Papers in Evolutionary Economic Geography

17.23

The visible hand of cluster policy makers: An analysis of Aerospace Valley (2006-2015) using a place-based network methodology

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September 2017

Abstract:

The paper focuses on cluster policies with particular attention to the role of R&D collaborative incentives in the structuring of knowledge networks in clusters. We disentangle the main network failures in regional innovation systems, and discuss the selection procedures designed by policy makers to enhance the production of innovation outputs. We draw evidence from the French Aerospace Valley *cluster from 2006 to 2015. The empirical analysis relies on a dataset of 248 granted research consortia, from which we build 4-cohorts knowledge networks enable us evidencing the evolving structural properties of the cluster over time. We suggest avoiding the bias and limitations of 1 and 2-mode network analysis by developing an original place-based network methodology that emphasizes on structural equivalence and groups behaviors. We discuss the results focusing on the convergence degree between the network statistical findings and the policy makers' objectives. Finally, the methodology allows us identifying who are the agents of the structural and technological changes observed during the period.*

Key-words: Cluster policy; Networks; Collaborative incentives; Groups behaviors; Aerospace Valley
JEL-codes: D85; O25; O30; R10

1. Introduction

One of the main reasons of the development of cluster policies relies on the growing awareness from academics and policy makers that network failures have to be merged with traditional market ones in the design of public innovation incentives (Woolthuis *et al*., 2005; Vicente, 2017). That is why cluster policies have been implemented in many countries since the end of the 1990s (Uyarra and Ramlogan, 2012). They coexist nowadays with innovation policies based on individual incentives, such as research tax credit and innovation grants sponsored by public agencies (Nishimura and Okamuro, 2011). Cluster policies aim at designing R&D collaborative incentives to strengthen knowledge networks in order to stimulate the expected benefits of local knowledge spillovers and cognitive complementarities (Broekel *et al.*, 2015). Cluster policies basics broadly rely on two related network failures. First, the potentialities of knowledge spillovers from science to industry can be inefficiently exploited due to the cultural divide and the weak absorptive capabilities between the two communities. Considering that positive impacts of knowledge spillovers are geographically bounded, in particular over the early phase of innovation processes (Audretsch and Feldman, 1996; Owen-Smith and Powell, 2004), cluster policy guidelines will tend to favor local incentives towards networks mixing public research organizations and companies. Second, entrepreneurship matters in clusters (Rocha and Sternberg, 2005; Delgado *et al.*, 2010). Their effectiveness can be assessed by the rate of SMEs and spinoffs birth and entry. This later is the mark of the degree of technological variety and renewal, and then, a significant indicator of the cluster long run dynamics. Here again, these births and entries are geographically bounded, and contained in the close perimeter of universities and big companies (Audretsch, 1995; Audretsch and Lehman, 2005). But the entry dynamics in not a significant condition of cluster success *per se*. New entrants, to upscale their innovation and reach mass-markets, need sometimes to benefit from collaborative opportunities, in particular in industries in which modularity and interoperability matter (Suire and Vicente, 2014). Then, collaborative incentives between SMEs and big companies are also a regular mean used in cluster policies to foster regional performance.

The aim of this research is to go more in depth into these policy guidelines, by offering an original view of dealing with the links between the implementation of these public collaborative incentives and the resulting structuring of clusters. We will focus on a single case study: the *Aerospace Valley* in Toulouse – France from 2006 to 2015, i.e. from the start of the policy to the year for which data are available. Our goal is not to find causality between the policy and the innovative performance of the cluster. To be able to do that, systematic analysis on several places should be done, and counterfactual analysis required. Our goal is less ambitious but in some extent highly essential for who wants to have a better understanding of how policy makers influence the organization of innovation processes in regions. Indeed, our basic starting assumption is related to the fact that, in spite of their control on the selection of R&D collaborations at the micro-level, policy makers cannot have a perfect control of the structure as a whole. In network theories, this type of micro-macro scales problems are typical (Watts, 2004; Newman *et al.*, 2006): the "macro-behavior" of the network and its structural properties, both resulting from the aggregation of ties, largely escape their own intention. Since clusters are foremost networks (Giuliani and Bell, 2005; Vicente *et al.*, 2011), such a research can be useful to highlight the strengths and weaknesses of cluster policies.

The contribution is divided as follows: *Section 2* goes back to the structuring of R&D networks in clusters and the design of public collaborative incentives aiming at repairing network failures. *Section 3* aims at exemplifying these incentives and their consequences in the evolving structure of a particular cluster. We start contextualizing the *Aerospace Valley* cluster in its historical and technological trajectories, before describing the cluster policy guideline developed in order to sustain its development. *Section 4* presents the data collection procedure which enables us building an original and complete dataset of public-funded collaborative R&D projects for this cluster. Then we discuss the methodological issues for building networks over the period. We disentangle the problems that generally arise for the study of networks resulting from the simple aggregation of collaborative and multilateral R&D consortia. To circumvent them, we suggest a place-based network methodology that focuses on structurally equivalent relational behaviors. *Section 5* shows how this methodology helps us identifying the evolving structural properties of knowledge networks in the cluster over time. *Section 6* discusses the results under a particular focus related to the convergence degree between the network statistical findings and the objectives stated by the policy makers, with a particular focus on who are the agents of the structural and technological changes observed during the period.

2. Network failures and the design of collaborative incentives in cluster policies

In spite of controversies on their economic relevance (Duranton, 2011), cluster policies have become a new standard of innovation policies since the 2000s (OECD, 2007). The basic idea is that an additional source of R&D productivity at the meso level remains hidden behind the simple aggregation of the innovative capabilities of each organization considered in isolation. Therefore, the expected economic return of cluster policies is directly related to the multiplier effect induced by network incentives and collaborative subsidies. This very broad objective can be broken down into a wide range of specific ones. Between a myopic process of general watering of collaborative subsidies and a very precise targeting of some particular collaborations, the spectrum of policy interventions is wide and raises the typical questions of selection (and self-selection) in policy design (Fontagné *et al*. 2013). Indeed, selection is the key principle as the key difficulty, due to the information asymmetries between grants providers and receivers. For individual as for collaborative subsidies, the problem remains the same. Cluster policy makers have designed filtering processes in order to reduce these asymmetries and better deal with these selection problems. Moreover, by influencing collaborative patterns of local agents, policy makers also influence the collaborative structure as a whole. Each selected collaboration contributes to the network structuring and connectivity. Here again, a new asymmetry occurs, since policy makers can have difficulties to perceive the aggregate network structure that evolves over time as far as new agents and new collaborations enter the network. Subsidizing a set of “good collaborations” does not necessarily imply shaping “good networks”. Therefore, understanding cluster policies as a mean to boost innovative outputs requires working both on the selection process of knowledge collaborations at the micro level (2.1) and on the monitoring of the connectivity properties of the network as a whole (2.2).

2.1 Filtering and selecting knowledge collaborations in clusters

For cluster public fund raisers, repairing network failures consists first in identifying the nature of these failures, in order to develop an oriented selection mechanism for the provision of collaborative grants. Not all collaborations are equally relevant to sustain. Policy makers have to grant a minimum of collaborations for a maximal expected economic return, by ranking strategic priorities for their collaborative incentive schemes.

- *Public knowledge dissemination and absorption*

One of the typical network failures at the origin of cluster policies relies on an insufficient level of reciprocal absorptive capabilities of knowledge between public research organizations and firms. In spite of the “public good” property of knowledge outputs produced by universities, the regional benefit from local knowledge spillovers does not only result from geographical proximity, but from the intentional effort of agents to interact in multiple ways in order to improve their mutual understanding in problem solving (Breschi and Lissoni, 2001; Bishop *et al*., 2011). A cultural divide and a weak social mobility and proximity between the two communities are often mentioned as a source of inefficiency in some regional contexts (Hemmert *et al*., 2014). Therefore, providing incentives for knowledge exchanges between academic and private R&D labs remains one of the main filtering mechanisms in cluster programs. Nevertheless, this type of support is not necessarily useful for clusters that have historically succeeded in overlapping academic and business networks. But because academic research plays a crucial role in network during the early stage of technological domains (Owen-Smith and Powell, 2004), this mean to foster academic knowledge dissemination is more relevant for clusters in which technological renewal matters. At the reverse, for clusters involved in the upstream phases of market development, the need for this type of public-funded collaborations is less crucial, and can be a source of crowding-out when implemented in an excessive myopic way.

- *SMEs entry and connectivity*

Like organic systems, cluster long run performances depend on the renewing degree of firms' demography. While some clusters succeed in engendering spinoffs and start-ups, others fail and tend to concentrate knowledge relationships between big and well-installed companies (Rocha and Sternberg, 2005). Beyond the question of new entries, the issue for cluster policy makers is also related to the growth and survival rates of nascent companies. Delgado *et al.* (2010) and Wennberg & Lindqvist (2010) show that clustering effects have a higher impact on new companies birth and survival than pure agglomeration externalities. In industrial domains in which systemic technologies require integration between separated pieces of knowledge disseminated between different companies, connections to the main companies holding the central part of the system are often for the new entrants the opportunity to cross the bridge between R&D and business prospects (Suire and Vicente, 2014). Therefore, repairing network failures in clusters consists in building selection mechanisms that are conditional to the attendance of young or nascent SMEs in consortia. Designing this type of incentives can decrease the homophilic relational behaviors between core-companies that relegate new entrants in the network periphery. In terms of expected economic returns, providing this type of collaborative incentives could be more effective than pure individual incentives that put SMEs in as situation of public fund dependence, without any sufficient guarantees that they succeed in isolation in finding market opportunities. But at the reverse, this filtering mechanism can be a source of crowding-out for clusters in which social networks between new entrepreneurs and managers of well-installed firms work well and enable them to collaborate in the design of systemic products.

