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Identifying the Relation Between a Supply Chain Network's Structure and Its Overall Financial Performance

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ABSTRACT

We construct a data set using financial performance data spanning forty publicly traded companies across several industry sectors over a three-year time-period to identify key structural features of supply networks. The data set for this study allows us to explore supply chain relationships beyond the first tier. For each network within the data set, we examine the network topology via several key structural parameters including node and edge counts, average degree, network diameter, average path length and the power law exponent. We observe that the emergent structure of supply networks is similar (inter-industry), although dominant supply networks are apparent, in some, yet not all the industry sectors. We then link the structural parameters with financial metrics and observe that higher average degree results in decreased overall financial performance of the supply network. Average degree is indicative of how many connections a firm has. A high average degree implies strong inter-connectivity among the firms in the network. Historical analysis of the data (2013-2015) points to an overall decrease in the average degree, especially at the higher tiers. Our analysis suggests that to increase the overall supply network's financial performance, a low average degree should be targeted.

Keywords: *supply chain network topology, empirical research, firm performance, Tobin's Q, ROA*

1. INTRODUCTION

Supply Chain Networks (SCNs) have in recent times evolved from simple sequential and linear process networks to highly dynamic processes that require information sharing and visibility to be available across the network coupled with decision making on real time basis. As such, it is important, not only, to identify the structure of a supply chain network, but also understand what drives its success. Ideally, it would be preferred if the structure of a supply chain network could be derived using theoretic constructs, however, the nature of the supply network process is both interactive and dynamic. With the massive explosion in data availability, a data-mining approach would be appropriate. By definition, a supply chain is a network between a company and its suppliers to produce and distribute a specific product. By examining a representative sample of networks, from multiple industry sectors we obtain a broad inter and intra industry analysis of supply chain network structure and use this to identify some of the key structural characteristics, which are typical of supply chains.

Through this research project, we have created dynamic visual mappings of publicly traded supply networks, using existing financial relationship data sourced mainly from FactSet, which when coupled with network visualization software and network science tools, allow a highly innovative visual mapping of a supply chain network to emerge. Our research applies a visual approach to explore the digitized mappings and uses these to identify key features that arise in a supply chain's structure.

The research problem, which this paper seeks to address, is to explore the associations between the key structural features of a supply chain network and some corresponding financial parameters. The main contribution of this work is to derive the key topological components of the supply chain network and examine how changes in the structure, which occur in real-time, impact its financial performance. Our structural measures are novel to the literature. The dynamic, temporal nature of the underlying data set makes these results particularly compelling.

The main contribution of this work is to examine how the key topological components of the supply chain network, which occur in real-time, affect its operation and drive its performance.

The objectives for this paper are:

- To use multi-tiered financial relationship data for a cross-section of supply networks and establish a general framework for the study of supply network structure.
- To identify significant statistical relationships between the dynamic network structure and key corresponding financial metrics.
- To make recommendations regarding the connection between structural parameters and financial performance.

2. LITERATURE REVIEW

There are several approaches that can be adopted to understand the structural topology of a supply chain network. As a starting point, supply chain structure can be examined using theoretical constructs, for example, Carter *et al*. (2015). Theoretical studies of supply chain structure are important because they conceptualize a supply chain as a network, a recent survey of such models can be found in Liao and Widowati (2021). But, with the availability of data and the real-time evolution of these networks, there is a need to test the validity of the theoretical models using live data feeds. With the explosion of available data, the empirical approach has risen in prominence in recent years. There are also several approaches to understanding structure which rely on applications from other areas of research, such as network science, graph theory or social network analysis (Orenstein, 2020). The focus of this review is to provide a context for the empirical approach and understand its relationship to the financial strand of research in this area.

Although there is an extensive theoretical literature, surprisingly there are few systematic and extensive empirical descriptions of actual networks themselves. While several empirical descriptions of actual networks do exist, they are somewhat limited mainly due to the difficulty in data acquisition. Those available tend to be detailed, relatively small-scale studies (see for example, Choi & Hong, 2002; Lomi & Pattison, 2006; Luo *et al*., 2012). The data described by Rosenkopf & Schilling (2007), demonstrate a substantial variety in network structures by examining alliances formed in 32 industries. Their research leads to a typology of network structure, and they develop a series of metrics, which characterize each of these typologies.

When dealing with empirical data, researchers have explored the connections between the tiers in the network. One application of empirical data to topological structure is described by Kito *et al*. (2014), who have constructed the supply network of the Toyota network using the data from the Marksline database. They have identified the tier structure of Toyota to be 'barrel-shaped', in contrast to the previously hypothesized pyramidal structure. In addition, the authors did not find the topology to be scale-free. However, the data is limited to the top tiers of the overall network, and the data is non-temporal (i.e., it relates to a single time interval).

