Supply network science: emergence of a new perspective on a classical field

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Abstract
Supply networks emerge as companies procure goods from one another to produce their own products. Due to a chronic lack of data, studies on these emergent structures have long focussed on local neighbourhoods, assuming simple, chain like structures. However studies conducted since 2001 have shown that supply chains are indeed complex networks that exhibit similar organisational patterns to other network types. In this paper, we present a critical review of theoretical and model based studies which conceptualise supply chains from a network science perspective, showing that empirical data does not always support theoretical models that were developed, and argue that different industrial settings may present different characteristics. Consequently, a need that arises is the development and reconciliation of interpretation across different supply network layers such as contractual relations, material flow, financial links, and co-patenting, as these different projections tend to remain in disciplinary siloes. Other gaps include a lack of null models that show whether observed properties are meaningful, a lack of dynamical models that can inform how layers evolve and adopt to changes, and a lack of studies that investigate how local decisions enable emergent outcomes. We conclude by asking the network science community to help bridge these gaps by engaging with this important area of research.

The aim of this article is to present an overview of research that studies emergent supply network topology using network science. While studies that characterise supply chains as complex adaptive systems date back to early 2000, large-scale empirical studies were not conducted until a decade later. It has been found that properties do not match the early hypotheses proposed, as they vary between different studies. Thus the extent to which network properties generalise remains an open question. Similarly, interpretations of node-level metrics vary between the studies, and there is a lack of reconciliation between the various link types that co-exist in supply networks. While significant progress has been made in the field, addressing these gaps will be an important step towards bringing theory to practice.

1. New tools for studying supply chains

Firms depend on each others' capabilities to deliver goods and services. As firms decide to work with one another, they create inter-firm networks of dependence, influencing properties such as the creation and spread of innovations and information (Gulati 1995; Schilling and Phelps 2007).

A supply chain is one type of an inter-firm network which forms as a set of companies that start sharing production and delivery responsibility for a finished product to be delivered to end-users (La Londe and Masters, 1994). Although the structure of supply chains has long been of great interest to the supply chain research community, studies have only focussed on what is controllable and configurable from a focal manufacturer's perspective, which constitute a small number of companies that are centred around a particular type of product model. This local perspective has been so prevalent in literature that the larger scale, emergent aspect of supply chain structure have been largely ignored until the pioneering works of Choi et al. (2001) and Pathak et al. (2007), which argued that the supply chain is a complex adaptive system, in that it emerges without a single entity controlling it, and thus CAS tools such as network science should be considered in their analysis. Although companies choose their own customers and first tier suppliers, they typically cannot control whom their suppliers choose to buy from. Researchers posited that as a result of emergence firms may share common suppliers, creating network structures rather than chains observed in CAS, thus the term supply network entered in the supply chain management literature. We use the terms supply chains and networks interchangeably in the rest of this paper. For a detailed discussion on supply networks being CAS please refer to Wycisk et al. (2008).

Further studies developed theoretical models that created plausible representations of supply networks and gathered empirical evidence (Thadakamalla et al. 2004; Hearnshaw and Wilson 2013, Brintrup et al. 2016). Both modelling and empirical work showed that the topology of the network is important both for operational performance (Kim et al. 2011) and for the network's robustness and resilience to disruptions (Nair and Vidal 2011, Kim et al. 2015, Zhao et al. 2011b, Ledwoch et al. 2018). Here, robustness is defined as a system's ability to withstand disruptions without the need to reorganise (Wieland and Wallenburg. 2012), whereas resilience is a system's ability to move to a new, more desirable state, or return to the original configuration after being disturbed (Christopher and Peck, 2004). Studies on the relationship between structure and robustness gained further tract as researchers have observed that global sourcing practices resulted in increased volatility and risk exposure (Christopher and Holweg, 2011). Cases such as the 2011 Tohoku earthquake and Thailand floods provided further evidence of emergent complexity as disruptions from unknown, small parts of the network resulted in large-multi-national firms experiencing massive delays (Basole and Bellamy 2014a, Garvey et al. 2015).

Whilst these efforts expanded our understanding of supply network topology, several challenges remain unaddressed. Most studies to date have focussed on applying textbook network science metrics and little attention has been given to their interpretation or the development of new metrics in the specific context of supply chains. Empirical work has been especially scarce, and findings seem to contradict earlier modelling efforts. While various network models have investigated firm-firm procurement relationships, the distribution of actual production responsibility on the network structure, and dynamical processes on the network have been largely ignored. Despite these shortcomings, network science has already shown significant premise in the analysis of supply networks and created much interest from the supply chain community. The early theorisations of supply chains as complex adaptive systems have been verified using empirical studies, which in turn showed several emergent patterns that impact performance, robustness and resilience of these systems. In the absence of empirical data computational models investigated how possible structures can arise, and evolve. However, most of the existing work remains in disciplinary siloes, primarily within operations management and management science. This creates a barrier to other scientific disciplines, despite the premise of network science serving as a lingua franca between disparate domains.

In this paper we provide a short review and consolidate the extant literature in this developing field, highlighting gaps that need to be addressed. While doing so, we aim to provide the multi-disciplinary communities of network science and supply chain research with a starting point to provide theoretical input to supply network modelling and analysis. Section 2 introduces supply network structures, and reviews studies to date from both macroscopic and microscopic perspectives. Section 3 highlights modelling challenges that remain to be addressed and Section 4 highlights emerging approaches in the field.

2. Lessons from network structure

2.1. What is a supply network structure?

The answer to this question often depends on the unit of analysis and on the intention of the researcher. The simplest abstraction of a supply chain views the process of production in terms of the movement of materials along a sequence or chain of interconnected firms. A classical textbook illustration of a Supply Chain (Figure 1) includes a manufacturer or an Original Equipment Manufacturer (OEM) as the focal node, its direct incoming links as "suppliers", with the final node with no outgoing links as the raw material provider. While the role of the OEM is making the final assembly, its suppliers and sub-suppliers could also be assembling several components or ingredients making the sub-systems that go into the assembly.