- *Local cohesiveness and global accessibility*

Clusters are not closed systems. Their success depends both of their internal structuring and their degree of embeddedness in global networks (Owen-Smith and Powell, 2004). Since the large fieldwork analysis of Storper & Harrison (1991) and Markusen (1996), it is acknowledged that clusters strongly differ in their balance between inward and outward knowledge relationships. Each organization manages its relational portfolio according to its own perception of the opportunities of voluntary knowledge exchanges and the risk of unintended knowledge spillovers. Geographical proximity increases these opportunities, but also increases these risks (Breschi and Lissoni, 2001; Boschma, 2005). When collaborations on knowledge open new opportunities but are likely to generate distrust and appropriation concerns (Gulati and Singh, 1998), building relationships with distant partners limits the risks of unintended spillovers. Moreover, global relationships enlarge the variety of external knowledge sources (Fitjar and Rodriguez-Pose, 2011), and are particularly strategic between distant competitors who want to turn together separated and competing technologies into interoperable ones (Balland *et al*., 2013). Therefore, network failures in clusters also refer to a lack of global connectivity, and the balance between local and global collaborative incentives constitutes a challenging point for cluster policy makers.

- *Technological relatedness, diversification and new growth paths*

Cluster dynamics are not never-ending stories of specialization, nor random processes of jump from one industry to another. The technologies and markets on which clusters evolve over time move along a gradient of related and unrelated diversification, giving rise to path renewal or path creation (Isaksen and Trippl, 2017). In the Silicon Valley, the photovoltaic industry in the 2000s has at a first glance nothing to see with the computer industry in the 1980s. Nevertheless it is noteworthy that they share knowledge on storage technologies for data and energy on one side, and nanostructures on the other side, coming both from the semiconductors industry continuously developed since the 1970s. Several factors explain these regional diversification processes (Boschma, 2017), from skills mobility (Neffke and Henning, 2013) to institutional agency (Borras and Edler, 2014). Among them, the dynamics of inter and intra-industry collaborations plays a critical role (Broekel and Brachert, 2015), and then appears as an additional source of network failures. In regions in which several clusters are identified as such by policy makers, the bridging between them constitutes a source of path creation potentialities. The debates on the superiority of related or unrelated diversification on cluster performances is far from being closed and empirical evidences are too contextual to enable the design of standard policy lessons. Nevertheless, diagnosis of the network structures of clusters can help policy makers better orienting their collaborative incentives on particular directions. As suggested by Suire and Vicente (2014), providing public incentives towards collaborations in closely related industries should be more effective for clusters that did not set up enough their technologies on mass markets, while collaborative incentives toward previously unrelated industries and skills can favor path renewal for clusters entering into a phase of transition.

2.2 Monitoring connectivity and the structural properties of networks in clusters

When cluster policy makers provide incentives for collaborations, they contribute to the circulation of knowledge between heterogeneous agents, like a *visible hand* trying to take the control of the expected positive effects of unintended knowledge spillovers. But having the perfect control of the evolving structural properties of networks is somewhat difficult, since all the new supported collaborations but also the renewing and ending ones continuously modify the properties of the structure. Then, beside network failures at the micro-level between certain types of organizations, policy makers have also to take into account network failures at the level of the network as a whole. To do that, the subsidies providers can design selection mechanisms of knowledge ties that help shaping and achieving particular properties, which are identified as key properties for the long run performance of clusters.

- *Connectivity vs. density*

The first challenge for cluster policy makers is to design selection mechanisms that deal with the difficult balances between network connectivity and density. A high level of relational density does not necessarily imply a high level of connectivity. It depends on how collaborative incentives are distributed among the organizations in clusters (Crespo and Vicente, 2016). For a given amount of relationships, knowledge can always find a path to flow between any pairs of organizations, or, at the reverse, can meet several breaking points. In extreme cases, when incentives are oriented toward the reinforcement of closure into separated cliques of organizations, increasing density cannot increase connectivity. If closure and cohesiveness in networks are important for enhancing trust and coordination, in particular when systemic innovations require complex processes of knowledge integration, cluster policy makers have also to take care of the overall connectivity in order to favor knowledge circulation and maintain new collaboration opportunities. If cluster policy guidelines generally stressed on the necessity to increase the overall density of networks in clusters (Vicente, 2017), cluster managers and subsidizers who are actually involved in cluster development have also to focus more surgically on particular bridging and missing links between cohesive groups.

- *Hierarchy*

Knowledge networks in clusters are neither pure centralized structures of interaction nor than pure “flat” ones (Markusen, 1996). In between, clusters are typified by networks in which organizations differ in terms of degree centrality. The extent of the relational portfolio of each organization depends on their size and their willingness to collaborate with others. On a one side, monitoring large portfolio of collaborations is not within every firm’s means, since time and human resources are required for that purpose. On the other side, whatever their size, the need for firms to access external knowledge is also a critical indicator of their willingness to collaborate. Consequently, cluster will differ according to their degree of hierarchy in the structure of knowledge interactions. A strong hierarchy, represented by a very sloping degree distribution, is generally the sign of mature clusters in which big and long-settled organizations have developed a large portfolio of knowledge collaborations (Brenner and Schlump, 2011). While weak hierarchy, represented by a very flat degree distribution, is at the reverse the sign of a burgeoning and nascent cluster which has not yet succeed in reaching a high level of coordination in knowledge exchanges. For markets in which competition and industrial organization are based on systemic and modular products, the existence of core-organizations able to manage the convergence and interoperability between separated pieces of knowledge is one of the key-conditions for clusters to reach a leading position on markets (Balland *et al*., 2013). When cluster display hierarchy, they exhibit a core-periphery structure (Borgatti and Everett, 1999) in which highly connected organizations designing technological standards co-exist with loosely connected ones, generally new entrants such as spinoffs and SMEs. In terms of industrial organization, this topological form of networks conveys a structure in which the growing capabilities of central organizations to manage the systemic process of innovation do not play against but co-exist with a dynamics of new entries (Klepper, 1996). This structure of knowledge interactions in clusters has been documented by Owen-Smith and Powell (2004) for the biotech industry in Boston, and by Cattani and Ferriani (2008) for the movie industry in Hollywood. Therefore, cluster policy practitioners have to pay attention on the existing structure of knowledge interactions. They can help some of the burgeoning organizations to become core-ones in nascent clusters or, at the reverse, provide incentives for entrepreneurship in mature clusters.

- *Assortativity*

Beyond the shape of the degree distribution, the shape of the degree correlation also matters. Called assortativity in network theories (Rivera *et al*., 2010; Ahuja *et al*., 2012), the degree correlation offers a formal view not only of the co-existence of highly and poorly-connected organizations in a same cluster, but on how both interact together. A network is strongly assortative when highly-(poorly-) connected organizations tend to form relationships with other highly-(poorly-) connected organizations, and disassortative when core-organizations tend to interact more with peripheral ones. Therefore, the assortativity of clusters is an indicator of the knowledge pathways between big organizations and less central ones, such as spinoffs and SMEs. As evidenced by Crespo *et al.* (2016), a too strong assortativity in mature clusters weakens their endogenous capabilities to renew themselves over time. The main challenge for successful and mature clusters is to avoid entering into decline when the markets on which they are well-installed also decline. Network assortativity, after a while, becomes a source of conformism and negative lock-in (Watts, 2004), due to an excessive redundancy of knowledge flows within the core-component of the network. As a corollary, fresh and explorative knowledge produced by peripheral organizations have difficulties to reach and irrigate the core of the network. Accordingly, disassortative structures of knowledge interactions enable clusters having a higher propensity to continually overlap emergent and mature markets, by multiplying pathways between the burgeoning ideas developed by new entrants and the market experience acquired by core-organizations. Therefore, policy makers have to consider this network property carefully in order to provide good collaborative incentives at the right moment. For that, they need to pay attention both to the existing structure of knowledge flows and the phase of the business cycle on which clusters are situated.

The concept of network failures is not only a pure and un-contextualized theoretical argument to justify public incentives for knowledge collaborations in clusters. It also requires an approach taking into account the territorial context on which these incentives are implemented. That is why the selection mechanism of collaborations has to rely on a diagnosis on the specificity of each cluster, in order to better target the potential missing links that could foster innovation at the reginal level. The actual network failures can be weak or strong, and depend on a wide range of critical parameters policy makers have to capture in order to better contextualize their intervention.

3. The context of *Aerospace Valley* in Toulouse

3.1. Cluster context: mature markets and the need for regional diversification and relatedness

Greater Toulouse (France) is a leading and historical place for aeronautics and space industries in Europe (Dupuy and Gilly, 1999; Niosi and Zeghu, 2005; Zuliani, 2008; Gilly *et al.*, 2011). The main oligopolistic companies of these two related industries and some of their plants are located in Toulouse (Airbus, Airbus Defense and Space, ATR, Thales Alenia Space, Safran, among others), and the city hosts the main French high schools of engineering and research in this technological domain (Sup'Aero, ONERA, Federal University of Toulouse, among others) as well as the headquarter of the National Center for Spatial Studies (CNES). This cluster displays three main characteristics: (i) its maturity, since it leads the European aeronautics and space industries, (ii), its centrality, since it is at the center of the whole of European industrial and innovation networks in the technological field; (iii) its developing diversification, since it faces challenges related to environmental constraints and new balances between military and civilian market opportunities, in particular in the transversal domain of on-board and embedded systems, that gives rise to the emergence of new industries, such as GNSS (Global Navigation Satellite Systems), drones, and other related industries.