Several researchers have also considered the topological analysis of actual supply networks using financial data (Bloomberg and Factset). Brintrup *et al*. (2015) have studied the Airbus supply network, and Brintrup *et al*. (2016) have examined the automotive industry to explore robustness characteristics. While these studies examine the structural component, the research does not evaluate the dynamic nature of these relationships. By contrast, Orenstein (2020) used Bloomberg and FactSet data to construct a pilot study of networks in the retail industry and evaluated the structural topology in the top three tiers along with the detailed inter-relationships. In addition, the data is provided over a three-year period, hence it includes a temporal component, and it is possible to examine how structure changes over time.

In conjunction with data-driven studies of topological structure, several researchers have considered the financial implications of the inter-relationships and consider the impact of risk, and how it propagates through the network of connections. Jussa *et al*. (2015) use a combination of Bloomberg and FactSet data to demonstrate the idea that a single shock at one company can be transmitted to other connected firms and develop a metric to identify key players in the supply network. Wu (2015) develops measures of centrality for the supply network using FactSet data and uses the metrics to demonstrate that the stock performance of 'supplier central' portfolios tends to predict the movements of the overall stock market. Wu (2016) finds that the revenue of a particular firm at the local level may have significant implications, sometimes affecting the revenue of firms up to multiple connections away. The results pertain to a specifically constructed data set. Wang *et al*. (2015) point out that because there is overlap in supply network sub-tiers, companies need to evaluate the entire supply network structure in order to assess the impact of risk accurately. Wu & Birge (2014) examine the relationship between network structure and stock returns across different industries. Carnovale & Yeniyurt (2014) consider the link between network structure and financial performance by examining specific financial metrics (return on equity, return on asset and return on sales). However, the data for the study is limited to the automotive industry between 1985 and 2003 and does not include a real-time component. Both Carnovale and Yeniyurt (2015) and Wu and Birge (2015) look at how supplier connections form and how these network connections (both first-hand and second-hand) affect firm performance. Their work suggests that firms that can understand and optimize their network structures can use them to their advantage to generate significant improvements. In another study, Carnovale *et al*. (2019) examine the impact of network structure on financial performance by exploring network cohesion and network power on financial metrics. They observe that managing the firm's levels of network power and cohesion facilitates improved financial performance.

The work by Arora and Brintrup (2021) discusses three measures that characterize the embeddedness of individual firms in a supply network. These are namely: centrality, tier position, and triads. They find that centrality impacts individual performance through a diminishing returns relationship. The analysis is based off a study of the Toyota network, which has been mapped out to produce a tiered structure. The data represents a single time slice (i.e., it is not dynamic like the data in this study). Another related study by Seiler *et al.* (2020) finds some evidence that profitability is related to connectedness and market share.

From the data-driven studies of network structure it has emerged that supply networks are indeed complex systems governed by numerous interactions, and that the robustness of the resultant networks are affected by structure. A need for an empirical consensus on the universal properties of supply networks as well as an understanding of their evolution is clearly a vital area for research. But examining structure in isolation is insufficient. In reality, supply networks are likely to include thousands of distinct firms and there is clearly a need to understand the link between network structure and the overall financial performance.

Our proposed contribution is to use financial performance data for a cross-section of supply networks in order to establish a general framework for the study of supply network structure. Previous contributions to the literature focus primarily on individual case studies, where the data source is static, i.e., they do not capture the temporal nature of the network expansion/contraction, are labor intensive to collect, and have poor explanatory power out of the sample. By expanding our sample through the ease of using FactSet, we can perform studies about how the structure of supplier relations can directly influence financial performance. This is a primary goal of this study.

3. RESEARCH METHODOLOGY AND DATA SET

We assume that we can represent a supply chain network as an unweighted directed graph $G=(N,L)$ with N nodes and L links or edges. We assume there are no cycles in the graph. In the context of this work, the nodes represent individual companies, which connect through edges. We use only supplier relationships. i.e., the degrees are all one directional. In the paper, we refer to G as the focal company, or focal node. Each edge represents a financial relationship between a pair of companies, essentially a binary relationship. As such, we can denote the network as an adjacency matrix (A). Any element of the adjacency matrix $A=a_{ij}$, is given as:

$$a_{ij} = \begin{cases} 1, if\ i \neq j\ and\ i\ and\ j\ nodes\ are\ connected\ by\ an\ edge \\ 0, if\ i \neq j, and\ i\ and\ j\ nodes\ are\ not\ connected \\ 0, if\ i = j \end{cases}$$

In order to map out the supply chain networks, we first acquired financial performance data for a sample of companies and organized the data by calendar quarter and tier for three consecutive years (2013-2015). In a supply network structure, it is not uncommon for a given company to appear in different tiers. Each time the said company appears in a particular tier, it is recorded. The companies span various industry sectors including Energy, Health Care, Industrial, Communication and Information Technology. The sector classification is derived from Yahoo Finance (https://finance.yahoo.com/industries/), which extracts the information from the GICS classification system (https://www.msci.com/gics). A summary listing of the companies that have been included in the study and the corresponding industry sector is provided in **Table 1**.