The node to which the manufacturer delivers is typically a warehouse or a wholesaler, and this is followed by a retailer and a customer. The chain that starts with the raw material provider and ends with the manufacturer is the "upstream" whereas the chain starting with the manufacturer ending with the customer is the "downstream".

It is important to note that supply chains show dependencies where each path needs to be traversed to make the end product, which is different from the structure of, for example, communication networks where the links typically indicate possible alternative pathways.

Figure 1 could be misleading in many ways. There could be multiples of each node type from the perspective of a manufacturer, the scale of which would be dependent on the complexity of the product being manufactured. An aerospace supplier could have thousands of tier 1 supplier nodes for a given airplane production programme while a chocolate producer would have tens of suppliers. This line of thought is indeed reflected in second, hierarchical network figure that also depicts supply chains (Figure 2), where each node is connected to multiple suppliers.

Secondly, the supply path between the raw materials and the manufacturer could be longer than one. An example in aircraft production would be 4 (Brintrup et al. 2015a), in car production would be 3 (Kito et al. 2014), in retail and food industry the supply network has been reconstructed up to 3rd tier (Orenstein et al. 2016). The term "Tier" is used to refer to the shortest path between the upstream nodes and the focal node, i.e. the manufacturer (Figure 2). Hence a Tier 1 supplier would be one that is one link away from the manufacturer, even if it delivers to other Tier 1 suppliers. Although, both Figures 1 and 2 assume a chain structure with no inter-tier connections, recent empirical studies have found inter-tier relationships to be prevalent in complex supply networks leading to a higher clustering coefficient than we would expect to randomly occur i.e. in an ER network of the same size (Choi et al. 2001, Borgatti and Li 2009, Lomi and Pattison 2006).

Thirdly, these depictions are drawn with a retail chain in mind where a product such as a jar of jam would be produced, delivered to a supermarket and sold to a customer. However, several businesses do not operate using a retailer and face customers directly. Moreover, distributor nodes are actually transition nodes where production does not take place, but deliveries are sorted and transported. Distributors, warehousing companies or logistic providers may exist between any of the nodes in the chain.

Finally, the scale and complexity of structure tend to be underestimated. It is worthwhile to note that from approximately 15,000-20,000 components that make up a car, the majority is outsourced (Sako 2004); whereas from millions of components that go into an airplane, 80% are outsourced, however studies tend to focus on tens of nodes rather than the thousands.

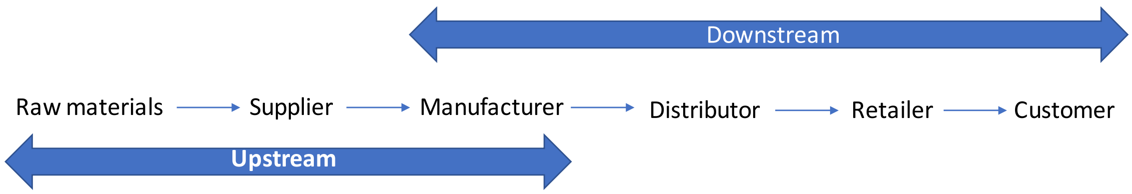

Figure 1. Linear supply chain

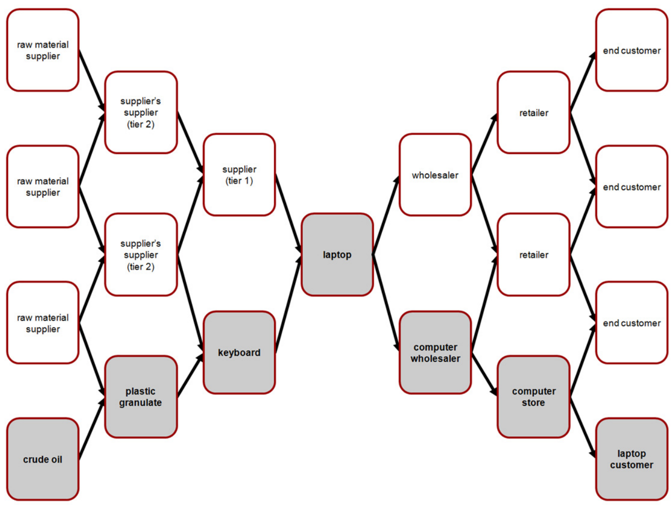

Figure 2. A supply chain with multiple nodes at each tier

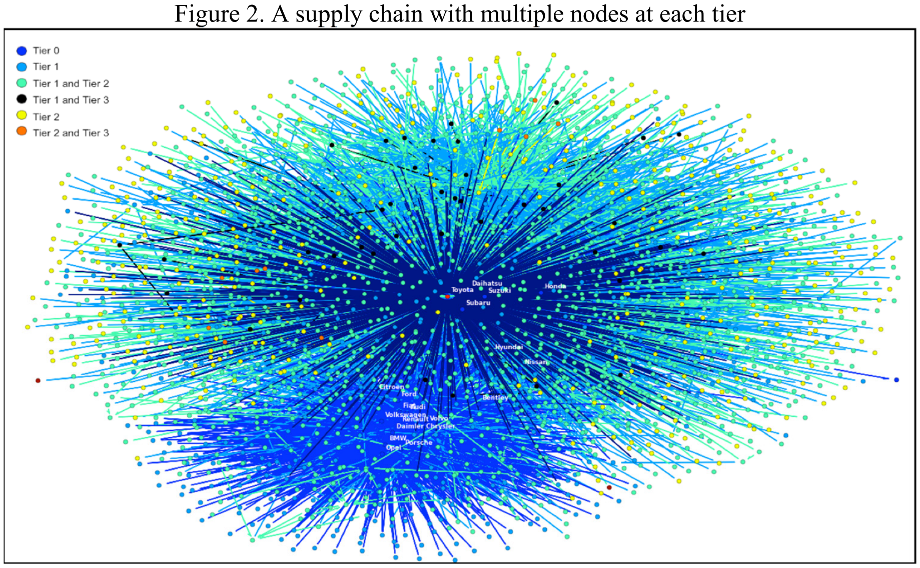

Figure 3. The global automotive industry.

