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Structure and evolution of global cluster networks: evidence from the aerospace industry

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Abstract

We use a new panel dataset to study the network of formal firm linkages within and across 52 aerospace clusters in North America and Europe. Our theoretical framework, built upon the knowledge-based cluster and global value chains literature, suggests that a reduction in spatial transaction costs has induced clusters to specialize in increasingly fine-grained value chain stages. This should cause the overall network to evolve from a geographically localized structure to a trans-local hierarchical structure that is stratified along value chain stages. Applying community structure detection techniques and organizing sub-networks by linkage type, we find empirical evidence in support of this proposition.

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1. Introduction

Industrial clusters have long been recognized as engines of regional economic growth. Numerous theories have been developed to explain why closely related firms co-locate geographically and how this can induce knowledge spillovers and innovation (Porter, 1998; Bresnahan and Gambardella, 2004). This has been supported by empirical studies which show that industrial clusters matter for regional performance, including entrepreneurship, innovation and job creation (Feldman and Audretsch, 1999; Porter, 2003; Delgado et al., 2010, 2014).

Much of the earlier literature has focused on co-location benefits to explain an industrial cluster's success, yet it is now known that this is too narrow. Recent studies have highlighted that geographical co-location does not guarantee linkage creation and knowledge spillovers (Maskell and Lorenzen, 2004). Furthermore, it has been established that companies increasingly set up formal linkages with firms outside of the geographical boundaries of an industrial cluster to hook on to the global production and innovation system. They set up vertical supply chain relationships with suppliers located in other industrial clusters to reduce their costs, creating global value chains (Sturgeon et al., 2008). And they establish horizontal partnerships with firms trans-locally to gain access to key knowledge that is unavailable within their own industrial cluster (Bathelt et al., 2004; Owen-Smith and Powell, 2004). As a consequence, recent theoretical work conjectures that the success of an industrial cluster depends on the network configuration of both its local and trans-local linkages (Bathelt et al., 2004; Wolfe and Gertler, 2004; Lorenzen and Mudambi, 2013).

Empirical work has lagged behind however. Presumably because of the difficulty of obtaining such data, there has been little research documenting how the density of formal connections between cluster firms has evolved locally versus trans-locally. There is even less information on how the composition of these connections across linkage types (horizontal versus vertical; intra-firm versus inter-firm) has changed over time (Glückler, 2007; Ter Wal and Boschma, 2009). These are the broad questions we aim to illuminate in this study by examining the overall network of firm linkages within and between industrial clusters in one specific industry, that of aerospace. Such an examination can give us a new set of facts to explain, and a better way to understand the larger economic structures within which industrial clusters are embedded. We provide a more detailed description of the specific questions that frame our study in Section 2 of the paper.

We take advantage of a unique hand-collected dataset on formal firm linkages within and across 52 aerospace clusters in North America and Europe for the periods 2002–2005, 2006–2009 and 2010–2014 to gain new insights into the structure and dynamics of the global cluster network.[1] Using community structure analysis, we show that the structure of the overall network has substantially evolved during the sample period. Industrial clusters have increasingly specialized in value chain stages over time, leading to both an intensification of horizontal linkages within industrial clusters and the trans-localization (offshoring) of vertical linkages across clusters. As a result of these trends, we find that geography has become a poorer predictor of the structure of the global cluster network during the sample period.

Our paper is structured as follows. Section 2 presents an overview of the literature and discusses the emergence of a network view of industrial clusters. Section 3 connects this literature to social network analysis and provides theoretical propositions. Section 4 explains our choice of the aerospace industry and describes our data collection procedure. Section 5 contains the empirical analysis and discusses the results. Section 6 outlines the implications for our thinking of industrial clusters, and provides concluding remarks.

2. Toward a network view of industrial clusters

Scholars have traditionally defined industrial clusters in terms of their geographical dimension, i.e., as 'a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities' (Porter, 1998). The conventional rationale is that many processes of knowledge creation and exchange are tacit and spatially sticky, requiring direct and repeated face-to-face contact (Storper and Venables, 2004). For firms, co-locating with

1 Coined by Bathelt and Li (2014), 'global cluster network' refers to the system of formal linkages among firms located in industrial clusters. It is important to note that the term not only refers to trans-local linkages between industrial clusters, but also to local linkages within the same cluster.

similar and related companies thus has the advantage that it can boost collective learning processes through frequent opportunities for formal and informal exchanges (Maskell and Malmberg, 1999). These exchanges can occur along both the horizontal and vertical dimension. Horizontally, similar firms with comparable activities can benefit from common access to a regional pool of specialized labor and from the opportunity to closely monitor and learn from its rivals (Li, 2014). Vertically, related firms can gain from intensely collaborating on problem solving within supply chains (Lundvall, 1992).

Recent studies point out, however, that cluster externalities are not merely 'in the air', but that they are at least partially driven by the social networks in which cluster firms are embedded. Giuliani and Bell (2005) show that firms in a Chilean wine cluster differ largely in their network of local linkages, with some very well connected to other local cluster firms and others acting in complete isolation. They find that peripheral inclusion in the local network hampers a firm's learning and innovation opportunities.[2] Boschma (2005) suggests that, besides geography, four other dimensions of proximity (cognitive, social, organizational, and institutional) explain the likelihood that firms create an inter-organizational network linkage.

Other studies, then again, suggest that inter-organizational networks are not constrained locally, but extend outside the geographical boundaries of an industrial cluster. Studies in the fields of both global knowledge sourcing and global value chains have highlighted that cluster firms often set up trans-local pipelines to firms and subsidiaries in other clusters to gain access to complementary knowledge and resources. The global knowledge sourcing literature has primarily focused on horizontal knowledge-seeking motives for cluster firms to create trans-local pipelines (Bathelt et al., 2004). The starting point is that firms benefit from knowledge diversity (Cantwell, 1989) and that clusters differ markedly in their knowledge profiles (Chung and Yeaple, 2008). As a consequence, cluster firms have the incentive to set up trans-local pipelines to other subsidiaries or strategic partners outside of the cluster to gain access to complementary knowledge pockets that are not available locally (Berry, 2014).

The global value chains literature has focused on vertical efficiency-seeking motives for cluster firms to set up trans-local linkages. Industrial clusters not only differ in their knowledge profiles, but also in their resource endowment profiles (Dunning, 1998). In line with the classical theory of comparative advantage, cluster firms thus have the incentive to reduce their costs and maximize their competitive advantage by offshoring value chain activities to other clusters where they can be carried out more effectively (Leamer and Storper, 2001; Sturgeon et al., 2008).

The recognition that the network of both local and trans-local linkages are important for a cluster firm's access to knowledge and resources has pushed scholars to go beyond the traditional local–global dichotomy and adopt a network view of industrial clusters. Clusters are rarely self-sufficient in terms of the knowledge and resource base they draw upon, and it is therefore limiting to consider them as closed or isolated systems (Wolfe and Gertler, 2004). Rather, an industrial cluster is a network of local linkages between firms, which is embedded in a larger 'global cluster network' of exchanges that spans clusters (Bathelt and Li, 2014). Successful industrial clusters are those where firms are

2 Glückler (2014) goes a step further by illustrating that a peripheral node's ability to introduce radical innovation depends on the structure of the overall network. Whether that innovation succeeds and spreads depends on the structure of the network and the way that the periphery is connected to the core.

effective at building and managing a broad network of linkages both locally and trans-locally for accessing relevant knowledge and resources (Bathelt et al., 2004; Wolfe and Gertler, 2004; Boschma and Ter Wal, 2007).