Table 1 Sample company tickers and industry sectors

Company Ticker Symbols	GICS Sector
SHW	Materials
VZ, T, TMUS, S	Communication Services
GM, F, KSS, SHLD, HD, AMZN, BBY, NKE, PII, SHLD, TOY, LOW	Consumer Discretionary
HSY, WMT, COST, CL, GIS, K, MDLZ, PG, TGT, TRW	Consumer Staples
XOM	Energy
JNJ, MRK, PFE	Health Care
BA, GE, CMI, ROK	Industrials
AAPL, CSCO, IBM, INTC, MSFT, ORCL, QCOM, STX, WDC	Information Technology

From this dataset, we constructed supply chain maps for each company using custom software. A sample visualization is provided in **Figure 1**. This graph depicts the Lowes supply chain for 2014 using Bloomberg data. The data from this source generates rich visualizations, yet the mechanism to generate a single image is cumbersome and the resultant map is static in nature, that is, one cannot examine how the structure changes over time. The snapshot is useful as it captures the shape of the evolved SCN, yet it is not practical for further analysis. Consequently, we used an alternative data source, FACTSET and generated an equivalent map (**Figures 2a-b**) of the network displayed in **Figure 1**. While the visualization is not as rich, the FACTSET source is easier to work with and the data can be examined over time. As such, **Figure 2a** shows the structure in 2013, whereas **Figure 2b** shows the structure in 2015. This is important, since in the context of this work, the implication of topological structure to financial performance over time is a key element of the discussion.

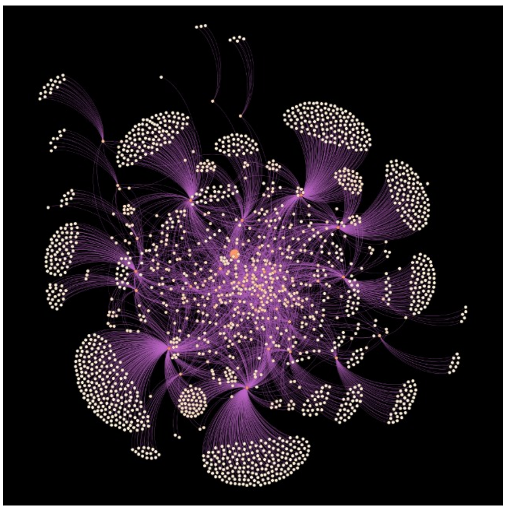
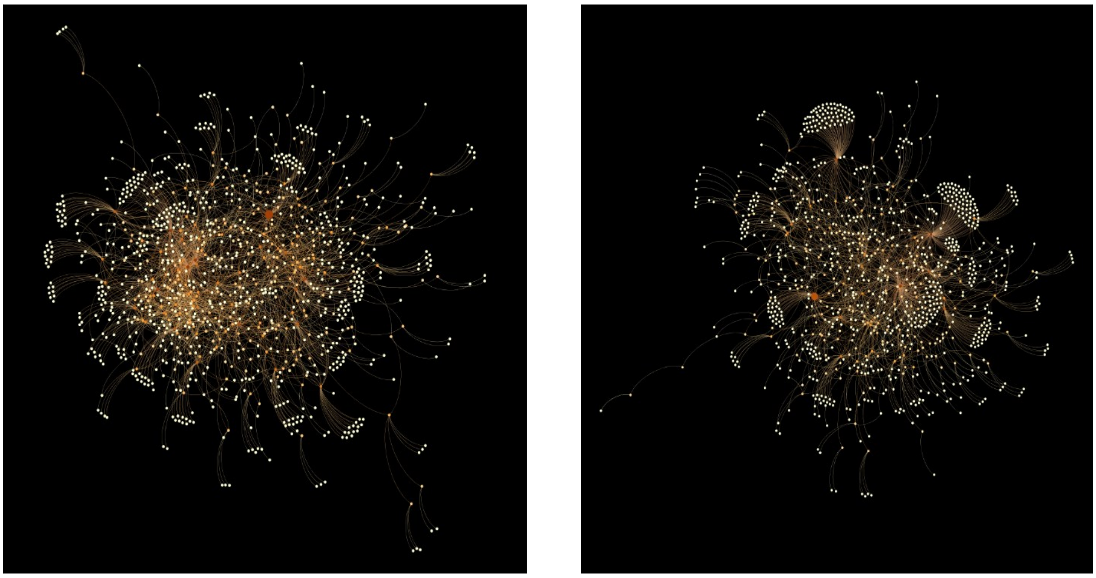


Figure 1: Topological structure of the Lowes supply network (Tiers 1-3)
(Source: Bloomberg 2014)



(a) (b)

Figure 2a-b Lowe's topological structure (Tier 1-3) in quarter 4
(Source: FactSet 2013-2015)

We then analyzed each company's visualizations by quarter and tier and recorded the structural metrics for each map. We also collected and recorded several financial metrics for the corresponding time-period. We then performed a series of regression analyses to identify key structural parameters that indicated improved financial performance of the entire supply network.