3.2. Cluster policy: the two stages selection process and the changing guidelines of collaborative incentives over the period

Aerospace Valley is a cluster governance structure born in 2005, as the result of the implementation of the still ongoing French Cluster Policy. The cluster has been selected by the French government as one of the seven "world-wide clusters" in the French cluster classification (beside the eleven "globally oriented clusters", and the fifty three "national clusters"). The aim of the national policy consists in fostering innovation by selecting a set of 2-dimensions vectors of regions and technological domains that are eligible for receiving grants for R&D collaborative projects. *Aerospace Valley* is thus one of these leading selected vectors, with "*greater Toulouse and its administrative NUTS2 region*" and "*aeronautic, space, and embedded systems*" as vector coordinates. The governance structure of the cluster is appointed to provide networking activities and facilitate the emergence of R&D collaborative projects between the industry and the academia. In particular the structure is responsible of organizing the first stage of the selection process for the national calls for proposal launched by the FUI (Single Inter-Ministry Fund) and the ANR (French Research Agency). This first stage consists in a certification process of the most promising R&D research consortia that meet the strategic objectives of the cluster. Once this certification done, the second stage of the selection process is organized at the national level. The FUI and ANR regularly launch calls for proposal for R&D collaborative projects for which only consortia certified at the cluster level can apply. The public incentives for collaborative innovation and cluster development are thus organized at two levels. First, the local certification process is an incentive for firms and public research organizations to work together in order to expect public funds for their research activities. Second, the national selection is a strong incentive for cluster managers to nurture synergies and collaborations in order to get an increasing number of grants and maintain their position in the French cluster classification.

The French cluster policy guideline relies on the awareness of the network failures identified in the literature. But this guideline is not set in stone since 2005. First, it has changed at the national level over the period. Second, cluster managers, in the limits of the French guideline constraints, have a degree of latitude to adapt their incentives for R&D collaborations. The main constraint that has not move since the birth of the policy concerns the necessity for R&D collaborative projects to gather private companies and public research organizations. At the reverse, other constraints and incentives have evolved over the period. First, the constraint of being located in the geographical perimeter of the cluster to be part of a project has been early relaxed. Too closely related to Porter' ideas of cluster organization, this constraint reduced collaborative opportunities and the influence of clusters abroad. Once relaxed, it became possible to apply at the national grants with projects certified by more than one cluster governance structures. Second, to deal with the Matthew effect according to which the selection process naturally allows the rich to get richer, strong incentives to include SMEs in R&D consortia has been designed at the national level and absorbed at the cluster level. Lately, strong incentives have been added in order to boost not only exploration, but also exploitation and markets, putting the concept of "factories of the products of future" beside the "projects factories" at the heart of the new guideline. Finally, with the possibility given by the national constraints to grant inter-cluster collaborative projects, many clusters including *Aerospace Valley* recently provide strong incentives toward industrial diversification, in order to better overlap mature and emerging markets.

4. Data collection and methodology

Identifying and characterizing networks in clusters using public-funded R&D collaborative projects requires particular cautions in terms of data collection, time window definition, and adapted methodologies of network analysis.

4.1. Data collection and disambiguation

Data collected on collaborative projects certified by *Aerospace Valley* and granted at the national level between 2006 and 2015 constitute the material used to analyze the evolving structural properties of the cluster. These data are extracted from *Aerospace Valley* website and the public national list of selected projects. They concern the FUI and ANR programs, both being the main national programs aiming at repairing network failures in innovation activities and restoring incentives to collaborate on knowledge. These data include project scientific abstracts, and information about the consortium members (location, institutional form). If the collection of projects does not suffer from limitations, that is not the case for the project members. Indeed, an extensive effort of identification and disambiguation was required to work with fine-grained data. This effort focused on an appropriate targeting of departments and plants actually involved in projects, in order to avoid the over representation of multi-plant companies and large public research organizations. Project websites, companies activity reports and scholars affiliation have been consulted in order to refine the database, and have an actual information on the location and the size of each node of the network. When contradictory information remained, e-mails to academics and engineers have been sent and the answers enable us reaching a sufficient fine-grained extraction.

Over the period, 248 projects have been granted. We split the period into four sub-periods using start date of projects in order to affiliate projects to cohorts with comparable time window and size. *Table 1* presents basic statistics on collaborative projects over the period.

Table 1 here

The nodes have been typified according to 4 categories: Big companies, SMEs (less than 100 workers), PROs (public research organizations), and others (including technological platforms and agencies, public institutions). Their location is also taken into account in a binary way by distinguishing nodes located into the administrative area of the cluster and the others. *Figure 1* describes the evolving demography of nodes according to these specifications.

Figure 1 here

4.2. Overpassing bias and capturing groups' behavior: the place-based network methodology

Analyzing how public collaborative incentives drive network structuring in clusters requires aggregating collaborative projects funded in a same time window (same cohort), and reproducing the process for all the other time windows. Several previous empirical studies applied this methodology in the context of regional cluster analysis (Owen-Smith and Powell, 2004; Giuliani and Bell, 2005; Vicente *et al.*, 2011; Ter Wal, 2013; Levy and Talbot, 2015; Crespo *et al.*, 2016). When collaborative projects are considered, network analysis can start by the construction of a *2-mode* network, i.e. an affiliation network drawn from a rectangular matrix and composed by one type of node (the organizations) connected to another type of node (the projects). In this type of networks, there are any direct ties connecting nodes of the same type. But at the reverse, two projects can be linked by one or several organizations, and two organizations can be tied by one or several projects. This type of network has been suggested by Uzzi and Spiro (2005) and Balland *et al.* (2013) since it allows having a first view of how projects in a same technological field can be linked together by multi-affiliated organizations. *2-mode* networks can be turned into *1-mode* networks (Breiger, 1974), in order to capture the structure of innovative activity in clusters. *1-mode* networks are drawn from a square matrix and are composed by a set of nodes representing organizations and a set of ties representing knowledge flows between them. This methodology has proven his reliability to identify critical organizations in knowledge dissemination at the micro-level, and salient structural properties at the meso-level. Nevertheless, as pointed by Vicente *et al.* (2011), this network-based analysis is not exempt of bias and limitations.

First, when networks are drawn from the aggregation of R&D consortia, i.e. from the aggregation of cliques of fully interconnected organizations, different bias can occur (Newman *et al*., 2001; Uzzi and Spiro, 2005). Most of all are related to the risk of confusion in ego-network properties such as degree centrality and brokerage, due to the heterogeneity in the size of cliques. They can give rise to misleading interpretation in the actual role of organizations in knowledge dissemination. To give an example of these misinterpretation risks, let us consider an organization that is affiliated to one 15-members consortium, and only to this one. It will have a high degree centrality, while, as shown by Bernela & Levy (2017), its influence and involvement in the innovation system can be very weak, in particular if this organization does not actually interact with all the other consortium members. Let us now consider another organization involved in 3 collaborative projects affiliating each one only 3 partners. Its degree centrality will be less significant due to a smaller relations portfolio, while one can expect a higher involvement in projects and a more strategic position in the network. Dealing with this issue is a challenge for network-based cluster analysis, in particular when the size of consortia strongly differ, as it is typically the case in that analysis in which the consortia size go from 2 to 32 organizations (see *table 1* above). Therefore, methodologies that correct this bias are required. The idea is to better apprehend the skeleton of the network by capturing the actual influence of nodes but without introducing noise related to the heterogeneous size of consortia.

Second, as early demonstrated by Pallotti and Lomi (2011), not only nodes position and direct ties explain knowledge dissemination in networks. Starting from the ideas on structural equivalence developed by Lorrain & White (1971) and Burt (1987), they show that groups' behaviors also matter. Structural equivalent organizations have similar patterns of relations to others, and thus share and face same resources and constraints (Stuart and Podolny, 1996; Gnyawali and Madhavan, 2001; Aarstad *et al*., 2009). They tend to contribute to innovation communities in a same way not only because they influence each other by direct ties, but because they face similar dependencies and relational contexts (Knoke, 1983; Burt, 1987; Mizruchi and Galaskiewicz, 1993). Identifying groups' behaviors based on structural equivalence enables having a complementary way to deal with the influence organizations have in the aggregate structure of knowledge interactions. By giving the skeleton of the network, it also allows better capturing the changes on the structural and relational patterns (Brieger, 1976; Borgatti and Everett, 1992; Doreian, 2012).

