influences performance. If it is supposed that performance is mediated by innovation then our results agree with Bellamy *et al.* (2014), which links network position to innovative output. Our results also agree with Kao *et al.* (2017), which links network position to technical efficiency.

We claim generally that market share over the network is important to profitability because the inclusion of *AS* in the *RE* model is robust. This finding is perhaps obvious. Nonetheless it provides important confirmation for strategic rethinking with respect to selective connectedness and prioritisation of business partners (to increase market share) (Cook *et al.*, 1983; Kim *et al.,* 2011). We also note that transactional data are necessary to study this effect because they are required for calculating aggregated strength. Thus, this finding also strengthens the reliability of our sample.

The robust, negative coefficient for *AUTH* suggests that it is disadvantageous to have diversified relationships with suppliers identified as authorities in the network. This notion was suggested by Maestrini *et al*. (2018) in a conceptual study. This is in accordance with the findings. One possible explanation for this apparent effect is the prevailing market conditions: the industry of focus is very competitive, which is why material suppliers have many opportunities for business. The focal companies (manufacturing companies) cannot necessarily expect scale effects when relationships are diversified over a variety of product types. Focal companies might rather benefit if they try to play-off many suppliers against each other by increasing their number of different suppliers. Such a strategy reduces the risk of strong dependencies. This explanation would also manifest in the effect of modifying the parameter β of Bonacich power. The parameter β allows to differentiate between benefits that result from being connected to well-connected nodes ($\beta > 0$) and the risk of being outplayed out by nodes that have many alternatives *BP* ($\beta < 0$). This thinking about where competition can emerge from, and how to mitigate against it, is also recognised as a future trend in supply chain management (Asgari, *et al.*, 2016).

Finally, in Table 5 we also recognise only a weak correlation between *RE* and *OP*, suggesting verification that these measure different characteristics of financial performance. Also, using the companies' number of employees (Table 4) to control our findings, we recognise that the model for *OP* (Table 8) is indifferent to the size of a company.

6 Contribution to theory, managerial implications and further research

To contribute to the literature on performance measurement of an organisation in a supply chain, we examine the link between network position and financial performance. The transfer of social network analysis to a supply chain network allows us to measure the position of an organisation in the supply chain network. The use of a variety of financial performance measures ensures that we evaluate financial performance comprehensively. Relating the performance of an organisation to its network-embeddedness is difficult not least because many unquantified factors, both positive and negative, may be influential (Hald and Mouritsen, 2018). Nonetheless, we argue that a link between the supply chain embeddedness and the financial performance (profitability) of a focal company can be seen through the network lens. This to an extent endorses an external perspective in performance measurement.

In particular, in a statistical analysis, we study network position properties for their influence on financial performance. To inform the choice of metrics that might be included in an enriched performance measurement system, we analyse a number of multiple linear regression models. By optimising the significant models, relating to *revenue per employee* and *operating profit*, we identify the strongest factors. We conclude that there is some evidence that these factors are degree centrality and aggregated strength.

Bonacich power ($\beta > 0$) also features as an important factor for performance of the companies in our sample, but we caution against making the general inference that being connected to the well-connected is important to performance. In their work, Bellamy and Basole (2013) describe Bonacich power as a "well-known measure not yet exploited in operations and SCM literature". This then underlines the timeliness of our work, and while our results tentatively indicate that the success of a company is linked to its connectedness we cannot claim that these neighbours should be well-connected. Nonetheless two companies in our sample appear to benefit from selective connectedness, suggesting that if connections with well-connected business partners are relatively strong, as measured by cash flows, financial performance (profitability) is improved.

There are some implications of our study. Our results indicate that connectedness and market share are important factors in financial profitability. Therefore, we might suggest to management the type of business partners (those well-connected) that should be their main focus. We describe a network perspective that could be implemented in corporate performance measurement systems. The measurement of indicators that encourage innovation, in-time and in-quantity logistics, a high level of quality assurance and information transparency on all levels ought to contribute to having closely-linked, reliable business partners.