We use several network metrics to characterize the topology of the supply network. These include the number of nodes, number of edges, average degree, network diameter, average path length and the power law exponent. We have also used both stock market valuation and accounting return as measures of supply network overall performance. In particular, these include Tobin's Q and return on assets. The definitions for the structural and financial metrics are provided in **Table 2**. In the results section we describe a series of statistical analyses that we have conducted using the empirical data. These include summary statistics, correlation, and the regression analyses.

Table 2 Variable definitions for network structural metrics and financial metrics

Variables	Definition
Firm Performance and Control Variables	
Capital expenditure	Capital expenditure scaled by Total Assets, which is calculated as *capxy/atq* from Compustat database.
Hard assets	Net property plant and equipment scaled by total assets = *ppentq/atq*.
Leverage	Market value leverage = *(dlcq + dlttq)/(atq-ceqq+prccq*cshoq)*.
Ln(sales)	Natural logarithm of quarterly sales = *Ln(saleq)*.
Missing R&D	Indicator = 1 if *xrdq* is missing and 0 otherwise.
MV of total assets	Also referred to as MV_assets. Market value of total assets = *at - ceq + prcc_f*csho*
R&D/TA	R&D expenditure (replaced by 0 when missing) over total assets = *xrdq/atq*
ROA	Return on assets = *100*niq/atq*(denoted in percent)
Tobin's Q	Also referred to as market to book ratio or market value over book value of total assets =*(atq-ceqq+prccq*cshoq)/atq*.
Supplier Network Variables	
Power Law Exponent	A power law is a relation of the type Y = kX^(α) , where Y and X are variables of interest, α is called the power law exponent, and k is a constant.
By Tier	Number of firms who are Tier (x) suppliers

Table 2 Variable definitions for network structural metrics and financial metrics (Con't)

Node Count	Number of connections between firms (suppliers) at Tier (x)
Edge Count	Ratio of number of edges to number of nodes at Tier (x); Indicates, on average, how many connections a firm has. Higher average degree implies good interconnectivity among firms in the Supply Chain Network
Average Degree	Ratio of edges to nodes. Indicative of how many connections a firm has. A high average degree implies strong inter-connectivity among the firms in the network.
Network Diameter	Largest distance between any two firms in the SCN; as this number increases, it may be more challenging to govern the network. More complex manufacturing processes can include large network diameters (i.e., many stages of production) indicating difficulty in governing the overall supply chain network under a centralized authority.
Average Path Length	The **average** number of steps along the shortest **paths** for all possible pairs of network nodes. It is a measure of the efficiency of information or mass transport on a network.

4. RESULTS

4.1 Overview

To gain an overall perspective of the data used in this study, **Figure 3** shows the ranking of the companies that were included by average degree (averaged over 2013-2015). **Figure 1** shows the normalized average degree is used to determine the relative size and dominance of companies in the study. One can see for example, that Boeing (BA) has a higher average degree (more connectivity) than say Costco or Nike. Hershey (HSY) is the smallest of the companies in the study. The ranking also highlights the similarities (in scale) of the companies in the study. For example, IBM and Apple appear to be close in rank. In addition, the normalized average degree demonstrates what proportion of companies within the sample have a respectively high average degree, medium average degree or low average degree. The top three companies (in terms of average degree) are Boeing, Verizon and General Electric. In the following section, we provide (a) summary statistics for the data, (b) correlations between structural and financial parameters and (c) regression analyses to identify significance in the relationships from (b).

4.2 Statistical Analyses

Table 3 shows the summary statistics for each of the structural metrics organized by Tier. The results indicate that the structural metrics of average degree, network diameter and average path length all increase as the network expands and includes additional Tiers. The next step of this analysis is to examine the relationship between each of these key structural metrics and the financial metrics, as well as identify which (if any) of the structural parameters are significantly associated with the overall financial performance of the supply chain network.