Rather than limiting the study to a simple *1-mode* network analysis, we suggest developing an alternate methodology that correct the bias at the same time that it considers groups' behaviors, without compromising the possibility to analyze nodes' position in networks. We use for that the so-called "network of places" approach early developed in sociology by Pizarro (2007). To define a place P_i of structural equivalent organizations, let us start by considering a finite set of organizations $I = \{i_1, i_2, i_3, \dots i_p\}$, each affiliated to one or more projects belonging to the set of projects, noted C (in order to consider each project as a fully interconnected clique), with $C = \{c_1, c_2, c_3, \dots c_n\}$. We can define a place P_i of an organization $i \epsilon I$ as a subset of C such that at least one of the organizations of I belongs to every one and only to the projects included in the subset P_i. Therefore, for $i \epsilon I$, $P_i = \{c_j \in E: i_i \in c_j\}$. If two organizations i, $j \in I$ have the same subsets of C, they belong to the same place. Then, they are structurally equivalent (Borgatti and Everett, 1992). Places become the new nodes of the network, that are connected by a relation R when $P_i \cap P_j \neq \emptyset$. Therefore, the set P of all the places defined in C and the set R of their relations constitute the network of places. This set P can be also defined as a set $P(k,l)$, where k represents the number of projects in which organizations are involved together, and l the number of organizations belonging to the place. This reduction process based on structural equivalence and groups' behavior gives the skeleton of the organizational *1-mode* network, without losing the organizations, which remain in the structure, but now as simple places' constituents. In addition, it provides a simple, accurate and fast algorithm for the study of structural equivalence (Doreian, 2012).

Figure 2 here

Figure 2 highlights in a stylized way the process that turns a network of projects (cliques of fully connected nodes) into a network of places, where nodes are now places gathering structural equivalent organizations. *Box 1* presents a structure of knowledge interactions composed of 4 collaborative projects, themselves each one composed (in transparency) of fully connected cliques of organizations. *Box 2* turns this structure into a simple *1-mode* network. *Box 3* sorts structural equivalent organizations into distinct groups, while *box 4* preserves in transparency the previous *1-mode* network, and displays now the network of places, that are connected by inter-organizational ties.

Table 2 here

We turn the *1-mode* network of organizations into a *1-mode* network of places in order to better focus on the groups' behaviors of the *Aerospace Valley* network skeleton. *Table 2* presents basic statistics of this new network.

Figure 3 provides an actual illustration, limited here at the fourth cohort of the *Aerospace Valley* cluster, in order to have a better view of how this reduction process gives the skeleton of the network and neutralizes the bias related to the strong heterogeneity of R&D consortia size.

Figure 3 here

5. Identification of the evolving structural properties of *Aerospace Valley* Cluster

By designing collaborative incentives and selection routines of R&D consortia, cluster policy makers expect reaching their objectives related to better public knowledge dissemination, SMEs entries, global connectedness and technological diversification. But is the visible hand of the policy maker as dexterous as that of the juggler to repair network failures? A detailed analysis of the skeleton of knowledge networks in clusters can help dealing with this question. It consists in discussing the degree-related structural properties of the network of places, in order to assess if selection routines meet the policy makers' objectives.

5.1. Degree distribution (hierarchy), degree correlation (assortativity)

Figure 4 here

If we stay at a pure structural level, the evolving properties of hierarchy and assortativity give a first overview of how the topological forms of the network of places have changed over the period. *Figure 4* summarizes these evolutions. First, hierarchy, which is measured by the gradient of the degree distribution, remains high but has declined over the period with a slight increase from cohort 2 to 3. It means that *Aerospace Valley* cluster is typified by a high but decreasing level of places centralization. Because places represent homogenous groups' relational behaviors, this high level of centralization indicates the coexistence between groups of organizations with different size of relational portfolio, from a couple a highly connected organizations that collaborate with many others to poorly connected organizations. But over the period, the influence and coordination capabilities of groups have been more distributed between a larger number of less central places. Second, the network of places is typified by a bell curve of degree correlation. It indicates a changing balance in the paths between highly and poorly connected places and the organizations that belong to them. Indeed, highly connected organizations in cohort 1 tend to collaborate more with poorly connected organizations than in cohort 2 and cohort 3. This pattern shows that the network tends to be more and more assortative, with an increasing tendency of highly connected organizations to interact together. Nevertheless, the assortativity decreases in the last period, showing a reverse tendency. The most noteworthy is that hierarchy and assortativity play together in a different way from cohort 1 to cohort 2 and from cohort 3 to cohort 4. In the first period, the decreasing hierarchy goes with an increasing assortativity, signifying that a more distributed influence in the network has engendered more paths between places that have close degree. But this is not the case in the last period, in which the influence has been more and more distributed in the network, but at this time with an increasing tendency of highly and poorly connected places to interact together.

5.2. Connectedness and **p**-*cohesive blocks modeling*

This result invites to go more in depth into the structural properties of the network of places in order to have a better understanding of the drivers of these changes in the matrix of knowledge flows. The idea is to highlight, in the line of Moody and White (2003) methodological proposal, how places connect together in a nested system of cohesive blocks and form a multiconnected network (Powell *et al.*, 2005). For each cohort, we extract the number of p-cohesive blocks. A cohesive block is a component defined as a subset of the network where the associated value of connectivity p gives the strength of cohesion of the block. The value p is then the maximal number of places in the subset above which the block cohesion disappears. Strongest cohesive blocks are cliques, i.e. those in which every place is directly connected to every other place. Therefore, we can characterize the network by a hierarchical nesting of cohesive blocks. The process consists in finding by iteration a maximal number q of p-cohesive blocks, with $q > p$. Once these blocks identified, their rank-size distribution offers a relevant mean to assess the "multilevel embeddedness" (*nestedness* in the terminology of Moody and White) of places in the overall network. This rank-size distribution offers a relevant mean to both identify cohesive blocks and order them according to both nested and fragmented groups. Indeed, cohesive blocks can overlap when places belong to multiple groups. The more cohesive blocks overlap, the more they bring closer in the distribution. Therefore, the shape of the distribution offers a relevant mean to observe how high and low value cohesive blocks connect together, and then how hierarchy and assortativity play together in the overall structure of knowledge flows.

Figure 5 here

Figure 5 describes the construction of the *p*-cohesive blocks and the iteration process offering the nested and hierarchical system of *p*-cohesive blocks for the cohort 1. For instance, the block B-1 is a *0*-cohesive block representing the entire network. The value is *0* since any places are able to give a cohesive structure. The block B-7 is one of the subset of B-1 defined as a *3*-cohesive block in which at least 3 places offer cohesion in a subset of 87 places. The iteration process goes on until B-20, which is the cohesive block having the highest value of cohesion. And finally, other cohesive blocks with a decreasing *p*-value are extracted from the part of the network that does not include subsets of the previous ones. The shape of the distribution displays two close peaks, i.e. two highly cohesive blocks (B-21 and B-20). In this cohort, these two strongest cohesive blocks overlap since two central places belong to both, explaining why they are ranked one after the other in the distribution. Therefore, for cohort 1, the distribution shows the high level of centralization of the network and the weakly distributed control of knowledge flows.

Figure 6 here

We repeat this process of nested construction of *p*-cohesive blocks for the four cohorts. Results are summarized by the four distributions in the *figure 6*. From cohort 1 to cohort 4, the maximal *p*-value decreases while the number of blocks increases. This observation confirms the previously observed decreasing hierarchy over the period, but also shows that the tendency of closure between leading places decreases as well, explaining why the number of "pockets" of influence increases in the overall network. This finding supports the idea of a more distributed influence in the coordination of R&D activities over the period and a gradual shift in the balance between closure and bridging that can better explain why in the last period hierarchy decreases at the same time than assortativity. Indeed, one can observe in *figure 6* that when the higher *p*-values decrease over the period, the "distance" between peaks in the distribution increases, which that shows that higher cohesive blocks are less and less closely connected each other by other highly connected places. This finding shows that more poorly connected places bridge highly cohesive groups, explaining the decreasing level of assortativity and a better connection between highly and loosely connected places.

6. Discussion of the findings

How to turn these findings on the evolving structural properties of *Aerospace Valley* into more qualitative readings related to the role of public collaborative incentives on the cluster structural change? As evidenced above, the network structure has changed over time, from a highly concentrated to a more distributed structure of dominant cohesive blocks of places. One can expect that the cluster policy guideline has impacted the cluster structuring towards a more decentralized pattern of coordination, in which the balance between closure and bridging has changed over the period, pushing organizations to reorient their collaboration pattern toward more path-breaking and less assortative relational behaviors. A suited solution consists in looking at the organizational demography of places. In doing that, the composition of places and how it evolves over time can allow identifying who the agents of structural change actually are.

6.1. The changing structural role of SMEs

One first way to assess the changing structural properties of *Aerospace Valley* over the period is to focus on the so-called elite component (Powell *et al.*, 2005) of the 4-cohorts networks. The elite-component is composed by the places belonging to the two highest levels of *p*-cohesive blocks. This elite component corresponds to the peaks of the multi-component distribution. *Figure 7* provides simple statistics of this component and how its demography evolves over time.

Figure 7 here

The first observation, as regard the organizational demography of the whole network (see *figure 1*), reveals that the compared shares of each organizational category in the whole network and in the elite one evolve according to a particular pattern. For big companies, as expected due to their intrinsic high relational capabilities, their presence in the elite network is largely superior to their presence in the entire network, but slightly decreases in the fourth period. SMEs at the reverse are less than proportionally present in the elite network than in the entire one in the two first periods, start to fill the gap during the third one, and succeed in reversing the pattern during the fourth one, with a presence in the elite network slightly superior as regard the entire network. Considering that the extent of relational portfolio is generally strongly correlated to the organization size, this pattern raises the question not only of the SMEs entries, but also the question of their evolving structural role in the cluster. Finally, becoming victim of the fast growing entry of SMEs in the elite network, the share of public research organizations decreased over the two last periods.