A natural tool to investigate the interwoven nature of linkages within and between industrial clusters is social network analysis (Giuliani and Bell 2005; Lorenzen and Mudambi, 2013). A central tenet in social network analysis is that an actor's structural position in a network affects its ability to gain access to information and knowledge (Freeman, 1979). In studies of economic geography, measures of network centrality have been found repeatedly to affect firm innovativeness (Powell et al., 1996; Owen-Smith and Powell, 2004; Giuliani, 2007; Whittington et al., 2009). Another network concept that has been applied to economic geography is the notion of homophily—similarity breeds connections (McPherson et al., 2001). Balland (2012) and Powell et al. (2005) find that new relations in collaborative and strategic alliance networks are more likely to emerge in geographical proximity than over large distance.

Arguably, researchers have only scratched the surface as to the potential of using social network analysis to gain insights into the organization and performance of industrial clusters (Ter Wal and Boschma, 2009; Glückler, 2013). Powerful methods that look at the *structure of the entire network* remain relatively unexplored. For example, the use of community structure detection techniques to investigate the structure and dynamics of the overall cluster network is underutilized (e.g., Barber et al., 2011).

The lack of large-scale datasets that capture the population of local and trans-local linkages across firms located in numerous industrial clusters across the world may be a reason why the analysis of the topology of the entire network has only made limited inroads into the industrial clusters literature. In previous work, scholars have primarily focused on the network of inter-organizational linkages in a single or relatively few industrial clusters. A popular approach to construct the network of knowledge-based relations between firms is the 'roster-recall' method which helps identify a firm's formal and informal connections (e.g., Giuliani and Bell, 2005; Boschma and Ter Wal, 2007; Morrison, 2008), yet a shortcoming of this data collection procedure is that it is difficult and expensive to apply to a large population across multiple industrial clusters (Ter Wal and Boschma, 2009). Other studies have used secondary data to construct the network of formal linkages between organizations (e.g., Bathelt and Li, 2014), yet these are primarily focused on a specific industrial cluster or a dyad of locations.

In sum, an influential and growing literature in economic geography has adopted a network view of industrial clusters. But largely due to the lack of large-scale empirical data, a number of important empirical questions remain. What does the global network of formal linkages within and across industrial clusters look like, and is there evidence that it has changed over time? Does the structure look differently depending on the type of linkages? What is the organizing principle that underlies the global cluster network? We examine these questions in the remainder of the paper by applying community structure detection techniques to a new hand-collected dataset on formal network linkages in the aerospace industry.

3. Propositions

We take the network view of industrial clusters as a starting point and supplement it with insights from social network analysis to propose a number of topological features of the global cluster network. In the development of our propositions, we focus only on formal linkages between firms located in industrial clusters.

A first property to expect is that community structure in the global cluster network is aligned with the geographic boundaries of industrial clusters. The topological property of community structure means the existence of some natural division of the network such that nodes within a group are tightly knit among themselves, while having relatively looser connections with the rest of the network (Girvan and Newman, 2009). As explained in Section 2, many processes of knowledge creation and exchange are spatially sticky, requiring face-to-face interactions (Storper and Venables, 2004). For firms, creating formal linkages with similar and related companies within the same industrial cluster can therefore be an effective strategy to acquire critical tacit knowledge from neighbors. Balland (2012) and Powell et al. (2005), for example, find that formal linkages between firms are more likely to emerge when two firms are located in the vicinity of each other, i.e., geographic homophily. This conjecture can be summarized as follows:

Proposition 1: *The global cluster network exhibits community structure along the geographical boundaries of industrial clusters.* We should not expect the network topology to be identical for the sub-networks of horizontal and vertical linkages. Geography should vary in its influence upon the topological clustering of different formal linkages: a firm's motivation to locate in an industrial cluster and create formal linkages locally varies across the horizontal and vertical dimension (Li, 2014). Horizontally, similar firms tend to co-locate in the same industrial cluster due to the existence of strong centripetal forces. Co-location provides firms common access to a regional pool of specialized labor and gives firms the opportunity to monitor and learn from rivals. Vertically, in contrast, related firms often co-locate for a very different reason: minimizing spatial transaction costs (Lundvall, 1992). The most straightforward reason why geographic proximity is beneficial in a vertical input–output relation is that physical distance raises transportation and logistics costs. Adding to this, proximity facilitates personal interactions which are required to monitor product quality, exchange tacit knowledge, and collaborate on problem solving within supply chains. Since the structure of link formation and motives for firm co-location vary across linkages types, we should expect that the global cluster network exhibits different topological properties when we split it into sub-networks by linkage type. Along these lines, Malmberg and Power (2005) report that vertical linkages are generally more spread out trans-locally than horizontal linkages. This conjecture can be summarized as follows:

Proposition 2: *Community structure in the global cluster network varies across the sub-networks of horizontal and vertical linkages.* We should expect the global cluster network to evolve over time. Digitization and globalization have reduced spatial transaction costs (Morgan, 2004). The emergence of the Internet and common communications protocols have enabled the codification of corporate knowledge, reducing the costs of coordinating and monitoring transactions at a distance (Leamer and Storper, 2001). Reductions in tariffs and transportation costs have further fueled this process by reducing the cost of transporting material goods across national and regional borders (Hummels, 2007). The decrease of spatial transaction costs reduces a firm's need to co-locate with another firm to create a formal linkage for knowledge transfer and should therefore weaken the organization of community structure along the geographical boundaries of industrial clusters (Ioannides et al., 2008).

Once again, one can expect that the reduction in spatial transaction costs affects the configuration of formal linkages differently depending on the linkage type. It has been widely documented that improvements in communication technology and reductions in trade costs have led to the trans-localization of vertical linkages as companies slice up their value chains and move value chain stages offshore (Leamer and Storper, 2001; Sturgeon et al., 2008). Since companies are able to codify the knowledge that they need to exchange with their buyers and suppliers, they see the benefit of co-locating with their suppliers diminishing. Therefore, firms start replacing their existing local buyer-supplier linkages by new trans-local connections with firms at remote yet cheaper locations.