Figures 1 and 2 view the network from a focal company perspective (the Manufacturer in Fig.1 and the Laptop producer in Fig. 2). It is worthwhile to note that manufacturers could share several suppliers upstream as well as supplying to overlapping downstream nodes, creating an industrial ecosystem perspective (Figure 3). The extent to which overlaps occur is an interesting question that is yet to be explored, however studies in the automotive sector have found that supplier sharing is common (Nobeoka 2002), leading to the interim lesson that the industry level supply relationships could show increasingly dense network structures (Kito et al 2014, Brintrup et al 2015a, Brintrup et al 2016). .

The academic domain of supply chain management is vast and interdisciplinary, and often includes disconnected perspectives from economics, engineering, social science domains. Although the above depictions primarily focus on the flow of production represented by directed links, several other types of links may co-exist. Companies might have shares in each other to exert control over the network, creating a financial link. Patents can be co-created for product design. Supply relationships can often co-exist with equity and technology transfer connections (Lomi and Pattison, 2006). Contractual links might be separate from actual flow of goods as the focal company might be contracting a supplier which then organises production and delivery from an alternative node (Kim et al. 2011).

It is, however, surprising that until the start of 2000s the topologies of these networks were largely omitted. One of the reasons behind this is a lack of data which in turn is due to confidentiality. Suppliers have an incentive not to disclose their own supply network to their customers, as they run the risk of being cut out as the middleman, losing bargaining power or inadvertently disclosing production sources to their competitors. Moreover, the OEM would not be able to validate data provided by the supplier. Hence, contractually forcing firms to disclose the identity of their suppliers tends to be unsuccessful. The OEM itself would not want to share network data as the network is seen as a distinct competitive advantage. There exist third party companies that provide supply network data collection service through surveys, however these tend to be outdated and unverifiable.

Another reason for the lack of studies is cultural. In a domain where majority of studies naturally focus on supply chain optimisation and configuration, the emergence of structure creates a cultural challenge - what can be done about it? When we move from dyadic connections along chains to the industrial ecosystem perspective, scale and computational complexity increases, making modelling efforts increasingly hard. Researchers thus overwhelmingly focus on small scale, controllable aspects of the network to optimise the flow of goods for local variables such as cost, resilience and throughput ignoring the larger network effect, or at best modelling it as noise.

The dynamic nature of the network poses another challenge with companies switching frequently between alternative suppliers, being acquired or spun off as separate business entities, letting go off old products and producing new ones (Wycisk et al., 2008). It is thus noteworthy that supply chain structures in literature typically only show a cross-sectional reality in time.

Given the multiple types of nodes, links and a dynamic nature, studying the topology of the network thus necessitates simplification, which often occurs by focusing on specific parts of the network such as downstream or upstream, the focal firm network or the industry network, and projecting the network onto homogeneous types of nodes and links.

We review these studies next.

2.2. Macroscopic structure

Studies of complex systems using network theory has shown that very different systems often share common organisational principles that impact their function and performance at the macroscopic scale, and that these principles can be quantitatively measured measured and generalised. Hence, although the microscopic principles of formation and purpose of an ecological network are vastly different than supply networks, structurally they may share similar characteristics. Here we use the term macroscopic to refer to the emergent properties of the network that are observable at large scale.

One of these quantitative measures, namely, degree distribution, has been widely studied in supply networks (Thadakamalla 2004, Zhao et al. 2011b, Nair and Vidal, 2011). Degree distribution refers to the frequency of the number of neighbours that nodes have, which has been linked to the robustness of a network to random and high-degree node disruptions (Watts 2002, Barabasi 2009).

After Choi et al. (2001), Surana et al. (2005) and Pathak et al. (2007) conceptualised supply chains as complex networks, initial used simulation and modelling studies focused on topology, where it has been observed that hierarchically distributed supply network models emerged as a scale-free network (Gafiychuk, 2000). A theoretical supply network is commonly constructed through network generation model, which can be defined as a set of rules that specify how the network grows. One example of a network generation model is preferential attachment, where a new node connects to existing ones with a probability proportional to number of their connections. Thadakamalla (2004), and later on Zhao et al. (2011a, 2011b), Wang et al. (2015), and Sun et al. (2017) constructed growth models for the generation of supply networks and observed the emergence of networks with a scale-free property; Suo et al. (2018) have observed emergence of shifted power-law. These models generally proposed that the scale-free property in a supply network would make the system robust to random failures and vulnerable to hub failures. More recently, Mari et al. (2015) proposed a model to design a resilient supply network structure where resilience was proxied by features usually associated with scale-free networks

(Barabasi and Albert 1999) these include: low supply path length, high clustering coefficient and high closeness centralities (compared to random networks). They created a similar model observing a scale-free property. Hernandez and Pedroza (2017) argued that while the scale-free model is robust, it does not result in the most agile network, where agility was proxied by fill rate i.e.the rate with which the network can satisfy customer demand.

These modelling efforts are valuable as they create plausible representations of supply networks and allow for a systematic comparison of different performance indicators such as resilience across different structural patterns, contributing to theoretical argument of how supply networks 'should be' constructed (Kogut 2000; Kim et al. 2015).