Regarding the ultimate goal of generalisation, our study may be understood as a step in the right direction. Thus, while our methodology is scalable to many and larger networks, our results are limited by the size of the sample and that the sample may not be representative of supply chains in general. Therefore, studies of other networks are necessary to verify our findings. However, collecting empirical data that go beyond a binary adjacency matrix for larger supply chain networks is a significant challenge

(Basole et al., 2018; Demirel *et al.*, 2019). Nonetheless, network "enlargement" might be achieved in a number of ways.

Enlargement through "repetition" may be feasible, wherein data are collected from networks with common characteristics, such as those for automotive parts (e.g. body parts or electrical components). Such data would then be combined to create a larger sample. Enlargement might be achieved through snowball-sampling (e.g. Handcock and Gile, 2010). Here, starting with a convenience sample, an egocentric network is enlarged by obtaining data on the ego-networks of the business partners of focal companies, and those of the partners of the partners, and so on. This approach raises interesting questions for the imputation (Wang et al., 2016) and the missingness (Smith et al., 2017) of network data. Simulation, wherein the detailed study of a small network provides the basis for the creation of data that emulates reality, will facilitate enlargement, but the issue of generalisation will remain. Nonetheless, this type of approach has been used by many (e.g. Nair and Vidal, 2011; Meng et al., 2017; Song et al., 2019). On the other hand, meta-analysis of distinct studies, similar to those addressing other areas of supply chain management (e.g. Geng *et al.*, 2017; Abreu-Ledon *et al.*, 2018) can build evidence to support a theory, or otherwise.

Alternatively, one might study similar questions in a completely different arena. Thus, in sport, the relationship between performance (e.g. Kharrat *et al.* 2020) and position (e.g. Clemente *et al.*, 2020) is interesting and important. Here, the benefit, but also a challenge for visualisation and analysis, is the large quantity of data that are available. While its connection to industry supply chains is a remote one, sport often provides a useful context for studying managerial and economic questions because there exists a degree of experimental control (Balafoutas *et al.*, 2019).

A final point on enlargement is that relating performance to some network characteristics is more demanding of data than others. Thus, to relate performance to connectedness to the well-connected (Bonacich power) requires data for a network with a rich structure, while relating performance to centrality does not. Hence, repeating the point above of Bellamy and Basole (2013), the connectedness of connected nodes is a measure that is under-exploited in the operations and supply chain management literature.

An alternative to data enlargement is to reduce noise in the data. Here, we might seek performance measures at a more detailed level, which, on the basis of a preliminary qualitative study, are deemed relevant to network characteristics. Thus, specific efficiency or financial measures more closely related to production and procurement (e.g. Kao et al., 2017) might be used and they may be statistically more powerful. Finally, aside from the matter of statistical significance in the context of a regression analysis, the relationship of performance to connectedness might be studied outside the linear paradigm of singular causation (Fiss, 2007).

In conclusion, and returning to the concept of externalising performance measurement, when asked about the future development of performance measurement, managers call for available, reliable and responsible information (Gomes *et al.*, 2004). Therefore, information should reflect that dynamic relationships exist between business partners. When one recognises that the efficiency and effectiveness of one's own organisation are influenced by interdependencies across supply chains, the integration of a network perspective in performance measurement with an internal financial perspective becomes important (Morgan, 2007; Piontek, 2009; Elgazzar *et al.*, 2012). Thus, it may be very important for a firm to put its desired supply chain relationships at the heart of its supply chain performance measurement system, a point argued by Hald and Mouritsen (2018) and observable in the analysis in our paper. On network theory, we add to the detailed debate on how a firm should design its supply chain networks (architecture and role) and whether it should put cooperation before competition (flows), thus adding to the general debate on how a firm might enrich its performance measurement system.

~~Finally, we remark that open problems remain. As stated, a larger study, with more focal companies or many networks or longitudinal data or all of these, would facilitate a more comprehensive model and richer analysis. Causal relationships might also be investigated. Nonetheless our paper takes an important step towards the goal of embedding supply-chain network position in performance management systems~~.

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