How to explain such a structural pattern? As mentioned in the presentation of the changing guidelines of collaborative incentives, a first trivial answer relies on the fact that policy makers have offered stronger incentives to involve SMEs in the R&D consortia. These incentives have produced visible and not surprising effects on the fourth period, with a jump in the number of SMEs involved in the entire network. But this answer does not suffice to explain why SMEs have succeeded in entering more than proportionally the higher *p*-cohesive blocks of the network of places, which was a neither intentional nor possible objective from policy makers.

The decreasing values of *p* and the changing distribution of *p*-cohesive blocks over the period find explanations in the relational capabilities and behaviors of SMEs as regard big companies. By entering step by step the elite network, SMEs have changed the pattern of the more central cohesive groups. First, SMEs being more constrained in the extent of their relational portfolio than big companies (Street and Cameron, 2007), the network hierarchy has decreased, giving rise to a core of the network less and less focused on a couple of highly connected monopolistic companies. From the start to the end of the period, SMEs have progressively reinforced their role in the connectedness and cohesiveness of the network, being less and less peripheral, and more involved in the overall coordination of technological dynamics. Their stronger presence in the highest cohesive groups, where triadic closure is higher than elsewhere in the network, shows that they are not only purveyors of fresh knowledge at the margin. At the reverse, they increasingly tend to attend the design of technological standards that drive the future market exploitation. Second, SMEs displays an alternate pattern of collaborations as regard big companies. Literature in Geography of Innovation has early shown that SMEs and big companies in some extent differ in terms of innovation strategies. Audretsch and Lehman (2005) have evidenced that nascent and big companies have different perceptions about the opportunities to turn knowledge exploration into markets. New entrepreneurs and R&D managers of well-installed companies differ in their timorousness facing uncertainties and risks in market-oriented researches, the former being steadily less conformist than the later. These consistent differences in innovation management also find their counterparts in the relational behaviors and strategies. Since they may be willing to absorb more risks than big companies managers, new entrepreneurs tend to favor weak ties over strong ones in order to explore new windows of technological opportunities. Considering the well-known inverted U-shaped relationship between tie strength and new knowledge creation (McFadyen and Cannella, 2004; Lowik *et al.*, 2012), these differences in relational behaviors might suggest that new firms are certainly more numerous on the left-hand side of the curve, while big companies monopolize a large part of its right-hand side. Therefore, between under and over-embeddedness, the evolving composition of elite places can explain why, as far as SMEs enter the elite part of the network, *p* decreases at the same time that the distance between the higher *p*-cohesive blocks increases. The tendency of SMEs to adopt bridging strategies over closure deconcentrates the nested systems of cohesive blocks observed when the elite groups were dominated by big companies, giving over time a more and more decentralized structure in the distribution of influential places.

6.2. cluster/pipeline structure as a driver of diversification and less assortative knowledge networks

A second way to assess the changing structural properties of *Aerospace Valley* over the period also consists in starting again by the demography of the network, but this time in relation with the inter-clustering dimension of selected R&D consortia. The public incentives to apply to multi-cluster projects, which have been implemented early after the initial policy guideline, have increased the extent of possible knowledge interactions for the organizations located in the *Aerospace Valley* area. The evolving structural properties of knowledge network probably find explanations in the way with which the different organizations of the cluster have benefited from these incentives.

Figure 8 here

Figure 8 displays over the period the shares between single and multi-granted collaborative projects, taking into account that the shares between the organizations affiliated to the *Aerospace Valley* cluster and others affiliated in other clusters remains roughly stable over the period (see *Figure 1* above). The more salient observation is related to the strongly decreasing share of single-granted R&D consortia over time, with stabilization at the last period. Less than half of the projects are supported only by the cluster association, while the others are sustained by at least another French cluster. A small part concerns projects supported by other aerospace clusters, this part being stable over the three last cohorts. But the most noteworthy evolution is related to the growing technological diversification of the network. Firstly, we observe a growing share of collaborative projects conjointly supported by French IT clusters during the three first cohorts. These pipelines are typical of many clusters and industries that invest in digitalization. For *Aerospace Valley*, these pipelines mainly concern both embedded systems and space industries, around the development of GNSS (Global Navigation Satellite Systems), which require technological convergence between telecommunications and spatial data transmission (Vicente *et al.*, 2011). Secondly, the same occurs for projects conjointly supported by other clusters specialized in many other industries, over time and with a particular growth during the last cohort. Therefore, knowledge pipelines also exist between different places and industries[1], and their recent development seems to be the sign of a structural change in the long run technological dynamics of the cluster.

Figure 9 here

How to explain the parallel between this growing technological diversification and the evolving structural properties of the *Aerospace Valley* network skeleton? *Figure 9* allows understanding this changing pattern during the last period. Indeed, if we consider all the places of the 4-cohorts network in which organizations connect at least two collaborative projects among which one of them is granted by a cluster out of the aeronautics and the IT industry, we observe that the share of SMEs has strongly increased from the three first periods to the last one, while big companies prevail in the first one and the public research organizations in the second and third ones. Here again, SMEs appear as the main agents of the cluster structural change, and not only at the topological level of the network, but also at the cognitive level. Their tendency to be less conformist than big companies in their search from partners at the relational level is also reflected in their higher willingness to break the industrial frontiers. The decreasing assortativity of the network during the last period is then supported also by technological bridging and relatedness, increasing the potential of diversification of *Aerospace Valley* over time.

7. Conclusion

Cluster policies have been often assessed in the literature, with a focus on their final objective, i.e. their ability to increase regional innovative outputs, employment or export aggregates (Falck *et al.*, 2010; Martin *et al.*, 2011, Brossard and Moussa, 2014), with sometimes opposite results. But few works have investigated their specific and intermediary dimension, i.e. their influence on the structuring of knowledge networks. This dimension is probably one of the critical factors of the performance of clusters, or at least the one that differentiates cluster policies from other individual incentives to innovate (Nishimura and Okamuro, 2011). Expecting high economic returns of cluster policies involves first shaping networks with good properties, so that the causality between cluster policies and regional performances also relies more on the topological properties of networks than on the existence networks *per se*. The paper was aiming at dealing with that challenge, by going in depth, prior to evaluation, into

[1] 15 industrial sectors are listed by the French cluster policy, each cluster being affiliated to one of them.

the links between the public micro-incentives to join R&D consortia and the evolving structural properties of knowledge networks in a particular cluster.

At the methodological level, searching from the structural properties of networks composed of R&D consortia has required avoiding the bias and overpassing the limitations of classical *1* and *2*-modes networks. The place-based network methodology has enabled us suggesting a new way to capture the evolving structure of the network skeleton, centered on a clear cut identification of structurally equivalent relational behaviors. This way to proceed has highlighted the evolving structural properties of the cluster over time. The evolving indexes of degree distribution and correlation show that the structure of knowledge interactions has changed over the period, from a highly hierarchical structure, centralized around a couple of long-installed oligopolistic companies, to a more democratic, less assortative, and multipolar structure of knowledge flows. The analysis of the evolving composition of places has allowed better understanding who the agents of the structural change in the cluster actually are. Indeed, one of the salient findings relates to the continuing entries of SMEs in the elite part of the network, which has changed the relational behavior of the agents of the core-component of the network, with a stronger tendency to favor bridging strategies over closure, at the relational as well as the cognitive levels. If we follow previous theoretical (Rivera *et al*., 2010; Crespo *et al*., 2014) and empirical findings (Uzzi and Spiro, 2005, Breschi and Lenzi, 2016; Crespo *et al*., 2016) on the efficient properties of local knowledge networks, this changing pattern in the *Aerospace Valley* network may involve the possibility of a more adaptive and innovative cluster.

At the policy level, even if the contribution is restricted to a single case study among the whole of clusters supported by the French policy, some lessons about the effects of public incentives developed in clusters can be drawn. At first glance, the broad objective of helping clusters to turn mature industry into diversified markets seems to have been achieved. Under the growing constraint to apply to inter-cluster projects, *Aerospace Valley* has reached a threshold in technological relatedness and transversality during the last period of the study. The cluster association staff has succeeded in nurturing less and less conformist collaborative projects, which afterward have been selected and granted at the national level. But did the local staff as well as the national experts actually control this new pattern of knowledge interactions? It is not sure. Or at least a part of this pattern has probably escaped them. Indeed, the growing incentives oriented to SMEs were at the origin merely dedicated to repair a network failure related to their difficulty to connect knowledge networks. For policy makers, nothing could have predicted that SMEs would enter the elite network more than the network *per se*, nor than they would have a stronger tendency to have non assortative behaviors and capabilities to blur technological frontiers. Therefore, the visible hand of cluster policy makers does not control all the process that shapes the structural properties of knowledge networks. The changing pattern of *Aerospace Valley* network took a long time. SMEs were first relegated at the network periphery, without any significant influence on the network structuring. They succeeded after a while in positioning themselves in the elite part of the network, without any more incentives, but with their own growing experience in the attendance at collaborative projects. But an open question still remains, which also probably escapes the intentions of cluster policy makers. The pressures to increase the attendance of SMEs at projects have strongly evinced public research organizations from the elite network. It could weaken the cluster in the near future, limiting the diffusion of fundamental and explorative knowledge through the entire network, and the long run dynamics of the cluster.

Following this research, a last question also remains open and is related to the challenging systematization of the place-based network methodology to improve the assessment of cluster policies. As it is mostly the case, cluster policies are designed at the national level and applied in a couple of selected regions (Uyarra and Ramlogan, 2012; Fontagné *et al.*, 2013). Considering that, the methodology developed in this research can help having a better understanding of why some clusters perform better than others when they receive the same incentive scheme but present different network failures, and different social and industrial contexts.