However, many properties of these theoretically constructed models were not evident in the empirical works that followed. Choi and Hong (2002) mapped of part of the Honda, Acura, Daimler Chrysler, which consisted of 70 members. Lomi and Pattison (2006) analysed the Fiat Panda network which included 106 automotive firms in Italy, and (Keqiang et al. 2008) examined the buyer-supplier networks in the Guangzhou automotive industry, consisting of 84 firms. Kim et al. (2011) and Lomi and Pattison (2006) stressed that suppliers are likely to have multiple intra and inter tier relations, as well as different types of links, such as equity transfers and production links. Several suggested that the supply network was "scale-free", meaning that suppliers attached to other suppliers with a probability based on a node's existing number of links, resulting in a hub-based structure (Gafiychuk et al. 2000, Thadakamalla et al. 2004, Nair and Vidal, 2011, Hearnshaw and Wilson 2013).

The observations however, were not verifiable as conclusions on the scale-free property are dependent on large sample sizes.

There are very few studies that explored supply networks with more than 1000 firms. Brintrup et al. (2011) and then Kito et al. (2014), showed that Toyota network's in-degree and out-degree follow log-normal and stretched exponential distributions. In fact, both authors highlighted that the empirical networks were not scale free, using a maximum likelihood test (Clauset et al. 2009) to fit a range of possible heavy-tailed distributions including power law, power law with exponential cut-off, exponential, stretched exponential, and log-normal. Both power laws and power laws with exponential cut-offs were rejected as appropriate descriptions of the data, and the best fits to the data were provided by a log-normal distribution and a stretched exponential distribution for the in- and out-degree distributions, respectively. These distributions mean that the network has hubs, but those hubs are not growing infinitely. Atalay et al. (2011) studied buyer supplier relations in the US economy, suggesting that the fat tail of the scale free model overestimates both the connectivity of the economy's most central nodes, and the number of minimally connected firms. Atalay et al. (2011) then created a network generation model that takes into account firm death, reviring of already existing connections and birth of new firms, and used a combination of preferential and random attachment to create a fit to the empirical network.

A follow up study on the global automotive industry consisted of 18,000 supplier nodes, also rejected the scale-free hypothesis (Brintrup et al. 2016). Orenstein et al. (2016) used large-scale data from the Bloomberg database to examine supply relationships between publicly listed companies in the Lowes, Nike and Home Depot networks. Although a maximum likelihood method was not used, the authors have observed evidence of power law noting a straight line on a log-log scale. The authors further noted that the power law exponent increased with the depth of the network, potentially pointing to a limit on growth and expansion.

Recently, Perera et al. (2016) also disputed the existence of a scale free topology in supply networks, observing that the community structures and assortativity/dissassortativity observed in empirical data do not correspond with the scale-free model as it has been analytically shown by Newman (2002) and Newman (2003).

As Borgatti and Li (2009) warn in their paper, transferring concepts from network science to supply networks is not straightforward and needs understanding from both sides. The debate on scale free degree distribution is a case in point. In the arguments that led to the scale free hypothesis in supply networks, the term scale free is used to refer to the existence of "hubs-firms" with large numbers of connections, and many firms connecting to these hubs (Kim et al. 2011, Hearnshaw and Wilson 2013). However, in network science literature there are quite a number of quantities with highly right-skewed distributions that nonetheless do not obey power laws such as log-normal distribution or stretched exponentials, or a power-law with a cut off (Newman 2005).

In fact, the lack of agreement on the scale of supply networks is not a surprising revelation when we think about the dynamics at work that may influence a node's decision to connect to another. Firstly, preferential attachment, one of several dynamics that can result in a scale free distribution, might not be valid in supply networks, although it has been used as an argument to support the scale free hypothesis. A supplier with multiple links might not be attractive to a manufacturer who needs dedicated service. Several classical studies refer to the transaction cost of starting and sustaining supplier relationships, and a firm's constraints to engage in multiple relationships at once (Williamson 1981). Often, suppliers will need to create dedicated product lines and invest in equipment to be able to produce material specific to the customer, and will need to reorganise their own supply network structures. However, too much customer specific investment is risky if the relationship does not last long creating, trade off effects.

On the other hand, these arguments are specific to tiers that are closer to the OEM, and standardisation and commoditisation occur at the periphery of the network creating market like dynamics (Williamson 1975). For example, in the automotive industry, modular product architectures led to increased competition between suppliers and reduced entry barriers, hinting to higher likelihood of connections for some product categories.

It is also worth noting that some of the studies mentioned above have considered industrial level networks i.e. ecosystems of multiple OEMs (e.g. Brintrup et al 2016), while most others have considered networks of a single, focal OEM node (e.g. Lomi and Pattison 2006, Keqiang et al 2008, Kim et al 2011, Brintrup et al 2011, Kito et al 2014, Orenstein 2016). Hence studying the extent to which ecosystem and focal node networks differ in terms of their scaling could be beneficial.

Moreover, it has been observed that the industry sector also impacts the degree distribution. Theoretical works hypothesised a small world effect, which has been confirmed by data from the automotive sector (Kito et al. 2014), however not by the aerospace industry (Brintrup et al. 2015a). Additionally, aerospace supply networks show less dense structures than automotive. The reason for this difference might be due the product modularity and standardisation. Aerospace production is characterised by low volume and high customization, leading to specialist suppliers with few alternatives. Moreover, high customization results in high entry barriers which explains less dense network structures. In the automotive sector, supplier switch-over and multi-sourcing are more common place, which may explain higher density of connections.

Currently, the degree distribution has not been generalised for supply networks, in the context of the industry sector. Thus, an interesting area worth future investigation is the relationship of product specific dynamics and emerging macroscopic patterns across different industries.