One should not expect that a reduction in spatial transaction costs leads to a similar degree of trans-localization of horizontal linkages. A reduction in spatial transaction costs does not necessarily alter the main centripetal force that induces similar firms to co-locate in an industrial cluster, which is its ability to gain access to a pool of location-based expertise and monitor its rivals. As a result, one should not expect that it leads to a significant rise in trans-local horizontal linkages, or at least not to the same extent as for vertical linkages (Morgan, 2004; Rodríguez-Pose and Crescenzi, 2008). On the contrary, it may even be that a reduction in spatial transaction costs leads to an increase in horizontal linkages within industrial clusters. Companies that gain the ability to separate an activity from the rest of the value chain have the incentive to locate that activity in the industrial cluster that has a comparative advantage in its production (Duranton and Puga, 2005; Grossman and Rossi-Hansberg, 2012). If many cluster firms contemporaneously offshore the same activity to the same industrial cluster, this generates an increase in the concentration of similar firms in the industrial cluster, which in turn can lead to a rise in formal local horizontal linkages due to geographic homophily. This leads to the following proposition:

Proposition 3: *Over time, community structure in the global cluster network has become less associated with geographical boundaries. This trend is particularly strong for the sub-network of vertical linkages.* The preceding discussion suggests that a reduction in spatial transaction costs induces a more fine-grained division of labor so that industrial clusters specialize in specific value chain stages rather than entire value chains, i.e., they move from *sectoral to functional specialization* (Duranton and Puga, 2005). In that case, this should lead to a transformation in the structure of the global cluster network. Horizontally, cluster firms would become ever more tightly knit with similar firms in the same industrial cluster. Vertically, in contrast, cluster firms would strengthen their trans-local connectedness with related firms located in industrial clusters that specialize in complementary value chain stages. As a result, the network should gradually tradition from a geographically localized community structure to a trans-local hierarchical community structure that is stratified by value chain stages. We summarize this in the following proposition:

Proposition 4: *The organizing principle defining the latent structure of the global network has evolved over time from a geographically localized community structure to a trans-local hierarchical community structure that is stratified by value chain stages.*

4. Data

4.1. Choice of the aerospace industry

To investigate our propositions, we follow the lead of numerous other studies on the dynamics of industrial clusters and focus on the aerospace industry (e.g., Niosi and Zhegu, 2005, 2010; Broekel and Boschma, 2012). The aerospace industry covers the manufacture of air and spacecraft and related machinery.[3] It has several key characteristics that are particularly relevant for our study.

First, aerospace is a knowledge-intensive industry that is characterized by high rates of innovation and R&D (Niosi and Zhegu, 2005). Second, since aerospace products have long lead times and steep development costs, companies in the industry rely heavily on formal inter-firm collaboration along both the vertical and horizontal dimension (Eriksson, 2000, 2006). Horizontally, aerospace companies often form inter-firm partnerships with other similar firms to pool resources and benefit from economies of scale (Dussauge and Garrette, 1995). Garrette et al. (2009), for example, find that close to 20% of all new aircraft developed since World War II were created through horizontal alliances between incumbents. Vertically, the industry is characterized by a high rate of subcontracting along the supply chain (Niosi and Zhegu, 2005, 2010). At the top of the industry, lead firms such as Boeing and Airbus mostly specialize in a system-integration role centered on the airframe of an aircraft, while outsourcing the production of major subsystems such as engines, avionics and control systems to technically sophisticated subcontractors called 'Tier 1 integrators'. These subcontractors, in turn, rely on Tier 2 suppliers for the production of smaller subsystems such as computer systems, wing flaps, gear boxes and so on. Third, aerospace companies tend to agglomerate in a limited number of industrial clusters around the world (Hickie, 2006). Lead and tier 1 firms act as attractors for other firms such as specialized suppliers, sub-contractors and service companies to co-locate, creating hub-and-spoke type industrial clusters (Gray et al., 1996). Most industrial clusters are located in developed countries (e.g., Seattle, Toulouse), even though there is a recent trend by lead and tier 1 companies of setting up manufacturing facilities in emerging industrial clusters in developing countries such as Mexico and Poland (Romero, 2011).

Fourth, despite the importance of industrial clusters, the value chains of aircraft have globalized. For the Boeing 787 Dreamliner, for example, more than 300 companies are involved that build parts at over 5000 factories worldwide. The wing structure is made in an industrial cluster in Japan, while the body structure is manufactured by a team of companies located in industrial clusters in Italy, Japan and the USA. The final integration and assembly takes place in the aerospace cluster around Seattle. To manage such a global partnership model (Kotha and Srikanth, 2013), lead and tier 1 firms build sophisticated trans-local pipelines, both intra-firm and inter-firm, to build bridges between various industrial clusters (Niosi and Zhegu, 2010).

4.2. Data collection procedures

We have hand-collected a panel dataset that maps the network of formal intra-firm and inter-firm connections in the aerospace industry both within and across 52 industrial

3 This corresponds to NACE Rev. 2 code 3030.

clusters. Although the literature highlights the importance of both formal and informal ties between firms for knowledge spillovers (Giuliani, 2007; Glückler, 2013), we only include formal linkages in our dataset since it is almost impossible to trace informal linkages using secondary data sources.

An oft-cited concern in the collection of network data is the ability to construct a dataset that reliably captures the complete set of linkages between nodes and over time (Wasserman and Faust, 1994). To address this concern, we followed a rigorous three-step procedure to construct our database.

Step 1: Industrial cluster identification

To locate potential aerospace clusters, we collected information from the Global Cluster Observatory, which is an access point to a set of regional and national cluster databases. The North American and European databases are comparable in the sense that they divide their respective geographic areas into sub-national regions and provide the same set of benchmark measures for each of these industry-region combinations. To ensure comparability, we limited our data collection to the databases from the *European Cluster Observatory, U.S. Cluster Mapping Project* and *Canadian Cluster Database*. We added to these databases information from Mexico's *INADEM* database which also uses a similar methodology to categorize industrial clusters.

To identify the aerospace clusters, we draw on a large body of prior work by using a location quotient (LQ) approach (Delgado et al., 2014). In our analysis, LQ computes the proportion of an industry's employment in a location relative to that industry's share of employment across North America and Europe as a whole. If a LQ is larger or equal to 1, we identify it as a potential industry cluster since there is a larger than average agglomeration of aerospace employment in that region. We added to this list of potential industrial clusters a number of well-known emerging aerospace clusters located in developing countries such as Aerospace Valley in Poland that showed weak LQ in 2002–2005, but then showed significant growth of their LQ over the time span of our sample.[4]

For each potential aerospace cluster, we researched whether there exists a formal cluster organization (e.g., Aéromontreal) that groups all the major decision makers in the specific sector, including companies, educational and research institutions, associations and unions. The identification of such formal cluster organizations is important since it can provide valuable information about the characteristics of the industrial cluster.

This first step provides us with a sample of 22 sub-national aerospace clusters in Europe and 30 sub-national aerospace clusters in North America.[5]

4 The LQ of all clusters was over 0.8 in 2010–2014. For Queretaro in Mexico, we only included it starting in 2006–2009 since the Aerospace Industrial Park of Queretaro was set up in 2006 (Romero, 2011).

5 The 52 aerospace clusters are: Aeromontréal, Southern Ontario, Greater Vancouver, Nova Scotia, Northwest Florida, Southern California, Hartford-Bridgeport, Wichita, Dallas-Fort Worth-Kileen, Boston area, *Central/Eastern Washington*, Washington, DC–West Virginia, Southwest Ohio, Southern Arizona, Metro Denver and Northern Colorado, Little Rock area, Baltimore-Salisbury, V*ermont Aerospace* & Aviation (VAAA), Georgia, Maine Aerospace Alliance (MEAA), Manchester-Concord, North Alabama, Ogden-Salt Lake City, Queretaro, Chihuahua, Sonora *Northwestern*, Jalisco, Baja California, Estado de Mexico, HEGAN Basque, BavAIRia cluster, Lombardia, Madrid, Andalusia, Campaniaerospace, Rhone-Alps, ASTech Paris, Swiss, Skywin, Aerospace Valley, Pole-Pegase, Aviation Valley, HAG, Izmir, FLAG, Transylvania, Siberian, Northwest, Hamburg, BBAA, Belfast.

