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

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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 foster knowledge collaborations. We draw evidence from the French Aerospace Valley cluster from 2006 to 2015. The case study is based on a dataset of 248 granted research consortia, from which we build 4-cohort knowledge networks that 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 structural properties of the cluster selected by the Program and the policy makers' objectives. Finally, the methodology allows us to identify the agents of the structural and technological changes observed throughout the period.

Keywords: Cluster policy; Networks; Collaborative incentives; Groups behaviors; Behavioral additionality; Aerospace Valley
JEL-codes: D85; O25; O30; R10

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1. Introduction

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; Maffioli *et al*., 2016). 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 (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 (Audretsch and Feldman, 1996), 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. The latter is the mark of the level of technological variety and renewal, and therefore represents 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 and Lehman, 2005). But the entry dynamics is not a significant condition of cluster success *per se*. New entrants sometimes need to benefit from collaborative opportunities, especially in industries in which modularity and interoperability matter (Suire and Vicente, 2014). Then, collaborative incentives between SMEs and big companies are also a regular means used in cluster policies to foster regional performance.

The aim of this research is to have a deeper insight of these policy guidelines, and to find and test adapted network methodologies to deal with (i) the links between the public micro-incentives for knowledge collaboration and the structural properties of the network that emerge from these incentives, and (ii) the identification of the agents at the origin of structural changes. In that respect, the place-based network methodology and the nested cohesive block analysis are developed and offer promising avenues. As a matter of fact, it is common in the literature to assess whether network position increases individual innovative performance (Zaheer and Bell, 2005; Cattani and Ferriani, 2008). Nevertheless,

very few contributions have studied the impact of cluster development programs not on the links between the actors' position and performance but on the links between the structural properties of networks these incentives produce and the patterns of knowledge dynamics at work within the cluster (Crespo *et al*., 2014; Giuliani and Pietrobelli, 2016). This question requires going beyond the different centrality degrees developed in the literature to measure individual position in networks. It requires investigating different concepts related to complex structural properties imported from network theories in order to better disentangle the consequences of different properties of network connectivity on the cluster development patterns. Moreover, it also requires overcoming methodological issues that arise when one deals with aggregate relational data at the regional scale. To improve our knowledge on that emerging research topic, 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 from which data are available. Aerospace Valley is one of the leading public-funded clusters granted by the French Cluster Program, and it is also the name of the association nurturing R&D collaborations and managing the international visibility of the cluster. As a consequence, Aerospace Valley can be considered as a particular cluster and knowledge network whose nodes are organizations involved in R&D projects selected by the association, and ties are collaborations having received public incentives. Our goal is not to find causality between the policy and the innovative performance of the organizations affiliated to the cluster program. To do so, systematic analysis on several places should be carried out, and counterfactual analysis required (Giuliani and Pietrobelli, 2016). Our goal is different and just as important for whoever wants to have a better understanding of how policy makers shape 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 and dyadic levels, policy makers cannot have a perfect real-time knowledge and control of the structure as a whole. In network theories, this type of micro-macro scales problems is typical (Watts, 2004; Newman *et al.*, 2006): the "macro-behavior" of the network and its structural properties, both resulting from the aggregation of ties, can escape their own intention. Since clusters are foremost networks (Giuliani and Bell, 2005; Vicente *et al.*, 2011), dealing with the links between micro incentives and macro structures can be an alternate means to discuss how innovation policies can shape collaborative patterns and the structure of knowledge networks, as previously documented in the context of European Framework Programs assessment (Breschi and Cusmano, 2004; Vonortas, 2013).

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 by explaining the historical and technological context in which the Aerospace Valley cluster has been selected by national authorities to be eligible to public-funded incentives for R&D collaborations, before describing the cluster policy guideline developed in order to sustain its development. *Section 4* presents the data collection procedure which enables us to build 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 the agents of the structural and technological changes over the period.

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

Cluster policies support the idea 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 is directly related to the multiplier effect induced by network incentives and collaborative subsidies. This multiplier effect is directly associated to the particular type of additionality – named behavioral additionality – generally expected by governments when they implement collaborative incentives in R&D activities (Fier *et al.*, 2006; Clarysse et *al.*, 2009). While input and output additionalities are usually expected from individual incentives to innovate when market failures are considered, behavioral additionality is put forward as the main argument of policy implementation when systemic failures are observed in regional or larger innovation systems (Luukkonen, 2000; Breschi *et al*., 2009; Gök and Edler, 2012). Network failures constitute a large part of these systemic failures (Woolthuis *et al.*, 2005) and concern the structural organization of innovation process (Vicente, 2017). Taking them into account can explain why cluster policies based on collaborative R&D grants have gradually substituted individual grants, and why the need for network-oriented methodologies to evaluate collaborative programs is getting more and more challenging (Vonortas, 2013; Giuliani and Pietrobelli, 2016). Fixing network failures implies a large spectrum of policy interventions and raises the typical question of selection. Indeed, selection is the key

principle as well as the key difficulty, due to the information asymmetries between collaborative grants providers and receivers. That is why cluster policy makers usually design filtering processes in order to reduce these asymmetries. Moreover, by influencing collaborative behaviors 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 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 means to boost innovative outputs through behavioral additionality requires working both on the selection process of knowledge collaborations at the micro level (2.1) and on 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 first consists 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 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 gap and a weak social mobility and proximity between the two communities are often mentioned as a source of inefficiency (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 means to foster academic knowledge dissemination is

more relevant for clusters for which technological renewal matters. The economic return of cluster policy as well as the behavioral additionality gained from collaborative incentives is expected to be higher in this type of context in which academic research and business communities remain poorly connected (Morrison and Rabellotti, 2007). 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 long-established 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 a situation of public fund dependence, without any sufficient guarantees that they alone might succeed 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 long-established firms work well.