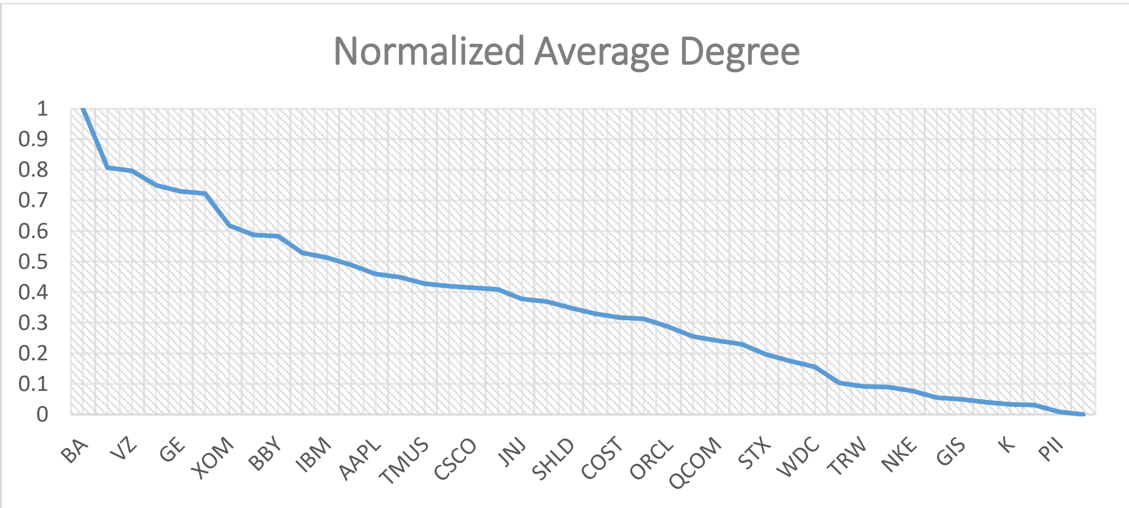


Figure 3 Ranking companies in the study by normalized average degree (averaged over 2013-2015)

Table 4 shows the corresponding correlation analysis between the structural metrics (arranged by Tier) and the corresponding financial metrics. We can observe that there is a noticeable negative correlation: as average degree increases, financial performance decreases. As the network expands (more nodes/firms are included in the SCN), the number of connections between these nodes should also increase but at a rate, that will sustain a low average degree.

Likewise, if firms are leaving the SCN, the number of connections between these remaining firms needs to be commensurate with the number of nodes. This effect is more apparent at the lower tiers: thus, the impact on financial performance of firms joining/leaving the SCN becomes weaker as more Tiers are included. As shown in the table, the correlation between Tobin's Q and the average degree is -0.44 for Tier 1 companies, which is highly significant both economically and statistically. This correlation is also significantly negative when the accounting performance of ROA is used. The correlation between Tobin's Q and the average degree is -0.37, -0.37, and -0.39 for Tier 2, 3, and 4 companies respectively.

At the first Tier, suppliers are connected to the focal firm in a ring form (i.e., the number of edges is approximately the same as the number of nodes). This leads to an average degree of approximately one. The data suggests that this structure is most beneficial to financial performance. As more tiers are included, we see that the average degree increases, yet the financial performance of the focal firm decreases. The analysis suggests that keeping the overall structure of the supply network simple, yields improved financial performance. Too many connections may effectively spoil the broth for everyone.

Weaker correlations for reduced financial performance are also noticeable for the other parameters of network diameter, average path length. By contrast, the power law exhibits a positive correlation, that is, financial performance improves as the power law increases. Since the power law indicates the degree of scale-free topology, it follows those networks, which exhibit scale-free architecture, may serve as an indicator of overall improved financial performance, providing we can identify significance in this relationship. We next examine the significance of the relationship between the structural variables and the selection of financial metrics.

4.2.1 Power Law and Supply Chain Network (SCN) Performance

Table 5 examines the relation between Power Law Exponent and supply network performance. The dependent variable is Tobin's Q for columns (1)-(2) and Return on Assets for columns (3)-(4). All variables are winsorized at 1% and 99%. See **Table 2** for variable definitions.[1] One can observe that the power law exponent is not significantly associated with firm performance. It is possible that the positive correlation observed in **Table 4** would need to be re-examined with a larger sample size spanning a wider timeframe before a conclusion concerning the relationship between the scale-free nature of the network and its financial performance can be drawn.

Table 3 Summary statistics

Variable	Mean	Std. Dev.	Min	Median	Max
Firm performance measures					
Tobin's Q	2.29	1.10	0.96	2.00	5.66
ROA	2.07	1.66	-2.86	1.92	6.72
Supply chain network structural metrics					
Power Law Exponent	2.06	0.13	1.84	2.04	2.45
Average Degree					
Tier 1	0.98	0.03	0.86	0.99	1.00
Tier 2	1.34	0.29	0.95	1.27	2.42
Tier 3	1.90	0.67	1.00	1.83	4.01
Tier 4	2.85	1.25	1.10	2.77	6.12
Average Path Length					
Tier 1	1.00	0.00	1.00	1.00	1.00
Tier 2	1.66	0.50	1.33	1.47	3.95
Tier 3	3.31	1.38	1.68	3.02	7.84
Tier 4	5.45	2.03	2.21	5.88	10.28
Network Diameter					
Tier 1	1.00	0.00	1.00	1.00	1.00
Tier 2	3.46	1.77	2.00	3.00	10.00
Tier 3	8.92	4.45	3.00	9.00	24.00
Tier 4	14.52	5.88	4.00	16.00	27.00

[1] Standard errors are in parentheses. The standard errors are double clustered at quarter and firm levels; *** p<0.01, ** p<0.05, * p<0.1.