Step 2: Firm identification

In step 2, for each aerospace cluster we identified the list of firms present for each of the three time periods 2002–2005, 2006–2009 and 2010–2014. In doing so, we included large and small firms that are part of both civilian and military segments of the aerospace industry. Part of this information was taken from the cluster observatories, which contain reports on cluster events in which companies participated. We validated and complemented this information from individual cluster resources such as formal industrial cluster websites and reports. In total, we identified 2812 separate firms.

Step 3: Linkage identification

In step 3, for each company we used public reports and news articles to carefully map its formal linkages with other firms for each of the three time periods 2002–2005, 2006–2009 and 2010–2014. We measured linkages on a binary scale: 0 for the absence and 1 for the presence of a formal relationship. Such an approach to measuring network ties is common in social network analysis (Dyer and Singh, 1998).

Linkages were categorized along two dimensions: geography and linkage type. First, we distinguished between local and trans-local linkages. We identified a linkage to be *local* if there was a formal relationship between firms located within the geographical boundaries of the same industrial cluster. We labeled a linkage as *trans-local* if the relation was between firms located in different industrial clusters.

Second, we differentiated between linkage types. As mentioned before, theoretical studies generally distinguish between horizontal and vertical linkages (Maskell and Malmberg, 1999). However, it is difficult to operationalize this distinction empirically since certain linkages exhibit characteristics that can be categorized as both horizontal and vertical. For example, it is often difficult to determine whether a multinational firm sets up a subsidiary for horizontal or vertical motives, or for a combination of both (Alfaro and Charlton, 2009). Furthermore, it can be difficult to evaluate if a firm's R&D partnership with another firm constitutes a horizontal or vertical linkage. In our empirical analysis, we therefore opted to distinguish between three linkage types: buyer–supplier, partnership and investment.

Buyer–supplier linkage. For each dyadic pair of companies in our sample, we carefully combed through company reports and public news to establish a buyer–supplier linkage. First, we identified whether a company features on the approved supplier list (ASL) of another firm and is located in one of the aerospace clusters in our dataset. Most aerospace companies in North America and Europe, particularly the large ones, have fairly complete ASLs. To ensure we did not miss buyer–supplier linkages, in a second step we searched various online sources to identify additional connections.

Investment linkage. Companies are considered to have an investment linkage with another company if they both have the same global ultimate owner. To identify these linkages, we first relied on official company reports to identify the list of a firm's subsidiaries that are located in the 52 industrial clusters. Next, we verified and complemented this information by using the Orbis database. In doing so, we only considered firms to be a subsidiary if they were owned entirely by a global ultimate owner. Finally, we added information from news websites.

Partnership linkage. We consider firms to have a partnership linkage if they have established a formal partnership such as a joint R&D program, a joint venture or a formal training partnership. To gather this information, we used primarily company reports and company websites, and supplemented it with news articles, and other credible information available on-line.

We interpret buyer–supplier and partnership linkages as proxies for vertical and horizontal inter-firm linkages, respectively. We treat investment linkages separately and recognize that we cannot identify whether it is horizontal or vertical.

Table 1 gives some sense of the coverage of our database across time periods and linkage types. Our dataset consists of 16,146 local linkages and 34,554 trans-local linkages across 52 aerospace clusters and three time periods. [6,7]

5. Analysis

5.1. Mapping the global cluster network

To analyze the role of geography in the structure and dynamics of formal linkages among firms located in industrial clusters, we start off by grouping network nodes (firm–cluster combinations) according to geography and projecting them visually. This enables us to see that the sub-networks have significantly different topological structures. In Figure 1, we order firms along the *X*- and *Y*-axis according to their geographic characteristics: first by continent (North America versus Europe), next by country, then by region and finally by industrial cluster. The illuminated spots in the figure represent formal linkages between firms, while the shaded areas denote a lack of linkages. Since firms are ordered according to their geographical location, illumination along the diagonal reflects the presence of dense local linkages. Similarly, illumination within country or regional blocks suggests regional agglomeration of linkages.

Complementary to the first figure, Figure 2 depicts industrial clusters on a geographic map using their GPS coordinates and we transpose the sub-network of linkages on this map. The size of the bubbles on the figure reflects the LQ of an industrial cluster. We use a color gradient to show the density of local linkages (normalized by the number of companies in the cluster) and use the thickness of the line to illustrate the density of trans-local linkages with other industrial clusters.

The two figures combined suggest important differences in the structure and dynamics of the buyer–supplier, partnership and investment sub-networks. The buyer–supplier sub-network depicted in Figure 1a exhibits dense illumination along the diagonal in the period 2002–2005, suggesting intense local buyer–supplier linkages in the earliest time period. In addition, it shows that illumination was concentrated within regional blocks, indicating that trans-local buyer–supplier linkages were mainly intra-regional in 2002–2005. Furthermore, it shows that the topology of the buyer–supplier sub-network has evolved over time. The brightness of the diagonal has decreased from 2002–2005 to 2010–2014, indicating that the density of local buyer–supplier linkages has dropped. At the same time, illumination has progressively strengthened both within and across regional blocks suggesting growth in trans-local buyer–supplier linkages both at

6 About 75% of the linkages came from official company reports. Tests confirm that the global cluster network is scale-free, implying that even if there is an unaccounted linkage, it will follow the general pattern of the network and its introduction will not significantly change the properties of the network. There is substantial variation in average degree centrality between countries (countries with many clusters like USA have a much higher number of linkages than countries like Romania with only one advanced cluster).

7 We removed isolates that did not have connections with other firms in the network, leaving 2770 nodes.

Table 1. Number of local and trans-local linkages, by type and time period

Linkages	Local			Trans-local		
	2002–2005	2006–2009	2010–2014	2002–2005	2006–2009	2010–2014
Buyer–supplier	4307	3237	2901	906	2681	3383
Partnership	692	1685	2468	1592	1905	2201
Investment	331	281	244	6117	7693	8076
Total	5330	5203	5613	8615	12,279	13,660

the regional and global level. Finally, an area in Figure 1a that exhibits a particularly strong increase in trans-local illumination is Mexico and Eastern Europe and Turkey. This reflects growing buyer–supplier linkages with emerging-market clusters such as Queretaro in Mexico and Aerospace Valley in Poland. This trend has also been observed in industry studies such as Romero (2011).

Figure 2a confirms that the density of local buyer–supplier linkages has fallen over time as seen in the evolution of the color gradient of many industrial cluster bubbles toward darker colors. Concurrently, the density of trans-local buyer–supplier linkages has increased substantially with lines between industrial clusters thickening, especially in the case of industrial clusters located in emerging markets. Interestingly, however, the emerging-market clusters do not show as much of a change in color intensity as developed-country clusters. Queretaro, for instance, even became a little lighter. In line with Gray et al. (1996), this can be explained by the fact that the subsidiaries of lead and tier 1 companies set up shop in these new industrial clusters and act as attractors for suppliers and sub-contractors, creating a hub-and-spoke style industrial cluster. At the same time, because these industrial clusters are relatively new and the number of companies in these industrial clusters is growing, there is no significant increase in color gradient since local linkage density is normalized by the number of companies. Also, it is important to note that new linkages across these emerging-market clusters are largely regionalized, meaning that companies located in these industrial clusters use the entire region as their supplier base, not just the industrial cluster where they are located. This suggests there is an important qualitative difference in the development of new industrial clusters: they become increasingly integrated in global supply-chain structures at early stages of their development.