Simply the size of the supplier network is treated as another dimension of supply network complexity. Maintaining numerous supplier relationships has been reported to have negative effects on the focal company. For example, Bode and Wagner (2015) has found that the number of suppliers amplify the frequency of disruptions. Terpend and Ashenbaum (2012) noted that expanding supply network results in weakened individual buyer–supplier ties and exacerbates the negative effects of buyer's coercive tactics on the suppliers. Adenso-Diaz et al. (2012) linked complex supply base with reduced reliability. Choi and Krause (2006) posited that reducing number of suppliers decreases transaction costs, and increase supplier responsiveness. Thus, many scholars encourage supply chain practitioners to simplify their supply networks On the other hand, Terpend and Ashenbaum (2012) also posited that, expanding the size of a supplier network yields risk-reducing benefits for the buyer and a smaller supply network allows a buyer to leverage its power. Most of the studies is however only on the first-tier suppliers, and rarely consider other structural properties.

Kito et al. (2014) used community detection algorithm developed by Leicht and Newman (2008) to detect modularity in the Toyota network and then applied functional cartography (Guimerà and Amaral 2005) to identify the role of different nodes within each module. They found that modules were heterogeneous in their structure, with centralised sub-networks in modules that produced parts specific to the automotive industry, while parts used across different industries such as electronics displayed more decentralised networks with a higher clustering coefficient. Similarly, Brintrup et al. (2015a) found that community structures were not a simple reflection of product architecture but both product structure and geolocation of suppliers played a role in the formation of communities.

Brintrup et al. (2015a) found that the Airbus supply network is assortative as high-degree nodes have a tendency to connect to other high-degree nodes. They argued that this could be an artefact of a bill of materials flow. Firms with high numbers of links could be leading their communities in certain areas of production and then connect to other high-degree firms doing the same thing, creating subassemblies that are passed on downstream. Assortativity means that large-degree connector firms play a cohesive role in stabilising the network, but also that disruptions at high degrees can quickly cascade to other high-degree nodes. Further studies on the existence of assortativity in different industries might be revealing from a network robustness perspective.

The above studies examined directed (material flow) and undirected (contractual) supplier-buyer networks; representing them in the form of a single type of node – a firm. Few studies investigated structural relationships between multiple node types. An exception is the work of Saavedra et al. (2009) on the two-tier supplier-manufacturer contractual network in the New York Garment Industry (NYGI), which was inspired by studies on plant–animal mutualistic networks. Here, a link between suppliers and manufacturers would indicate a joint production. The authors created a generalised model for the formation of pollination networks where a nested pattern of interaction has emerged, similar to the NYGI network. The authors argued that complementarity in node characteristics, a hierarchical organisation that limits the number of potential partners and the environmental context create common cooperative mechanisms underpinning both ecological and socioeconomic systems.

This work was later extended by Brintrup et al. (2015b) where two types of nested bipartite networks in supply chains were found. First of these was the supplier-manufacturer network, and the second one was suppliers and products they produce. The authors explained that nestedness occurs when suppliers produce proper subsets of what other suppliers produce, and rare products are produced only by those suppliers that already produce high numbers of product types. Similarly, the manufacturers that procure from few suppliers procure from those that supply to most other manufacturers in the network. Suppliers that supply to few supply only to those manufacturers that procure from most others.

The significance of a nested structure is its robustness, since it has been found out that despite suppliers failing, nested topologies maintain a connectivity on a minimum level that still enables supply network to function (Saavedra et al., 2008). However, nestedness has a caveat. If a supplier that fails is a well-connected supplier offering a wide range of products, the risk of a large-scale failure occurs (Sugihara and Ye, 2009). Moreover, small suppliers face more competition as their production can be redundant. These findings are contrary to conventional supply chain wisdom that large integrator firms focus on economies of scale and small specialist firms focus on specialisation (Brintrup et al., 2015b).

The above studies showcase the significance of supply network topology in relation to network performance, robustness, and resilience, hinting also at the potential value of observing additional node and link types in supply networks.

2.3. Microscopic structure

Several authors proposed using microscopic network metrics to identify firms occupying special positions in a supply network. The term microscopic here refers to those metrics that characterise an individual node's position in the network. Microscopic metrics have multiple interpretations in various domains where network science has been used, such as power, exposure to risk, span of control and level of autonomy (Borgatti and Everett 2006). The role of network embeddedness (Choi and Kim, 2008) and triadic network relationships were among the first investigations under this topic (Choi and Wu 2009a, Choi and Wu 2009b). The most common microscopic metrics include: degree centrality, betweenness centrality, eigenvector centrality, authority and hub centralities, and closeness centrality. For their definitions and interpretations, please see Borgatti (2005), Newman (2010), and Kim et al. (2011).

Borgatti and Li (2009) interpreted how various common centrality metrics could be used in a buyer-supplier network context. Kim et al. (2011) further interpreted some of these metrics, differentiating between directed material flow and undirected contractual relationship networks of firms. In materials flow, they relate betweenness centrality to operational criticality, in-degree centrality to supply load, and out-degree to demand load, where the term load refers to the supply/demand volume. In the contractual network, they relate degree centrality to the scope of strategic influence a firm can have over the network, closeness to its ability to control the flow of information, and betweenness centrality to mediative power a firm can have over the interactions of firms. Basole and Bellamy (2014a) and Borgatti and Li (2009) characterised betweenness centrality as an indicator of high control over interactions in the network.

The characterisation developed by Kim et al. (2011) has since been used to explore other possible interpretations of centrality metrics. Bezuidenhout et al. (2012) and Mizgier et al. (2013) used degree, betweenness and radiality centralities for bottleneck identification. Ledwoch et al. (2016) investigated how centrality metrics could be used to identify risk, where Katz centrality was proposed to measure a supplier's risk of spreading disruptions, and authority and hub centralities were applied to measure the risk of a link failure using distances between geographical locations. Closeness centrality was used to measure speed of disruption spread. They deploy these concepts in the Honda Acura network structure first examined by Choi and Hong (2002), and find that centrality measures enriched with historical data could reliably be used to identify geolocation risk.