8. References

Aarstad, J., Haugland, S.A., Greve, A., 2010. Performance Spillover Effects in Entrepreneurial Networks: Assessing a Dyadic Theory of Social Capital. Entrep. Theory Pract. 34 (5), 1003-1019.

Ahuja, G., Soda, G., Zaheer, A., 2012. The genesis and dynamics of organizational networks. Organ. Sci. 23 (2), 434-448.

Audretsch, D., 2005. Innovation and industry evolution. MIT Press, Cambridge.

Audretsch, D., Feldman, M., 1996. Innovative clusters and the industry life-cycle. Rev. Ind. Organ. 11 (2), 253-273.

Audretsch, D., Lehmann, E., 2005. Does the knowledge spillover theory of entrepreneurship hold for regions? Res. Pol. 34 (8), 1191-1202.

Balland, P.A., Suire, R., Vicente, J., 2013. Structural and geographical patterns of knowledge networks in emerging technological standards: evidence from the European GNSS industry. Economics of Innovation and New Technology 22 (1), 47-72.

Bernela, B., Levy, R., 2017. Collaboration networks in a French cluster: do partners really interact with each other? Pap. Reg. Sci. 96 (1), 115-138.

Bishop, K., D'Este, P., Neely, A., 2011. Gaining from interactions with universities: multiple methods for nurturing absorptive capacity. Res. Pol. 40 (1), 30-40.

Borgatti, S.P., Everett, M.G., 1992. Regular blockmodels of multiway, multimode matrices. Soc. Networks 14 (1), 91-120.

Borgatti, S.P., Everett, M.G., 1999. Models of core/periphery structures. Soc. Networks 21 (4), 375-395.

Borras, S., Edler, J., 2014. The Governance of Socio-Technical Systems: Explaining Change. Edward Elgar Publishing, Cheltenham, UK.

Boschma, R., 2005. Proximity and innovation: a critical assessment. Reg. Stud. 39 (1), 61-74.

Boschma, R., 2017. Relatedness as driver of regional diversification: a research agenda. Reg. Stud. 51 (3), 351-364.

Breiger, R.L., 1974. The Duality of Persons and Groups. Soc. Forces 53 (2), 181-190.

Brieger, R.L., 1976. Career Attributes and Network Structure: A Blockmodel Study of a Biomedical Research Specialty. Am. Sociol. Rev. 41 (1), 117-135.

Brenner, T., Schlump, C., 2011. Policy Measures and Their Effects in the Different Phases of the Cluster Life Cycle. Reg. Stud. 45 (10), 1363-1386

Breschi, S., Lenzi, C., 2016. Co-invention networks and inventive productivity in US cities. J. Urban Econ. 92, 66-75.

Breschi, S., Lissoni, F., 2001. Knowledge spillovers and local innovation systems: a critical survey. Ind. Corp. Change 10 (4), 975-1005.

Broekel, T., Brachert, M., 2015. The structure and evolution of inter-sectoral technological complementarity in R&D in Germany from 1990 to 2011. J. Evol. Econ. 25 (4), 755-785.

Broekel, T., Fornahl, D., Morrison, A., 2015. Another cluster premium: Innovation subsidies and R&D collaboration. Res. Pol. 44 (8), 1431-1444.

Brossard, O., Moussa, I., 2014. The French cluster policy put to the test with differences-in-differences estimates. Econ. Bulletin 34 (1), 520-529.

Burt, R. S., 1987. Social Contagion and Innovation: Cohesion versus Structural Equivalence. Am. J. Sociol. 92 (6), 1287-1335.

Cattani, G., Ferriani, S., 2008. A core/periphery perspective on individual creative performance: Social networks and cinematic achievements in the Hollywood film industry. Organ. Sci. 19 (6), 824-844.

Crespo, J., Vicente, J., 2016. Proximity and distance in knowledge relationships: from micro to structural considerations based on territorial knowledge dynamics (TKDs). Reg. Stud. 50 (2), 202-219.

Crespo, J., Suire, R., Vicente, J., 2014. Lock-in or lock-out? How structural properties of knowledge networks affect regional resilience. J. Econ. Geogr. 14 (1), 199-219.

Crespo, J., Suire, R., Vicente, J., 2016. Network structural properties for cluster long run dynamics: Evidence from collaborative R&D networks in the European mobile phone industry. Ind. Corp. Change 25 (2), 261-282.

Delgado, M., Porter, M., Stern, S., 2010. Clusters and entrepreneurship. J. Econ. Geogr. 10 (4), 495-518.

Doreian, P., 2012. Positional Analysis and Blockmodeling. In: Meyers, R.A. (Ed). Computational Complexity: Theory, Techniques, and Applications. Springer, New York, NY, 6913--6927.

Dupuy, C., Gilly, J.P., 1999. Industrial groups and territories: the case of Matra-Marconi-Space in Toulouse. Camb. J. Econ. 23 (2), 207-223.

Duranton, G., 2011. California Dreamin': The feeble case for cluster policies. Rev. Econ. Analysis 3, 3-45.

Falck, O., Heblich, S., Kipar, S., 2010. Industrial innovation: Direct evidence from a cluster-oriented policy. Reg. Sci. Urban Econ. 40 (6), 574-582.

Fitjar, R., Rodríguez-Pose, A., 2011. Firm collaboration and modes of innovation in Norway. Res. Pol. 42 (1), 128-138.

Fontagné, L., Koenig, P., Mayneris, F., Poncet, S., 2013. Cluster policies and firm selection : Evidence from France. J. Regional Sci. 53 (5), 897-922.

Giuliani, E., Bell, M., 2005. The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. Res. Pol. 34 (1), 47-68.

Gilly, J.P., Talbot, D., Zuliani, J.M., 2011. Hub firms and the dynamics of regional innovation: case studies of Thales and Liebherr in Toulouse. Eur. Plan. Stud. 19 (12), 2009-2024.

Gnyawali, D.R., Madhavan, R., 2001. Cooperative Networks and Competitive Dynamics: A Structural Embeddedness Perspective, Acad. Manag. Rev. 26 (3), 431-445.

Gulati, R., Singh, H., 1998. The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. Admin. Sci. Quart. 43 (4), 781-814.

Hemmert, M., Bstieler, L., Okamuro, H., 2014. Bridging the cultural divide: Trust formation in university–industry research collaborations in the US, Japan, and South Korea. Technovation 34 (10), 605-616.

Isaksen, A., Trippl, M., 2017. Innovation in space: the mosaic of regional innovation patterns. Oxford Rev. Econ. Pol. 33 (1), 122-140.

Klepper, S., 1996. Entry, exit, growth and innovation over the product life cycle. Am. Econ. Rev. 86 (3), 562-583.

Knoke, D., 1983. Organization Sponsorship and Influence Reputation of Social Influence Associations. Soc. Forces 61 (4), 1065-1087.

Levy, R., Talbot, D., 2015. Control by proximity: evidence from the 'Aerospace Valley'competitiveness cluster. Reg. Stud. 49 (6), 955-972.

Lorrain, F., White, H.C., 1971. Structural equivalence of individuals in social networks. J. Math. Sociol. 1 (1), 49-80.

Lowik, S., van Rossum, D., Kraaijenbrink, J., Groen, A., 2012. Strong ties as sources of new knowledge: How small firms innovate through bridging capabilities. J. Small Bus Manage. 50 (2), 239-256.

Markusen, A., 1996. Sticky places in slippery space: a typology of industrial districts. Econ. Geogr. 72 (3), 293-313.

Martin, P., Mayer, T., Mayneris, F., 2011. Spatial concentration and plant-level productivity in France. J. Urban Econ. 69 (2): 182-195.

McFadyen, M.A., Cannella, A.A. Social Capital and Knowledge Creation: Diminishing Returns of the Number and Strength of Exchange Relationships. Acad. Manage. J. 47 (5), 735-746.

Mizruchi, M.S., Galaskiewicz, J., 1993. Networks of Interorganizational Relations. Sociol. Method. Res. 22 (1), 46-70.

Moody, J., White, D.R., 2003. Structural Cohesion and Embeddedness: A Hierarchical Concept of Social Groups. Am. Sociol. Rev. 68 (1), 103-127.

Neffke, F., Henning, M., 2013. Skill relatedness and firm diversification. Strateg. Manag. J. 34 (3), 297-316.

Newman, M., Strogatz, S.H., Watts, D.J., 2001. Random graphs with arbitrary degree distributions and their applications. Phys. Rev. E 64, 026118

Newman, M., Barabási, A., Watts, D.J., 2006. The Structure and Dynamics of Networks. Princeton University Press, Princeton,, USA.

Niosi, J., Zhegu, M., 2005. Aerospace Cluster: local or global knowledge spillovers ? Ind. Innov. 12 (1), 5-29.

Nishimura, J., Okamuro, H., 2011. Subsidy and networking: The effects of direct and indirect support programs of the cluster policy. Res. Pol. 40 (5), 714-727.

OECD, 2007. Competitive Regional Clusters: National Policy Approach. OECD Publishing, Paris.

Owen-Smith, J., Powell, W.W., 2004. Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community. Organ. Sci. 15 (1), 5-21.

Pallotti, F., Lomi, A., 2011. Network influence and organizational performance: The effects of tie strength and structural equivalence. Eur. Manag. J. 29 (5), 389-403.

Pizarro, N., 2007. Structural Identity and Equivalence of Individuals in Social Networks: Beyond Duality. Int. Sociol. 22 (6), 767-792.