In the partnership sub-network (Figure 1b), we see opposing tendencies. In 2002–2005, there was little illumination along the diagonal, implying that partnership linkages were largely trans-local. Over time, however, we see a growing density of local partnership linkages, as the diagonal of the diagram becomes illuminated in the period 2010–2014. Figure 2b confirms the strong growth of local partnership linkages. While the color of the cluster bubbles was dark for virtually all clusters in 2002–2005, they have taken on lighter colors in 2010–2014, suggesting an increased density of local partnership linkages. But this does not seem to come at the cost of trans-local linkages. The increased thickness of lines between clusters suggests that trans-local linkages have also been on the rise.

The investment sub-network diagram presented in Figure 1c suggests closed cohesive networking at the firm level as multinational firms represent cohesive fully connected

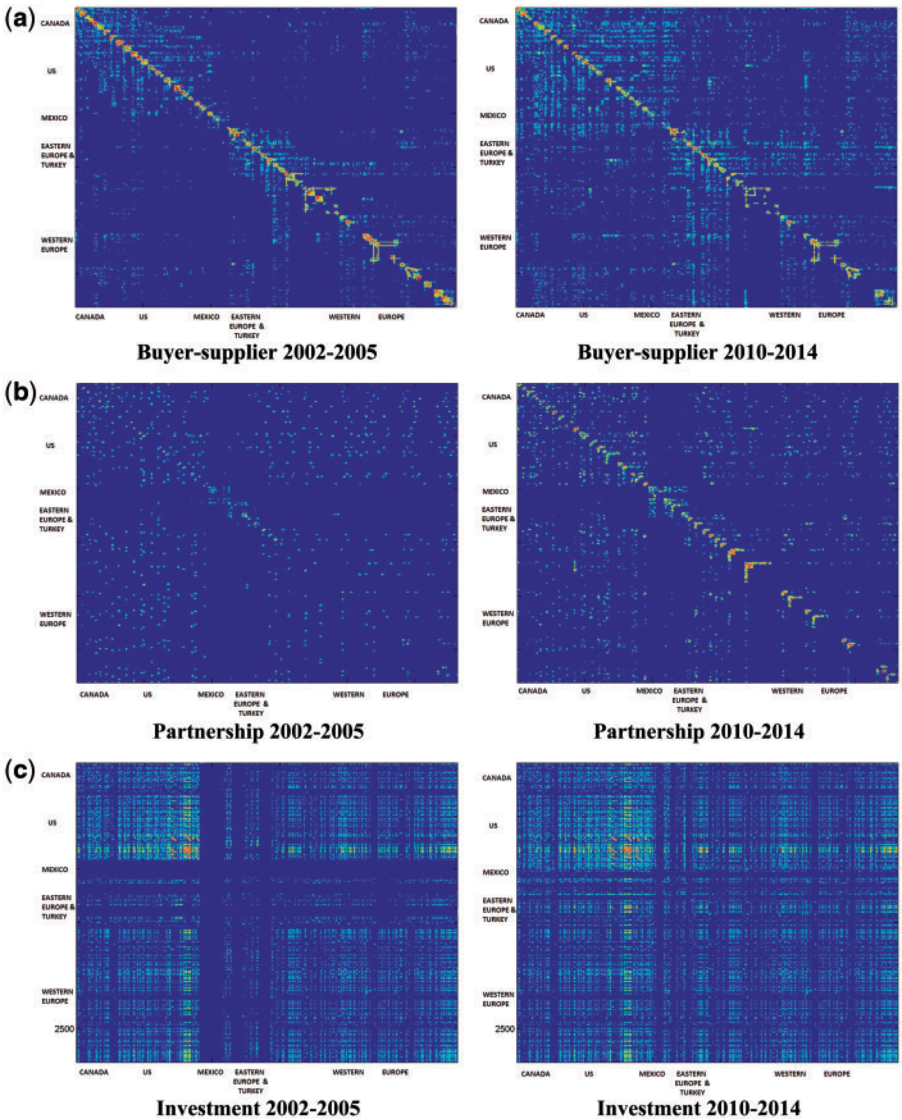

Figure 1. Geography and network linkage matrix.

networks. Furthermore, investment linkages are essentially trans-local (Figure 2c). As far as the overall structure of the network is concerned, we see important temporal tendencies similar to those in the buyer–supplier sub-network: emerging-market clusters become important destinations for foreign investment from firms located in developed-country clusters (Romero, 2011). In 2002–2005, industrial clusters in Mexico and Eastern Europe and Turkey had relatively few investment linkages, leading to a dark cross in Figure 1c. In 2010–2014, this cross has largely disappeared.

Taken together, these results suggest that the sub-networks are driven by different dynamics. For partnership linkages, the process is linked to increased local

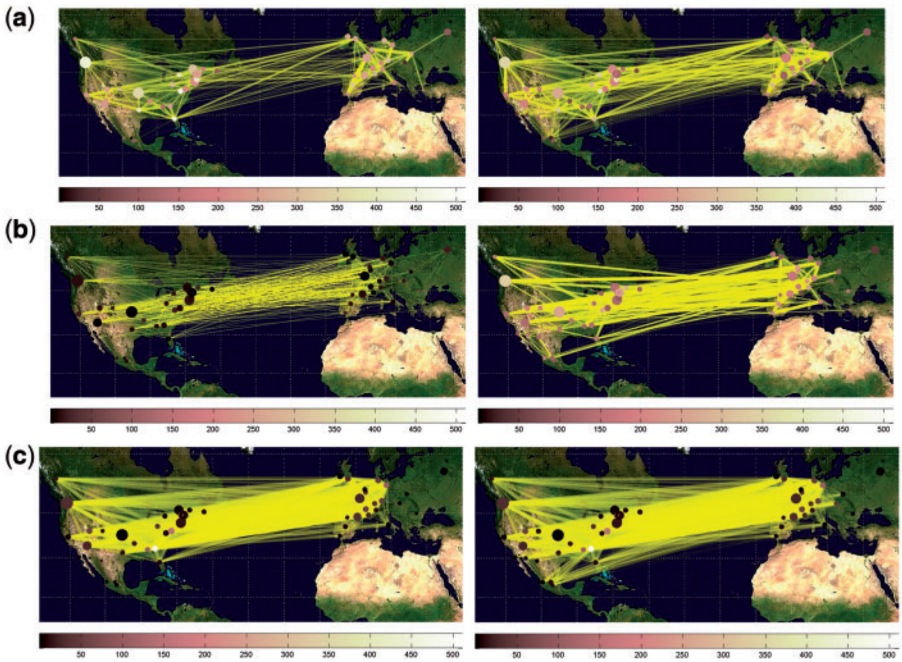

Figure 2. (**a**) Geographic map of buyer–supplier sub-network (the size of the bubble reflects LQ, color gradient reflects the density of local linkages (normalized by the number of companies in the cluster) and the thickness of the line illustrates the density of trans-local linkages with other industrial clusters). (**b**) Geographic map of partnership sub-network (the size of the bubble reflects LQ, color gradient reflects the density of local linkages (normalized by the number of companies in the cluster) and the thickness of the line illustrates the density of trans-local linkages with other industrial clusters). (**c**) Geographic map of investment sub-network (the size of the bubble reflects LQ, color gradient reflects the density of local linkages (normalized by the number of companies in the cluster) and the thickness of the line illustrates the density of trans-local linkages with other industrial clusters).

agglomeration. Buyer–supplier and investment linkages, on the contrary, have become trans-localized. These trends indicate that there are important changes in the geography of inter-firm networking and underline the need for a rigorous and systematic analysis of the extent to which geography is the organizing principle of the global cluster network as well as of the sub-networks by linkage types. We proceed with this exercise in the next section.