This table shows the summary statistics for key variables. Our sample is from years 2013-2015. All variables are winsorized at 1% and 99%. There are 417 observations for each variable. See **Table 2** for variable definitions.

Table 4 Correlations between each pair of variables**.** All variables are winsorized at 1% and 99%. Significance at 5% level is shown by a "*"

	Tobin's Q	ROA
Average Degree		
Tier 1	-0.4359*	-0.3491*
Tier 2	-0.3705*	-0.2458*
Tier 3	-0.3652*	-0.3192*
Tier 4	-0.3903*	-0.3134*
Network Diameter		
Tier 2	-0.2700*	-0.1453*
Tier 3	-0.3603*	-0.3230*
Tier 4	-0.2413*	-0.2192*
Average Path Length		
Tier 2	-0.2124*	-0.1245*
Tier 3	-0.3265*	-0.2522*
Tier 4	-0.2410*	-0.2023*
Power Law Exponent	0.2359*	0.1380*

4.2.2 Average Degree and Supply Chain Network (SCN) Performance

We observe that the average degree is significantly negatively correlated with the financial measures even after controlling for a set of factors that might affect firm performance documented in previous literature, Benson and Davidson, (2009) and Himmelberg *et al*, (1999). As shown in **Table 6a** column (1), when the performance is measured using Tobin's Q, the coefficient on the average degree is -18.6, which is highly significant both economically and statistically. The standard deviation of the average degree in Tier 1 is 0.03, which amounts to an associated decrease in Tobin's Q of 0.558, about half of the standard deviation in Tobin's Q. This finding suggests that the association between the average degree and Tobin's Q is highly significant economically as well. This negative coefficient stays highly significant after we add a set of control variables as shown in column (2). The negative association between Tier 1 average degree and firm performance can also be seen from the accounting measure of ROA, as shown in the rest of this table. When we move up the tiers from Tier 1 in **Table 6a** to Tier 4 in **Table 6d**, the negative association between the average degree and Tobin's Q is less strong but is still apparent. It follows that the average degree is a significant indicator of supply chain performance: when the average degree increases the overall performance of the supply network decreases. Thus, the rate of network expansion (addition of firms to the SCN) needs to be commensurate with the number of associated connections, and that too many connections will cause the overall financial performance of the supply network to decrease. A simple architecture of nodes and edges implies improved financial performance. In fact, the data points to this effect, in that the normalized average degree is decreasing in the 2013-2015 time-period.

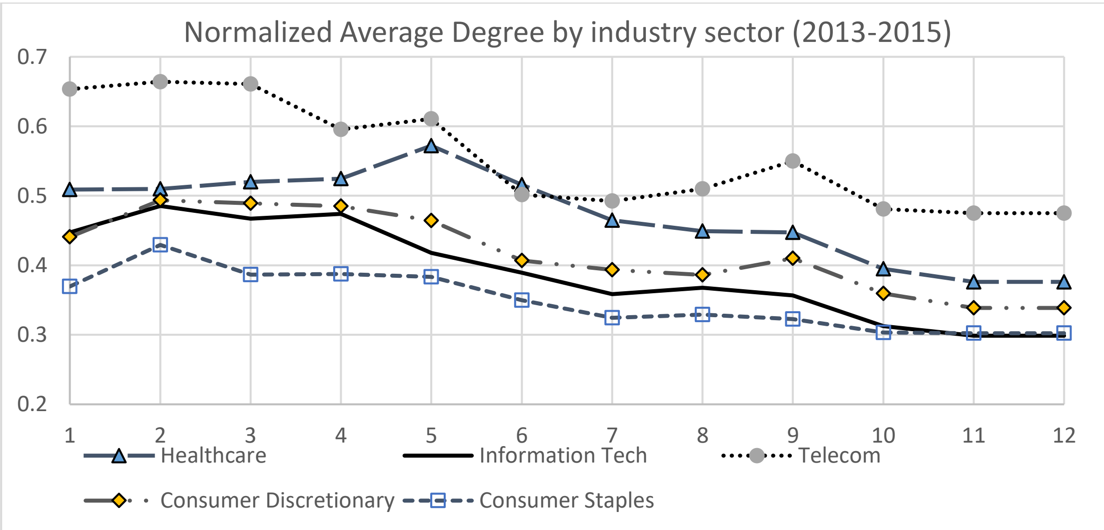


Figure 4 Normalized average degree by industry sector shown from Q1 of 2013 until Q4 of 2015

Figure 4 shows a selection of industry sectors (**Table 1**) where the normalized average degree is decreasing during the time period of observations. While the normalized average degree is decreasing, the rate of this decrease varies by industry sector. For example, the normalized average degree in the telecommunications industry experiences a larger drop than consumer staples. In terms of relative change, telecom has the highest change in average degree, followed by healthcare, consumer discretionary, information technology and consumer staples. One can conclude that the network structure in the telecommunications industry is less stable than information technology or consumer staples.