Powell, W.W., White, D.R., Koput, K.W., Owen-Smith, J., 2005. Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. Am. J. Social. 110 (4), 1132-1205.

Rivera, M.T., Soderstrom, S.S., Uzzi. B., 2010. Dynamics of dyads in social networks: assortative, relational and proximity mechanisms. Ann. Rev. Sociol. 36, 91-115.

Rocha, H., Sternberg, R., 2005. Entrepreneurship: The role of clusters theoretical perspectives and empirical evidence from Germany. Small Bus. Econ. 24 (3), 267-292.

Storper, M., Harrison, B., 1991. Flexibility, hierarchy and regional development: the changing structure of industrial production systems and their forms of governance in the 1990s. Res. Pol. 20 (5), 407-422.

Street, C.T., Cameron, A.F., 2007. External relationships and the small business: A review of small business alliance and network research. J. Small Bus. Manage. 45 (2), 239-266.

Stuart, T.E., Podolny, J.M., 1996. Local search and the evolution of technological capabilities. Strateg. Manag. J. 17 (1), 21-38.

Suire, R., Vicente, J., 2014. Clusters for life or life cycles of clusters: In search for the critical factors of clusters resilience. Entrep. Region. Dev. 26 (1-2), 142-164.

Ter Wal, A., 2013. The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure. J. Econ. Geogr. 14 (3), 589-620.

Uyarra, E., Ramlogan, R., 2012. Cluster Policy: A Review of the Evidence. NESTA Working Paper.

Uzzi, B., Spiro, J., 2005. Collaboration and creativity: The small world problem, Am. J. Sociol. 111 (2), 447-504.

Vicente, J., 2017. Network failures and policy challenge along the life cycle of clusters. In: Fornahl, D., Hassink, R. (Eds), The life cycle of clusters: A policy perspective. Edward Elgar Publishing, Cheltenham, UK, 56-75.

Vicente, J., Balland, P. A., Brossard, O., 2011. Getting into networks and clusters: evidence from the Midi-Pyrenean GNSS collaboration network. Reg. Stud. 45 (8), 1059-1078.

Watts, D.J., 2004. The ‘‘new’’ science of networks. Annu. Rev. Sociol. 30, 243-270.

Wennberg, K., Lindqvist, G., 2010. The effect of clusters on the survival and performance of new firms. Small Bus. Econ. 34 (3), 221-241.

Woolthuis, R.K., Lankhuizen, M., Gilsing, V.,2005. A system failure framework of innovation policy design. Technovation 25(6), 609-619.

Zuliani, J.M., 2008. The Toulouse cluster of on-board systems: A process of collective innovation and learning, Eur. Plan. Stud. 16 (5), 711-726.

Tables

	#nodes	#projects	Mean size projects	Min size projects	Max size projects
Cohort#1	313	56	7,84	2	32
Cohort#2	314	52	7,88	2	22
Cohort#3	395	78	6,79	2	25
Cohort#4	323	62	6,65	2	13

Table 1: network descriptive statistics

	#places	Mean *k* per place	Min *k* per place	Max *k* per place	Mean *l* per place	Min *l* per place	Max *l* per place
Cohort#1	118	2	1	18	2,65	1	18
Cohort#2	104	1,88	1	14	3,02	1	12
Cohort#3	150	1,85	1	14	2,63	1	17
Cohort#4	112	1,71	1	7	2,88	1	10

Table 2: descriptive statistics (network of places)

Figures

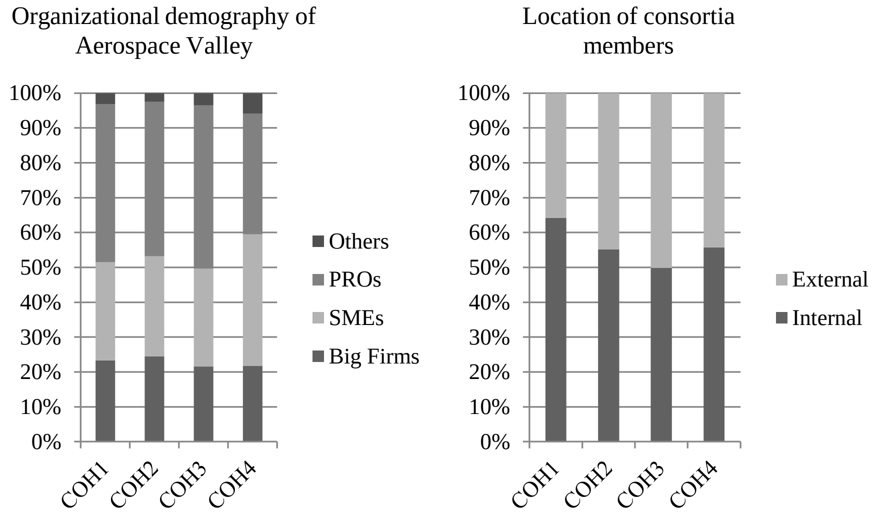

Figure 1: evolving demography of Aerospace Valley network

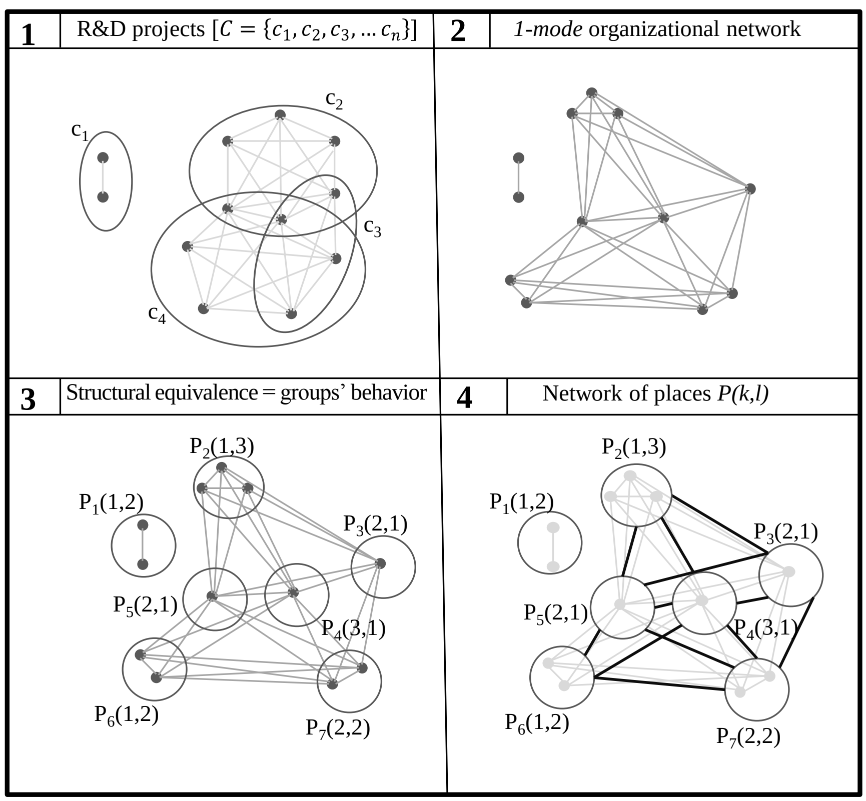

Figure 2: a stylized construction of a network of places

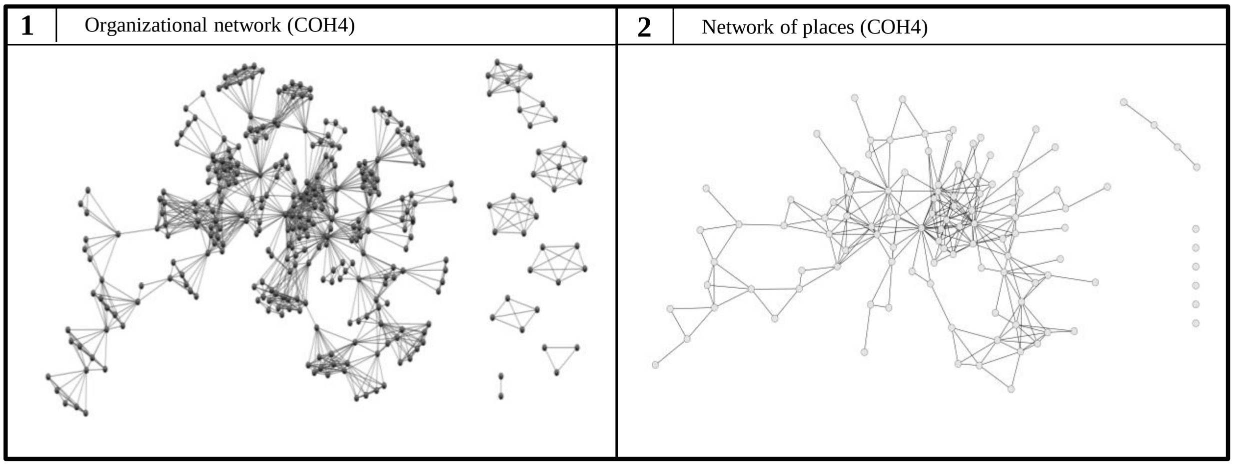

Figure 3: 1-mode network and network of places (Aerospace Valley cluster, cohort#4)