5.2. Geography as organizing principle

To test whether geography is a significant predictor of community structure in the global cluster network, we use a maximum-likelihood approach as described in Jackson (2008). We use four-order geography-based partitioning to conduct this analysis. The first-order partitioning investigates whether the division between North America and Europe is a significant predictor of community structure. The second-order partitioning conducts a similar analysis using the five geographic partitions—USA, Canada, Mexico, Western Europe and Eastern Europe and Turkey. The third-order partitioning separates 14 partitions (4 US regions, 2 Canadian regions, 3 Mexican regions and 5 European regions). The fourth-order partitioning separates the 52 industrial clusters. Table 2 presents results for the overall network and sub-networks.

For the overall network, the results in the last column of Table 2 show significant geography-based community structure in the period 2002–2005 with the first-order partitioning significant at the 5% level and second-order partitioning significant at the 10% level. However, we find evidence that over time geographic partitioning reflects the 'true' underlying community structure less well. Between 2002–2005 and 2010–2014, the *p*-values of the fitness tests have declined for all four orders of partitioning. In 2006–2009 and 2010–2014, none of the four-order partitionings is significant at the 10% level. This implies that geography is becoming a poorer predictor of the overall network's community structure.

For the buyer–supplier sub-network, the results in Table 2 are similar to that of the overall network. There is clear geography-based community structure in the period 2002–2005 with all of the four-order partitionings significant at the 1% level. At the same time, we find evidence that over time geographic partitioning reflects the 'true' underlying community structure less well. Between 2002–2005 and 2010–2014, the *p*-values of the fitness tests have declined for all four orders of partitioning for the buyer–supplier sub-network. In 2010–2014, only the first-order partitioning at the industrial cluster level remains significant at the 5% level. This suggests that geography remains a predictor of the buyer–supplier sub-network's community structure, but that the trans-localization of buyer–supplier linkages is rendering its predictive power weaker.

For the partnership sub-network, once again, we see an opposing trend. In 2002–2005, geographic partitioning was a poor predictor of the true community structure in the partnership sub-network. Over time, nonetheless, the *p*-values of the fitness tests decline for some of the partitionings. In 2010-2014, we find that the fourth-order partitioning becomes significant at the 10% level. These results suggest that the increased localization of linkages in the partnership sub-network is starting to render geography as a predictor of the partnership sub-network's community structure.

Note that we cannot conduct this analysis for the investment sub-network since it is composed of islands of fully cohesive but disconnected sub-networks. Instead, we compute the firm-level statistical probability that the focal firm conducts investment in its local cluster, in its region, in its country and finally, in its continent. The results indicate that the investment sub-network behaves like the buyer–supplier sub-network. In 2002–2005, the probability that a firm invests in its own continent is significant. At the same time, this effect disappears in later periods. This suggests that the trans-localization of investment linkages is over time making geography a poorer predictor of the investment sub-network's community structure.

At this point, it is useful to compare the analysis with our theoretical predictions. Our evidence is consistent with our first three propositions. In line with Proposition 1, we find that at least in the period 2002–2005, community structure was geography-based, albeit at the regional level and not at the industrial cluster level. We also find strong empirical validation of Proposition 2, in that community structure varies across the three sub-networks by linkage types. In line with Proposition 3, we find that the global cluster network becomes less associated with geographical boundaries over time, and that this is entirely driven by trends in the buyer–supplier and investment sub-network.

Table 2. Statistical significance of different partitioning schemes (p-value of the fitness test)

Partitioning order	Buyer–supplier			Partnership			Investment			Global aerospace network		
	2002–2005	2006–2009	2010–2014	2002–2005	2006–2009	2010–2014	2002–2005	2006–2009	2010–2014	2002–2005	2006–2009	2010–2014
First order (North America versus Europe)	0.000	0.003	0.021	0.218	0.264	0.352	0.054	0.127	0.255	0.054	0.102	0.205
Second order (USA, Canada, Mexico, Western Europe, and Eastern Europe)	0.000	0.148	0.623	0.152	0.239	0.584	0.383	0.421	0.662	0.092	0.413	0.511
Third order—(4 US regions, 2 Canadian regions, 3 Mexican regions, 5 European regions)	0.003	0.072	0.664	0.469	0.383	0.217	0.473	0.564	0.706	0.384	0.567	0.586
Fourth order (the number of industrial clusters)	0.000	0.046	0.055	0.201	0.098	0.052	0.739	0.805	0.871	0.209	0.218	0.221

In the partnership sub-network, in contrast, we find that community structure has become more associated with geographical boundaries over time.

These results raise important questions about the processes behind these dynamics. Do particular companies drive the trans-localization of buyer–supplier and investment linkages? Are there particular companies responsible for increased local agglomeration in the partnership sub-network? If geography loses its overall predictive power, what becomes the new organizing principle of the global cluster network at the later stages of its development? The next sections tackle these questions by analyzing new linkage formation patterns and by using community structure algorithms that separate the network into communities based on topological clustering.

5.3. New linkage formation patterns

To understand the type of companies that are responsible for the dynamics of the global cluster network, for buyer–supplier and partnership sub-networks we separately create a sub-matrix which only captures the new linkages that each node in the sub-network created between the periods 2002–2005 and 2010–2014.[8] Then for each sub-network we separately construct the empirical distribution of the number of new links per node. Finally, we apply the non-parametric Kolmogorov–Smirnov test to examine whether the distributions were similar for the two sub-networks.

The test rejects the null hypothesis, suggesting that the distribution of new linkages per node is significantly different for the two sub-networks.[9] Particularly, we find that the distribution of the number of new links per node in the buyer–supplier sub-network is significantly more dispersed relative to its mean value than in the partnership sub-network.[10] This larger dispersion is caused by an ensemble of outlier nodes that created 30 or more new links between the periods 2002–2005 and 2010–2014. The top 15 outliers are lead firms and tier 1 suppliers in developed-country clusters which all have created over 50 new buyer–supplier linkages that are primarily trans-local.[11] Next on the list are subsidiaries of these large companies in emerging-market clusters such as Bombardier Queretaro or Rolls-Royce Sonora which have created both local and trans-local buyer–supplier linkages.

In the partnership sub-network, in contrast, there is little evidence that the dynamics of new linkage creation are dominated by lead and tier 1 firms in developed-country clusters. Companies of different sizes form partnerships. For instance, industry leaders Bombardier Aerospace and Bell Helicopter Textron Canada have a R&D project to build lighter fuselages for better energy performance and reduced carbon emissions. At the same time, numerous small- and medium-sized enterprises in the Hamburg cluster cooperate on a R&D project aimed at developing new MRO technologies and more efficient production processes.