Table 5 Association between power law exponent and firm performance

Dependent Variable	Tobin's Q		ROA	
	(1)	(2)	(3)	(4)
Power Law Exponent	1.971*	0.528	1.740	0.750
	(1.011)	(0.725)	(1.306)	(1.052)
Ln(sales)		-1.122		-2.982*
		(1.175)		(1.617)
[Ln(sales)]^2		0.051		0.162*
		(0.063)		(0.089)
Leverage		-4.968***		-7.874***
		(1.201)		(1.478)
R&D/TA		8.264		10.596
		(16.010)		(16.716)
Missing R&D		0.430		0.224
		(0.327)		(0.338)
Capital expenditure		3.350		-3.396
		(3.367)		(7.751)
Hard assets		0.086		-0.694
		(0.743)		(0.926)
Quarter fixed effect	No	Yes	No	Yes
Observations	417	402	417	402
R-squared	0.056	0.408	0.019	0.386

This table examines the relation between Power Law Exponent and firm performance. The dependent variable is Tobin's Q for columns (1)-(2) and Return on Assets for columns (3)-(4). All variables are winsorized at 1% and 99%. See **Table 2** for variable definitions. Standard errors are in parentheses. The standard errors are double clustered at quarter and firm levels; *** p<0.01, ** p<0.05, * p<0.1.

Table 6a Regression analysis between average degree (tier 1) and supply network performance

Dependent Variable	Tobin's Q		ROA	
	(1)	(2)	(3)	(4)
Tier 1 Average Degree	-18.620***	-15.342*	-22.498***	-19.645**
	(6.610)	(8.081)	(6.871)	(7.735)
Ln(sales)		-0.478		-2.148*
		(0.902)		(1.166)
[Ln(sales)]^2		0.027		0.130*
		(0.051)		(0.069)
Leverage		-4.278***		-7.009***
		(1.227)		(1.392)
R&D/TA		-0.322		-0.387
		(16.764)		(17.291)
Missing R&D		0.183		-0.089
		(0.360)		(0.366)
Capital expenditure		1.194		-6.193
		(3.110)		(7.016)
Hard assets		-0.000		-0.795
		(0.698)		(0.897)
Quarter fixed effect	No	Yes	No	Yes
Observations	417	402	417	402
R-squared	0.190	0.461	0.122	0.421

This table examines the relation between Tier 1 Average Degree and firm performance. The dependent variable is Tobin's Q for columns (1)-(2) and Return on Assets for columns (3)-(4). All variables are winsorized at 1% and 99%. See **Table 2** for variable definitions. Standard errors are in parentheses. The standard errors are double clustered at quarter and firm levels; *** p<0.01, ** p<0.05, * p<0.1.

Table 6b Regression analysis between average degree (Tier 2) and supply network performance

Dependent Variable	Tobin's Q		ROA	
	(1)	(2)	(3)	(4)
Tier 2 Average Degree	-1.390**	-0.843***	-1.391**	-1.140**
	(0.537)	(0.285)	(0.563)	(0.545)
Ln(sales)		-1.234		-3.129*
		(1.169)		(1.593)
[Ln(sales)]^2		0.063		0.178**
		(0.063)		(0.088)
Leverage		-4.640***		-7.439***
		(1.107)		(1.368)
R&D/TA		6.926		8.791
		(15.288)		(15.627)
Missing R&D		0.363		0.135
		(0.314)		(0.322)
Capital expenditure		3.313		-3.463
		(3.383)		(7.806)
Hard assets		-0.088		-0.925
		(0.681)		(0.856)
Quarter fixed effect	No	Yes	No	Yes
Observations	417	402	417	402
R-squared	0.137	0.434	0.060	0.405

This table examines the relation between Tier 2 Average Degree and firm performance. The dependent variable is Tobin's Q for columns (1)-(2) and Return on Assets for columns (3)-(4). All variables are winsorized at 1% and 99%. See **Table 2** for variable definitions. Standard errors are in parentheses. The standard errors are double clustered at quarter and firm levels; *** p<0.01, ** p<0.05, * p<0.1.