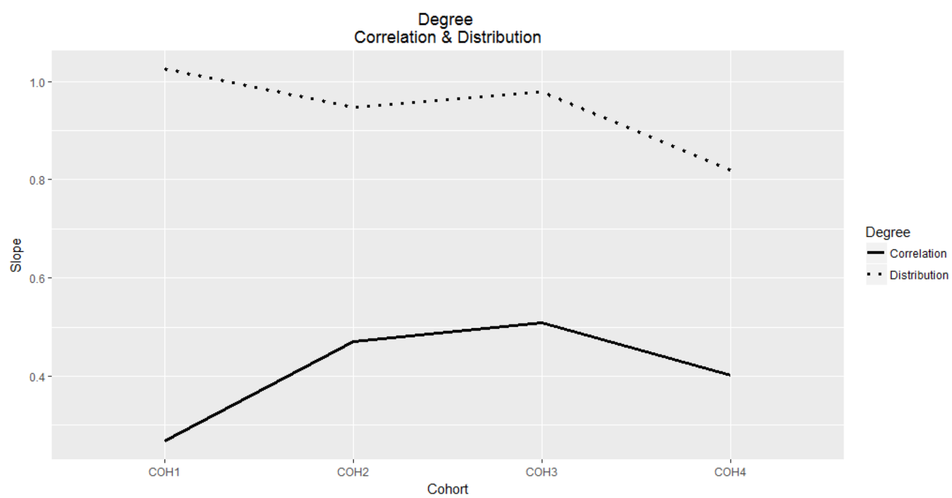

Figure 4: Degree distribution and correlation over time

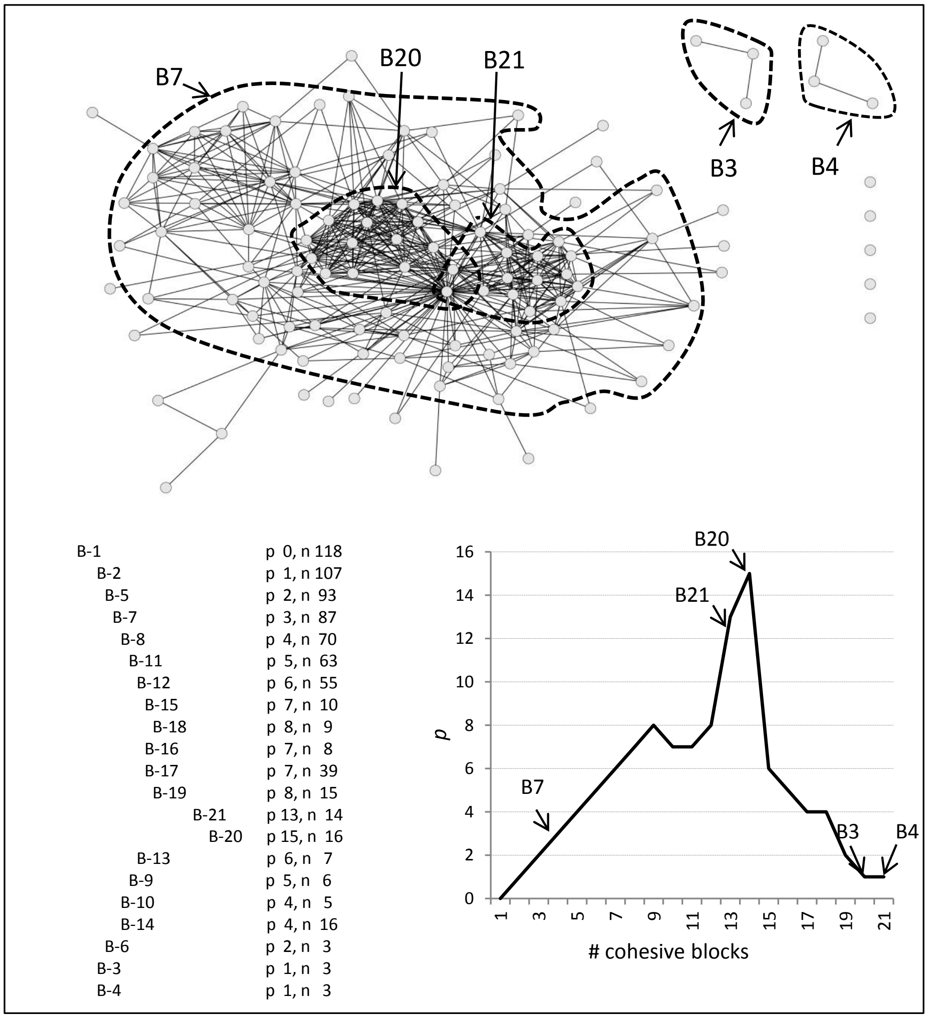

Figure 5: the construction process of the p-cohesive blocks of the cohort 1

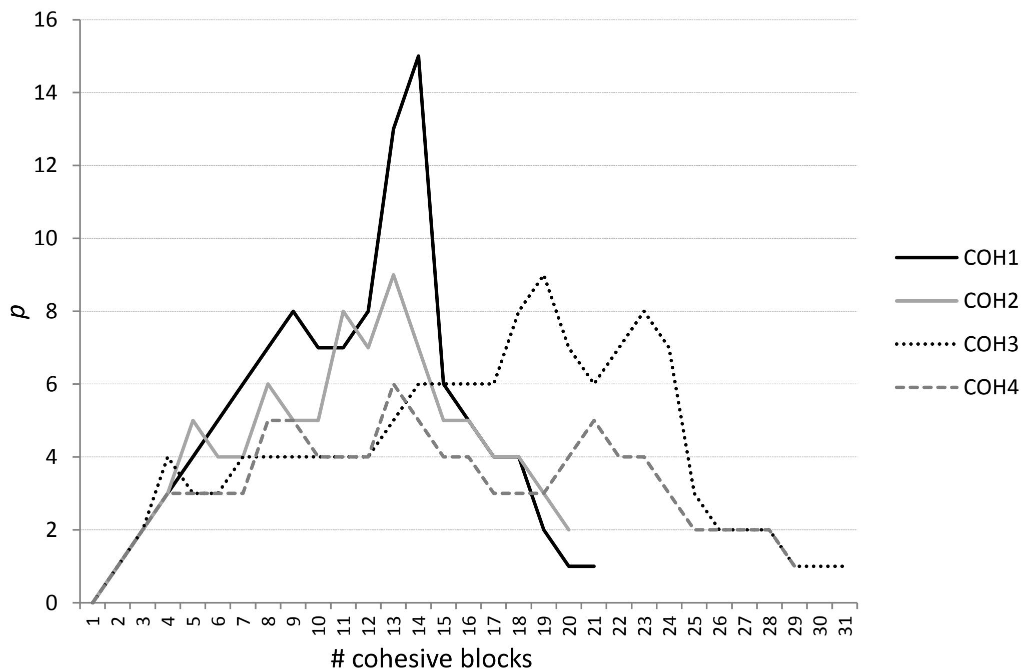

Figure 6: p-cohesive blocks (4 cohorts)

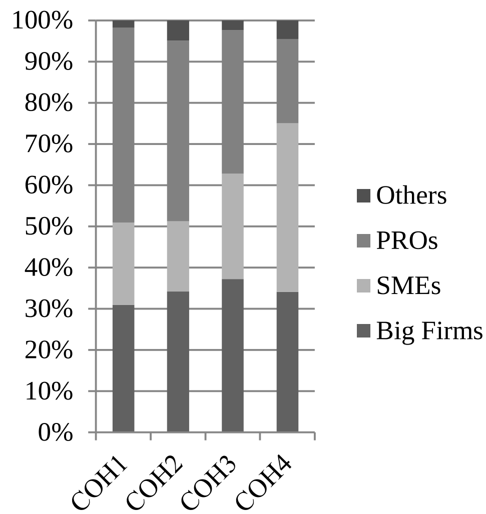

Figure 7: The elite component of the Aerospace Valley network

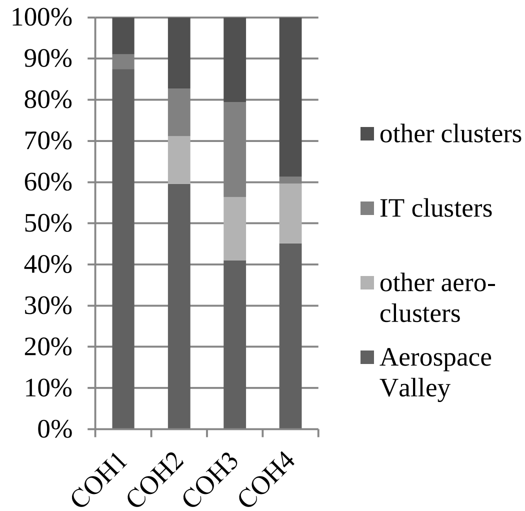

Figure 8: Single & multi-granted projects and diversification

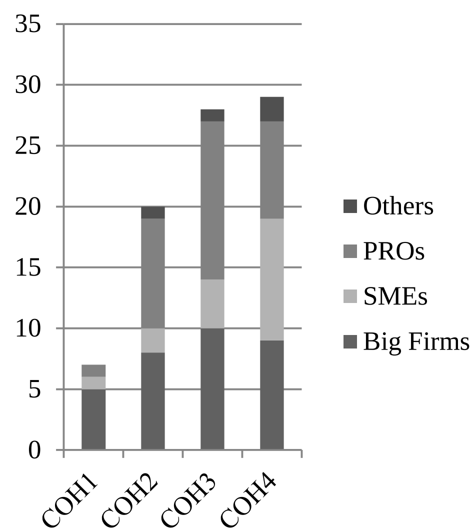

Figure 9: Organizations linking aerospace industry and other technological fields