8 We cannot conduct a similar link formation analysis on the investment sub-network since it consists of islands of fully cohesive linkages between subsidiaries of the same firm with an absence of connections between these firm-networks.

9 $D = 0.3663$; $p = 8.5\mathrm{e}{-102}$.

10 The mean of the empirical distribution in the partnership network is 8.75 and the variance is 64.25, while the buyer–supplier network has a mean of 4.09 and variance 21.36.

11 Boeing, Airbus Group, Bombardier, Lockheed Martin, Northrop Grumman, Raytheon, BAE, HS/UTC, GE, Safran, Rolls-Royce, Honeywell, General Dynamics, L-3 communications, Cessna/Textron.

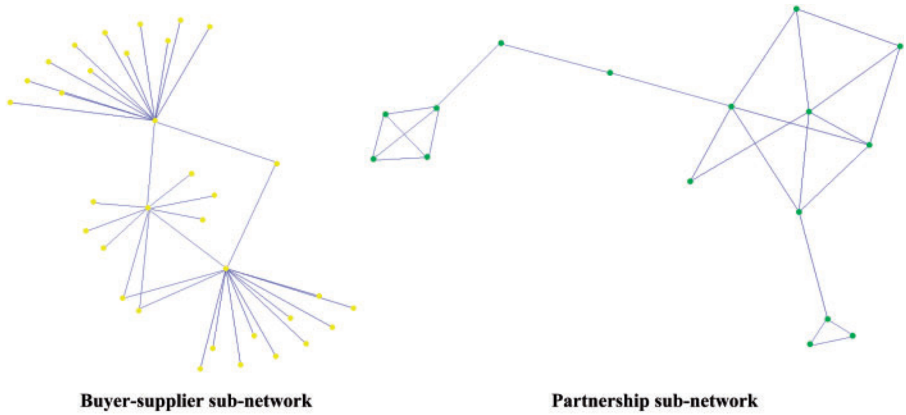

Figure 3. Linkage formation structure for the buyer–supplier and partnership sub-network.

We could not replicate this analysis with the investment sub-network, but we still analyzed the companies that produce the largest investment networks over time. Similar to the buyer–supplier sub-network, we find that they are primarily lead firms and tier 1 suppliers that have set up subsidiaries in emerging-market clusters. These results suggest that the observed temporal dynamics in the buyer–supplier and investment sub-networks are largely driven by lead and tier 1 firms which have reorganized their supply network by switching to trans-local suppliers, often in emerging-market clusters.

In a final step, we apply adapted Koyuturk et al.'s (2006) MULE algorithm to the sub-matrices of new linkages in order to detect frequently occurring patterns and modules of new linkage formation. Figure 3 presents the typical new link formation pattern for both the buyer–supplier and partnership sub-network between the period 2002–2005 and 2010–2014.[12] It clearly shows that the buyer–supplier sub-network features a hierarchical hub-and-spoke pattern of new linkage formation, while the partnership sub-network exhibits a more evenly distributed modular pattern of new linkage formation.

Combined with our previous results, the hub-and-spoke pattern of new linkage formation in the buyer–supplier sub-network provides further evidence that the adoption of a global partnership model by lead and tier 1 aerospace firms lies behind the dynamics in the buyer–supplier sub-network (Niosi and Zhegu, 2010; Kotha and Srikanth, 2013). Lead and tier 1 firms increasingly switch to suppliers and sub-contractors that are located in emerging-market clusters such as Queretaro in Mexico and Aviation Valley in Poland. These new nodes, in turn, create new links with specialized suppliers and sub-contractors that are located either locally or regionally. As aerospace value chains become increasingly global, geography loses its predictive power in the community structure of the buyer–supplier sub-network and a hierarchical structure emerges across locations in the global cluster network.

12 We did not run this analysis on the investment sub-network: by how the investment sub-network was created, the typical patterns represent fully cohesive firm-level networks.

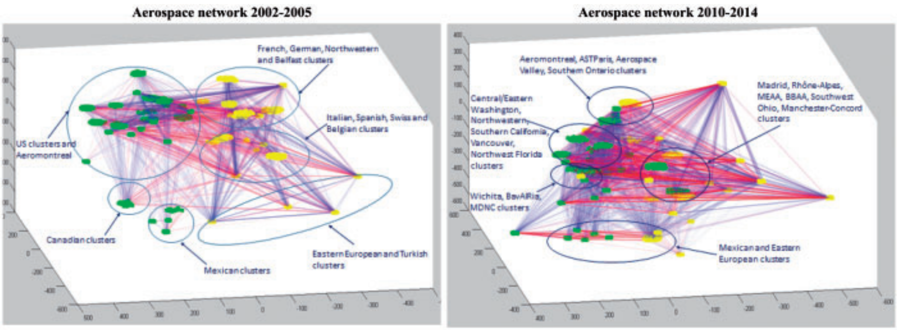

Figure 4. Community structure analysis (bubbles to the left reflect North American clusters, bubbles to the right depict European lusters. Vertical linkages reflect trans-local buyer-supplier linkages, while red lines reflect trans-local partnership linkages).

The modular pattern of new linkage formation in the partnership sub-network suggests that there is no such hierarchical structure in the partnership sub-network or at least not to the same extent. Partnership linkages are primarily created among groups or clubs of nodes (firm–location combinations) that conduct complementary activities. These partnership linkages are increasingly becoming localized, explaining the growing predictive power of geography in community structure detection.[13] A representative example is research partnership linkages among Bombardier Aerospace, Bell Helicopter Textron Canada and CAE in the Aéromontreal cluster aimed at developing advanced flow simulation methods that shortens time-to-market and increases aviation safety.

5.4. Value chains as organizing principle

Given that geography is a poor predictor of the overall aerospace network's community structure, and especially in later years, are there other factors that could serve as the organizing principle of the network? To investigate this, we use so-called 'anonymous' community structure algorithms that decide by themselves the most appropriate community structure without prior knowledge about the network. This approach organizes the data into communities based solely on the data. There are no assumptions made regarding the specific members of each community or the number of communities to be identified.

We use a combination of spectral and hierarchical clustering algorithms to identify the structure of the global cluster network. We use a layout and visualization method developed by Traud et al. (2009). In this method the network layout problem is first simplified by splitting it into a number of much simpler sub-network layout problems. We identify *communities* by using a spectral modularity optimization algorithm (Newman, 2013) and place the centers of these communities using the Kamada–Kawai forced directed layout method (Kamada and Kawai, 1989). Finally, inside each community we apply the Kamada–Kawai algorithm to create the local layout of each

13 It is important to reiterate that trans-local partnership linkages are also growing, but not as fast as local partnership linkages.

sub-network. We then match each community core with the industrial cluster within which it is most embedded.

These procedures result in a 2D (XY axes) layout of industrial clusters in the entire network as well as linkages between them. Next, using Newman's (2004) hierarchical clustering algorithm, we stratify the network along the Z-axis (clusters with similar structural properties are placed at similar levels of hierarchy). This provides us with the 3D plots in Figure 4.