More recently, Yan et al. (2015) created a nexus supplier metric. A nexus supplier is a critical supplier due to its position in the network and may have significant impact on focal firm's performance. Three types of nexus in three different network types have been proposed: (1) an operational nexus supplier in a material flow network which is characterised by high degree, betweenness and eigenvector centrality, (2) a monopolistic nexus supplier in the extended industrial ecosystem with high betweenness centrality, and (3) an informational nexus supplier in the ego network of the manufacturer with highly diverse connections. While the operational nexus impacts the day to day running of the network, the monopolistic nexus is not easily substitutable and the informational nexus has more strategic access to information.

Joint venture formation in supply networks has been another strand of research. Carnovale and Yeniyurt (2015a) investigated supply networks from a joint venture perspective, where nodes are firms in an industrial network and links are equity relations between them. By sampling the Thomson Financial SDC Platinum database, they capture supply relations in automotive industry in a form of a directed binary relationship. They found a diminishing returns effect between degree centrality and firm performance, concluding that having too many joint venture partners can negatively impact a firm's financial performance measured by return on assets, investments, equity and sales revenue. They also calculate "remoteness centrality" by taking the inverse of closeness centrality. They find that a firm's remoteness has a detrimental effect on return on equity, implying that firms that have limited access to supply chain partnerships also have difficulty in accessing the extended supply chain network to leverage their equity. In a further study on the same network Carnovale and Yeniyurt (2015b) identify the relationship between a firm's betweenness centrality, the density and the number of weak components in the firm's ego network (Scott and Carrington, 2011), and the firm's brokerage measure (Gould and Fernandez, 1989). They find that the number of weak components is positively related to a firm's innovative capability, while brokerage and density of the ego network are inversely related, and betwenness centrality has no effect. They conclude that "it is not just how well a firm individually innovates, but also how well the firm can leverage its supply network connections for innovation". Carnovale and Yeniyurt (2017) also investigated the role that microscopic network structure plays in new equity based joint venture formations. They have found that eigenvector and closeness centrality of the focal firm has a positive effect on the likelihood of initiating a new manufacturing joint venture.

The relationship between firm's performance and supply network structure is still an emerging field. Basole (2016) has observed that high-performing supply networks are characterised with high average degree, high average betweenness centrality, and high average closeness centrality. However, Kao et al. (2017) note the difficulty of devising a measure to understand firm performance in the context of complex economies. Ecosystem level networks include manufacturing firms, retail chains, utility companies and others, and the definition of performance can vary widely among them, making selection of a single performance measure problematic. They propose calculating the mean productive efficiency of a firm's in a network using data envelopment analysis, in which the outputs from one node become the inputs to the subsequent node. Kao et al. (2017) use this method to estimate efficiencies of firms embedded in the network. They show that a firm's high betweenness centrality is linked to increased efficiency while its closeness centrality has the opposite effect. The authors raise the issue that supply network researchers have followed sociologists in focusing on small scale structures. However, fields such as biology, computer science and physics have shifted focus from the node-level social capital framework to large scale network structures (Borgatti et al. 2009). Such a 'non-social' system level lens is valuable in explaining operational reasons behind the way networks form and evolve.

Kao et al. (2017) indeed raise an important point. The earlier works on supply network structure used "Social Network Analysis" and have mostly been from a strategic management lens. The day to day material flow on supply networks would need an operational lens. While structure affects both, studies on these viewpoints tend to be disjointed, with the exception of rare studies that view them holistically such as that of Yan et al. (2015). There needs to be a unification of the various types of networks that characterise the inter-disciplinary domain of supply chains, and what microscopic and macroscopic measures mean in different contexts, and across both day-to-day operational and strategic time horizons.

In addition, it appears that many studies to date blindly apply network topological measures without much attention to their correlation. Network science has a wealth of topological measurements, and they are often correlated, implying redundancy (Costa et al. 2007). Costa et al. (2007) suggest that decorrelation approaches such as principal component analysis could help identify the most significant effects, but ultimately, one has to rely on her/his knowledge of the context and available measurements in order to select a suitable set of features to be considered. The extent to which centrality measures provide unique information is an open question in supply network analysis.

We review some of the missing ingredients in the study of supply network topology next.

3. Missing ingredients

3.1 Connecting the dots: Reconciling inter-disciplinary supply network projections

While research in supply network topology has grown steadily over the last ten years, the field is still in its infancy. Further studies need to be carried out on the emergence of macroscopic structures in different industrial settings and across different product layers. One issue to tackle here is the definition of boundaries of analysis. While some empirical works have studied triads as the smallest possible network structure on supply networks (Choi and Wu 2009a), others explored ego-networks of individual OEM's and deduced lessons from structure (Kim et al. 2011). Further studies investigated ecosystems of several cross-cutting industries (Atalay 2011, Brintrup et al. 2015).

Another source of disjoint is the multidisciplinary nature of supply network studies. Research has shown structure to have significant effects on operation, resilience, and innovatio, but, studies are confined to disciplinary siloes. For example, Wichmann et al. (2017a) largely focus on the analysis of supply network structure from a social network lens despite the prevalence of works that have focussed on the influence of structure on supply network operational variables reviewed in Perera et al. (2016).

Table 1 shows the various projections of supply network structures that have thus far been studied. While firm-firm networks have received the most attention at both macroscopic and microscopic perspectives, other areas have received much less attention and focussed on the microscopic perspective.