Table 6c Regression analysis between average degree (Tier 3) and supply network performance

Dependent Variable	Tobin's Q		ROA	
	(1)	(2)	(3)	(4)
Tier 3 Average Degree	-0.599**	-0.369**	-0.790***	-0.826***
	(0.246)	(0.160)	(0.252)	(0.274)
Ln(sales)		-1.425		-3.718**
		(1.154)		(1.534)
[Ln(sales)]^2		0.074		0.218**
		(0.062)		(0.086)
Leverage		-4.505***		-6.731***
		(1.108)		(1.326)
R&D/TA		6.357		6.259
		(15.368)		(13.371)
Missing R&D		0.359		0.041
		(0.315)		(0.303)
Capital expenditure		3.304		-3.290
		(3.320)		(7.616)
Hard assets		-0.110		-1.189
		(0.669)		(0.785)
Quarter fixed effect	No	Yes	No	Yes
Observations	417	402	417	402
R-squared	0.133	0.427	0.102	0.429

This table examines the relation between Tier 3 Average Degree and firm performance. The dependent variable is Tobin's Q for columns (1)-(2) and Return on Assets for columns (3)-(4). All variables are winsorized at 1% and 99%. See **Table 2** for variable definitions. Standard errors are in parentheses. The standard errors are double clustered at quarter and firm levels; *** p<0.01, ** p<0.05, * p<0.1.

Table 6d Regression analysis between average degree (Tier 4) and supply network performance

Dependent Variable	Tobin's Q		ROA	
	(1)	(2)	(3)	(4)
Tier 4 Average Degree	-0.343***	-0.263**	-0.416***	-0.532***
	(0.130)	(0.109)	(0.136)	(0.166)
Ln(sales)		-1.698		-4.192***
		(1.054)		(1.451)
[Ln(sales)]^2		0.092		0.248***
		(0.056)		(0.082)
Leverage		-4.281***		-6.406***
		(1.111)		(1.356)
R&D/TA		7.030		8.047
		(15.087)		(13.140)
Missing R&D		0.335		0.014
		(0.308)		(0.282)
Capital expenditure		2.896		-4.159
		(3.277)		(7.465)
Hard assets		-0.175		-1.266*
		(0.654)		(0.740)
Quarter fixed effect	No	Yes	No	Yes
Observations	417	402	417	402
R-squared	0.152	0.439	0.098	0.440

This table examines the relation between Tier 4 Average Degree and firm performance. The dependent variable is Tobin's Q for columns (1)-(2) and Return on Assets for columns (3)-(4). All variables are winsorized at 1% and 99%. See **Table 2** for variable definitions. Standard errors are in parentheses. The standard errors are double clustered at quarter and firm levels; *** p<0.01, ** p<0.05, * p<0.1.

5. CONCLUSIONS AND FURTHER WORK

In this analysis of three years and a sample of 44 companies, we find that the most important performance related structural parameter, which exhibited significance across both financial performance measures, was the average degree (across all tiers). When we examined the network diameter, average path length and the power law exponent, we did not find consistent significance after adding the control variables. While network diameter and average path length represent how close firms are within the supply network, average degree explains the degree of connectivity in the structure. Our analysis shows that network connectivity affects financial performance more significantly than the relative distance between the firms.

We find a negative association (law of diminishing returns) between the average degree and firm performance. In other words, as the number of suppliers increases, the responsibility that a firm has increases and this effect can be observed as an increase in the average degree. The tiered average degree will also increase when the first-tier suppliers have many suppliers themselves and this effect will continue as the number of tiers increases. While increased responsibility brings on increased performance, there is a threshold beyond which the effect diminishes and starts to impact firm performance. This finding ties in with the results of Arora and Brintrup (2021) who show for a single time slice that degree centrality is negatively correlated with firm performance. This is encouraging since average degree and degree centrality are closely correlated. When a node has more connections, the result is an elevated degree centrality, which translates into a higher average degree.

Therefore, as our results suggest, in order to maintain competitiveness, the average degree in a supply network should be kept below a certain threshold. This can be achieved either, by increasing the number of nodes relative to a fixed number of edges, or, by decreasing the number of edges relative to a fixed number of nodes. In the context of the supply network, this translates into keeping the rate of firm expansion within the SCN, in line with edge expansion. The effect of average degree on financial performance is more significant at the lower tiers, that is, the effect is less noticeable as more Tiers are included in the SCN. In order to maintain a competitive edge, the focal company should strive for a simple architecture of nodes and edges, particularly at the lower tiers.

As the data collection in this study is time consuming, the sample size was limited to just over 400 observations. We have since been expanding our data collection by developing a custom data collection and analysis tool. We plan to examine the results from this paper in the light of a larger sample (ten years of data for an extended group of companies, covering the same industries). In addition, the power law exponent for the supply network, which might serve as a comprehensive indicator of financial performance, was obtained using a crude method involving statistical binning, which can sometimes introduce significant bias into the results. Using a larger sample, we will re-calculate the power law exponent using Clauset and Newman (2009), which addresses the deficiencies from the statistical binning method. We will then re-examine if the positive correlation observed between the power law and the financial metrics is indeed significant. If the significance can be confirmed, this would imply that a scale-free architecture for the supply network could lead to enhanced financial performance.

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