Figure 4 demonstrates the results of the analysis by portraying the global cluster network in 2002–2005 and 2010–2014. Since investment networks represent fully cohesive firm-level networks, we do not model them on the diagram to avoid noise. In the figure, green circles are North American clusters, whereas yellow circles are European clusters. Blue linkages are buyer–supplier linkages, whereas red linkages are partnership linkages.

Figure 4 reveals a number of properties of the global cluster network in 2002–2005. First, in line with our earlier analysis, geography plays an important formational role in the 2002–2005 aerospace network. On the diagram, we see a clear differentiation between the green North American clusters on the left and the yellow European clusters on the right. Furthermore, zooming in to the continents, we see that there is a close bundling of multiple industrial clusters, which may also be a sign that geography undergirds community structure. Second, we find evidence that the network is stratified with three distinct levels of hierarchy. On top lie the traditional industrial clusters located in developed countries, while emerging-market clusters lie at the bottom. Canadian clusters (excluding Aéromontreal, which is placed at a higher level of hierarchy) form a distinct mid-tier group. The vertically natured trans-local buyer–supplier linkages connect hierarchically distinct industrial clusters at the regional level, leading in the figure to a large number of vertical blue lines between emerging-market clusters and developed-country clusters. At the same time, the horizontally natured trans-local partnership linkages primarily connect hierarchically similar developed-country clusters at both the regional and the global level, implying that in the figure the red lines are mostly horizontal.

The figure for the period 2010–2014 confirms that the community structure of the global cluster network has evolved substantially over time. The differentiation between the green North American clusters and the yellow European clusters becomes more muddled, confirming that geography has become a less clear predictor of the global cluster network's community structure. Furthermore, if we focus on the Z-axis, we see that the network becomes even more stratified than before, exhibiting more levels of hierarchy. Similar to the period 2002–2005, trans-local buyer–supplier linkages predominantly connect industrial clusters on different levels of the network hierarchy, leading in the graph to mostly vertical blue lines (but now denser). Trans-local partnership linkages, in contrast, connect industrial clusters that are more or less at the same level of hierarchy, leading in the graph to mostly horizontal red lines.

As indicated in Proposition 4, a plausible explanation for this increased stratification of the network into hierarchies is that aerospace clusters are gradually transforming from sectoral to functional specialization. That is, whereas aerospace clusters used to specialize in a large portion of the aerospace value chain, they are increasingly specializing in a sliver of the value chain. Dense trans-local buyer–supplier linkages thus emerge between industrial clusters that specialize in complementary vertical stages of the same value chain. At the same time, strong local and trans-local partnership linkages develop between industrial clusters specialized in the same value chain stage. Taken together, these findings imply that the organizing principle behind the global cluster network has shifted from a geographically localized community structure to a trans-local hierarchical community structure that is stratified by value chain stages. That is, as value chains have globalized, the clustering of linkages in the global network is less determined by geographical boundaries, and more by the value chain structure.

To further investigate whether industrial clusters are moving from sectoral to functional specialization, we explore whether industrial clusters with similar indices in the network hierarchy also specialize in similar slivers of the value chain. For instance, Campania aerospace cluster specializes in three areas: building of complex components, maintenance and specialized parts sub supply, manufacturing and tools. Using information of this kind we create a matrix with different specializations and for each cluster assign 1 if it had expertise in this area, and 0 otherwise. Next we conduct a correlation analysis between cluster specialization and network hierarchy index for the time period 2010–2014. The analysis shows a high correlation of 0.89. While this requires more rigorous analysis, it gives us a preliminary indication that industrial clusters which occupy similar positions in the structural hierarchy of the global aerospace network specialize in similar value chain stages. This analysis supports Proposition 4: the global aerospace network has been evolving from a geographically localized community structure toward a trans-local hierarchical community structure that is stratified along value chain stages.

6. Conclusion

Using a hand-collected dataset of formal firm linkages both within and between aerospace clusters, we have unearthed a new set of facts about the changing nature of industrial clusters in the aerospace industry. Between 2002–2005 and 2010–2014, the global cluster network has transitioned from a geographically localized community structure to a trans-local hierarchical community structure that is stratified by value chain stages. A plausible explanation for this transformation is that industrial clusters in the aerospace industry are gradually transforming from sectoral to functional specialization. Whereas industrial clusters used to specialize in large portions of aerospace value chains, they are now increasingly specializing in finer sliced value chain stages. This has led cluster firms to build dense vertical buyer–supplier connections with other industrial clusters which are specialized in complementary value chain stages. At the same time, it has led to an intensification of horizontal partnership connections within industrial clusters. While there has been previous work suggesting some of these facts (Niosi and Zhegu, 2010; Romero, 2011), the completeness and global scale of our data has enabled us to empirically validate these trends more reliably. In ongoing research on cluster innovation performance using data from clusters in the IT/telecom and biotech/pharma industries, we notice evidence of similar patterns (Turkina and Van Assche, 2016). The generality of our findings in other industries is nonetheless something that needs to be further explored in future research.

Our analysis has also revealed a number of other facts that have implications for our thinking of industrial clusters. First, we show that geographic boundaries of industrial clusters have become a poor predictor of the overall network's community structure over the sample period. Cluster firms have largely expanded their connections with firms located in other industrial clusters, raising the question of how important trans-local connectedness is for an industrial cluster's economic performance (Boschma and Ter Wal, 2007; Turkina and Van Assche, 2016).

Second, our study underscores the importance of distinguishing between different linkage types when conducting research on global patterns of industrial cluster dynamics. Our analysis shows that the configuration and dynamics of buyer–supplier, partnership and investment linkages vary sharply. Patterns of new linkage formation vary significantly across sub-networks by linkage type. The buyer–supplier sub-network features a hub-and-spoke pattern of new link formation, while the partnership sub-network exhibits a more evenly distributed modular pattern of new link formation. Furthermore, geographic patterns vary widely across sub-networks. Between 2002–2005 and 2010–2014, many buyer–supplier and investment linkages have moved trans-locally, often to emerging-country clusters in Mexico, Turkey and Eastern Europe. Conversely, partnership linkages have become relatively more localized. All this suggests the need for future research to evaluate how the structure of sub-networks varies by linkage type and the implications for an industrial cluster's performance.

Third, our analysis highlights the usefulness of network methods in uncovering patterns in the data which are difficult to both see and interpret using conventional methods used in economic geography. While we have focused only on one industry in this paper, we believe network methods such as community structure detection are likely to be fruitful for the study of organizational and industrial dynamics across both space and time at various levels of aggregation.

Finally, our paper has limitations that suggest directions for future research. First, while our database has a spatial and time dimension that exceeds that of most previous research, it does exclude important features. First, our analysis is limited to the network of formal linkages that exist between firms located in industrial clusters. As a result, we do not take into consideration the role of informal ties between firms in knowledge spillovers (Giuliani, 2007; Glückler, 2013). Second, we only capture formal linkages between firms located in industrial clusters, thus omitting ties companies may have with companies outside of industrial clusters. Third, our dataset does not capture the world's most dynamic region in the aerospace industry, which is East Asia and particularly China. Our dataset could also benefit from being extended to other major knowledge-intensive sectors to validate the generalizability of our results. All of these possible extensions suggest that there is significant room for a wider research agenda on the structure and dynamics of the global cluster network.

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