Table 1. Summary of supply network types

Node type	**Link type**	**Direction**	**Reference**	**Microscopic/ Macroscopic**

Firm-Product	Produces	Undirected	Brintrup 2015b	Macroscopic
Firm- Firm	Co-produces	Undirected	Saavedra et al 2008 Saavedra et al 2009	Macroscopic
Firm- Firm	Buys from/sells to	Directed	Thadakamalla et al. 2004 Lomi and Pattison 2006 Keqiang 2008 Zhao et al. 2011a, 2011b Brintrup et al. 2011, 2015a, 2016 Atalay et al. 2011 Terpend and Ashenbaum 2012 Kito et al. 2014 Mari et al. 2015 Orenstein et al. 2016 Hernandez and Pedroza 2017 Perera et al. 2017	Macroscopic
			Dong 2006 Kim et al. 2011 Bezuidenhout et al. 2012 Mizgier et al. 2013 Yan et al. 2015 Kao et al. 2017 Ledwoch et al. 2018	Microscopic
Firm- Firm	Co-patents	Undirected	Choi and Krause 2006 Schilling and Phelps 2007 Azedegan 2011 Bellamy et al. 2014 Carnovale and Yeniyurt 2015b	Microscopic
Firm- Firm	Owns/has financial equity	Undirected	Lomi and Pattison 2006 Carnovale and Yeniyurt 2015a Carnovale and Yeniyurt 2017	Microscopic
Firm- Firm	Competes with	Undirected	Brintrup 2015b	Macroscopic
Firm- Firm	Delivers	Directed	Choi and Wu 2009a, 2009b Kim et al. 2011	Microscopic

Unifying the various projections of supply networks is not an easy task. Development of structured frameworks for analysis will need inter-disciplinary communication and consensus. An analytical source of inspiration might come from the relatively recent field of Multiplex networks, which gained attention as a result of limitations posed by analysing multiple link types in isolation (for a detailed review please see Boccaletti et al., 2014). In multiplex networks each type of interaction is represented on a single layer and connections between layers are formulated. Multiplexity refers to the existence of more than one type of link between two network entities whose interplay can impact the structure and function of the network. Transportation networks are a typical example. Between two types of locations in a city multiple modes of transport such as tube or bus connections might exist, and disruptions on one layer of the network result in passenger flow transfer to another. De Domenico et al. (2016) notes that multiplex networks exhibit interesting properties as opposed to single-layered networks. They state that multiplex networks are more resilient to random failures than their individual layers, however they can induce congestion even if the individual layer is not congested. In supply networks multiple layers might exist in the form of material flow, contractual and financial links. Lomi and Pattison (2006) show an empirical evidence that indeed interorganizational networks extend across multiple layers. Questions on the impact of a layer's structure on the formation and disturbance of another layer would be a logical next step in supply network research.

3.2 The role of products

A neglected element of supply network studies is the product perspective. Supply chains form and function in order to procure components that make up an end product. Components are heterogeneously distributed across the suppliers. In other words, a component might be supplied by many suppliers, and a supplier could be supplying many different components. Consider a simple production chain of yarn to fabric to car seat to car. In this chain production could be divided across companies in multiple ways. A buyer might buy fabric to produce car seats, which it then sells to a car producer. Alternatively the car producer could buy the fabric and produce car seats, without outsourcing this activity to an intermediary supplier. The disruption of a company in these alternative chains may result in the loss of different numbers of products, impacting the network differently. A company might also produce multiple products resulting in it being positioned across multiple pathways of dependencies.

Only considering on the topology of firm-firm connections might be misleading in the analysis of disruptions. For example eigenvector centrality has been proposed as a means of identifying risky lower tier suppliers that the network depends on (Yan et al. 2015), but empirical studies have suggested a "diamond shape" for at least some supply networks (Kito et al. 2015). The diamond shape implies consolidation of links across a fewer number of suppliers at the raw material tier, compared to tiers closer to the OEM. Eigenvector centrality measures the importance of each node by the centrality of nodes it is directly or indirectly connected to. As raw material tiers are relatively few source nodes connecting the rest of the chain, this measure might not be as informative or struggle to differentiate between suppliers. What would be important in differentiating is the types of products suppliers produce and whether those products could be procured from elsewhere. When we look at historical supply network disruption events that motivated the study of topology, we see products playing a central role. A recent high profile example is the disruption of a little known paint pigment supplier Merck in Japan caused several OEMs to halt production by up to 20% after the 2011 Tohuku earthquake, as no alternatives could be found (Carvalho et al. 2016).

Taking redundant product distribution into consideration could also give some hints regarding competition in the network as suppliers with overlapping product portfolios provide both robustness to the network's function while competing at the same time (Brintrup et al. 2015b). Hence analysing how production is distributed over the supply network would help us gain a more thorough understanding of the criticality of a company, and how to develop more fine-grained disruption scenarios that focus on more frequent disruptions impacting individual product lines rather than the rare disruptions halting entire production in a company.

3.3 Understanding the dynamics of supply networks

The field of supply chains has a long history of dynamical modelling at the local scale (e.g. see Angerhofer et al. 2000, Min et al. 2002, Sarimveis et al. 2008 for reviews). Models are built to examine how node-level variables such as production rates, buffers and buffer placement, failures, demand and supply uncertainty effect output and optimise production accordingly. However, as Singhal and Singhal (2012) state, supply chains are inherently complex and its dynamics can be understood only when the system is considered as a whole.

The first category of studies relate to how a supply network forms and evolves. Few studies on supplier-buyer networks include Thadakamalla et al. (2004), Atalay (2011), Mari et al. (2015) and Hernandez and Pedroza (2017) and supplier-product networks include Brintrup et al. (2015b). Pathak et al. (2007) argued that supply networks continuously evolve over time, and are far from being static and centralised. More research could be pursued to understand how network formation occurs at different tier levels by modifying microscopic interaction rules. An interesting question is the relationship between optimisation at the local scale and emergence at the global scale. Further studies need to be conducted on whether these to mechanisms have contradictory elements and if so, how trade offs are achieved.

Other studies focussed on the simulation of risk diffusion on supplier-buyer networks. For example Basole and Bellamy (2014a) modified the Suspected-Infected-Recovered epidemic disease spread model by Anderson and May (1992), relaxing the assumption of permanent immunity. The model has been further expanded by Basole et al. (2016). Zeng and Xiao (2014) developed a cascading failure model based on load entropy to study failure propagation patterns in clustered supply networks. They found that network load entropy enables to predict large failure cascades, therefore enhancing supply network vulnerability management.

Studies also focussed on disruptions on material flow. Ledwoch et al. (2018) found that scale-free and random structures need significantly different inventory levels to cope with disruptions and that targeting hubs for inventory buffers is not always the best strategy. Nair and Vidal (2011) tested the robustness of random and scale free supply network structures using a multi-agent model, positing that increased clustering coefficients and longer average path lengths make the network more vulnerable to disruptions. Jun-yan et al. (2017) developed a multi-agent model in a similar vein to Nair and Vidal (2011), creating a scale-free model through local agent interactions.

Finally, Battiston et al. (2007) studied dynamics of bankruptcy propagation in supply networks with credit-credit relationships. They found that the more firms fail, the higher interest is charged, causing even more firms to fail.

The relationship between network topology and network operational parameters such as inventory distribution and production throughput is another topic that is worthy of future investigation given early studies that hint this point. Such studies can build on the long history of system dynamics models in this area (Sterman 1989), with recent work showing that relatively simple network structures already generate complex dynamics (Edali and Yasarcan 2014, Edali and Yasarcan 2016).

3.4 From descriptive to prescriptive

Supply network topology research is in its infancy and perhaps because of this the first range of studies have included exploratory studies that investigate emergent structures. These studies give us a much-needed understanding, but sit uncomfortably with the long standing supply chain planning and control community. Research needs to be conducted in reconciling how our new found understanding of emergence can inform the development of localised control and optimisation. Some interesting topics worthy of investigation could include network topology optimisation for operational variables, and the effectiveness of optimisation and control under different topological constructs. Supply chain research communities that investigate system dynamics, optimisation, and network flow logistics would benefit from interaction with network science community to identify how developed models are impacted from topology.

3.5 Lack of data

While the reconciliation of multiple disciplinary siloes and network layers is a modelling and analytical challenge, the lack of large scale empirical data is a significant barrier to addressing these issues in going forward. As we have shown in this paper, the scarcity of empirical studies decelerates exploration in the field, and causes premature generalisations especially in the macroscopic analysis of supply network structures. Recent data sources included financial databases such as Bloomberg, FactSet or industry specific databases provided by regulatory bodies or supplier brokerage agencies. Financial databases typically only show publicly listed companies limiting the dataset. Industry specific databases, as the name suggest, do not contain cross-industry dependencies, and limit the level of analysis to maximum tier 3 as beyond this tier companies seem to serve to multiple industrial sectors. Insurance companies and third-party supply chain intermediary companies have access to cross-industry data could provide a valuable source in addressing the data gap. Recent developments in machine learning based approaches that allow the automatic collection of publicly available data (Wichmann et al. 2017b), and graph mining approaches where links between suppliers are predicted (Rodewald et al. 2015) could be complimentary tools in addressing the data challenge. As research in this domain develops a repository where researchers make anonymised data available to the community would be very useful.

3.6 Lack of appropriate null models

In the study of networks it is often useful to develop null models as a comparative benchmark, which would allow the extraction of whether observed properties are meaningful or unique to the network being studied. Most microscopic observations to date on supply network topology have either not used any null models or appropriated random (ER) network models for hypothesis testing. The extent to which a random benchmark is useful and how appropriate null models could be developed are open questions that remain to be addressed. In particular null models where specific network properties can be preserved would be useful to identify whether a given supply network contains over/under representation of those properties.

4. Conclusions and outlook

In this paper, we present a critical review of theoretical, model based and empirical studies which conceptualise supply chains from a network science perspective. Supply networks now comprise of thousands of firms embedded in a complex, dynamic, constantly evolving ecosystem. Such systems need new approaches to replace the local perspective that has been adopted by supply chain practitioners since many decades.

Although the new study of complex supply networks through the lens of network science has been gaining track, the field is still in its infancy compared to other domains such as biological and social networks.

Since 2000, several bodies of work showed that supply network topology has significant impact on robustness, resilience, network performance at the macroscopic level, and operational criticality, information flow, spread of innovations and joint venture formation at the microscopic level. Although studies started out using standard network metrics, recent work shows an evolution towards more fine-grained interpretations of network metrics and the development of new ones. Empirical work has been scarce, partly due to a lack of large scale data. Empirical analysis has not always been consistent with theoretical models, particularly at the macroscopic scale. Thus more work needs to be carried out in the empirical analysis of large scale structures and the deduction of network properties across a wider range of industrial settings.

While studies focused on a different types of links in supply networks including contractual, material flow, financial and innovation networks; findings from these studies typically remain in disciplinary siloes without much cross-referencing. Studying how these different supply network layers impact the function and performance of each other would be valuable and allow network science to break these barriers.

Little attention has been paid to how dynamical properties interlink with network topology, and the few studies that exist point to significant impact on inventory and cost, making this gap an important area to be addressed.

Recent automation and digitilisation trends in supply chains may play a key role in addressing data issues, thus giving the research community a unique opportunity to expand current knowledge beyond local perspective; and grasp an understanding of complex behavioural patterns that are often described as noise in today's supply chain modelling research community.

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