- *Local cohesiveness and global accessibility*

Clusters are not closed systems. Their success depends both on their internal structuring and their degree of embeddedness in global networks. 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 benefits from 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 (Morrison *et al*., 2013), and are particularly strategic between distant competitors wishing to collaborate on how to turn separated and competing technologies into interoperable ones (Balland *et al*., 2013). Therefore, 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 jumping from one industry to another. The technologies and markets on which clusters evolve over time move along a gradient of related and unrelated diversification. In the Silicon Valley, the photovoltaic industry in the 2000s has at first glance nothing to do with the computer industry in the 1980s. It is nevertheless 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 which has 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 are far from being over and empirical evidences are too contextual to enable the design of standard policy lessons. However, diagnosis of the network structures of clusters can help policy makers better orientate 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 failed to set up their technologies on mass markets, while collaborative incentives toward previously-unrelated industries and skills can favor path renewal for clusters entering a phase of transition.

These network failures, presented separately for convenience, are not necessarily independent of each other. For example, when there is a lack of diversification within a region, this may be the consequence

of a lack of global connectivity of the cluster, since the diversification opportunities result from collaborations with partners outside the region (Fitjar and Rodríguez-Pose, 2011; Morrison *et al.*, 2013). Likewise, the connectivity of SMEs to networks is not independent from the overlapping of academic and business networks, in particular when this concerns university spinoffs and their need to connect the business community (Mustar, 1997; Sternberg, 2014). Relying on one of these network failures is not without consequences on the others, and these interdependencies must be taken into account by cluster policy makers.

2.2 Connectivity and the structural properties of networks in clusters

When cluster policy makers provide incentives for collaborations, they contribute to the circulation of knowledge 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, even impossible, since all the new supported collaborations but also the renewing and ending ones continuously modify the properties of the structure. If failures at the dyadic level can be easily fixed, repairing structural failures is not within policy maker's reach. They are difficult to fix, but some of them have been identified as key properties that matter for the long run performance of social networks (Watts, 2004; Rivera *et al*., 2010; Ahuja *et al*., 2012) but also clusters and regions (Crespo *et al*., 2014; Breschi and Lenzi, 2016).

- *Connectivity vs. density*

The balance between network connectivity and density is an important feature of networks, and one of the critical parameter of their aggregate performance. Network connectivity has been considered as an important feature of knowledge network since it enhances information flows and knowledge spillovers (Fleming *et al.,* 2007). 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. Closure and cohesiveness in networks are important for enhancing trust and coordination, in particular when systemic innovations require complex processes of knowledge integration. But cluster policy makers also need to pay attention to the overall connectivity in order to favor knowledge circulation and maintain new collaboration

opportunities. Although cluster policy guidelines generally stress on the necessity to increase the overall density of networks in clusters (Vicente, 2017), cluster managers who are actually involved in cluster development also have to focus more surgically on particular bridging links between cohesive groups.

- *Hierarchy*

Knowledge networks in clusters are neither pure centralized structures of interaction nor 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. On the one side, monitoring large portfolio of collaborations is not within every firm's reach, 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, the cluster will differ according to the level 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-established organizations have developed a large portfolio of knowledge collaborations (Brenner and Schlump, 2011). On the other hand, a weak hierarchy, represented by a very flat degree distribution, is the sign of a burgeoning and nascent cluster which has not yet succeeded 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 clusters display hierarchy, they often 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. 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 new entries. 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. Other network-based analysis of clusters document this type of structure in developing countries, whether in mature technology-intensive industries (Giuliani *et al.*, 2018), or in agro-industry like wine or cheese industry (Giuliani and Bell, 2005; Giuliani, 2013; Crespo *et al*., 2014). Therefore, cluster policy practitioners have to pay attention on the existing structure of knowledge interactions. They can help some of the burgeoning organizations 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 on how highly and poorly-connected organizations 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, assortativity 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 on renewing 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 (Vonortas, 2013). As a corollary, fresh and explorative knowledge produced by peripheral organizations has difficulties to reach and irrigate the core of the network (Fleming *et al*., 2007). Accordingly, disassortative structures of knowledge interactions enable clusters to have 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. For that purpose, they need to pay attention to the phase of the business cycle on which clusters are situated.

The concept of network failures is not only a pure and uncontextualized theoretical argument to justify public incentives for knowledge collaborations in clusters. It also requires an approach taking into account the territorial context and the historical contingencies on which these incentives are implemented. 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. In particular, as intriguingly shown by Fleming *et al.* (2007), salient structural properties developed in the literature, like small-world properties, can win and lose in significance according to the territorial and technological contexts in which these properties are studied. In the same vein, Crespo *et al.* (2016) showed that hierarchy and assortativity play differently in the performance of clusters when the maturity and renewal stages are introduced as key controls in the search from the significant properties of cluster performance.

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 (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. The aerospace industry displays specific properties in terms of industrial organization. It traditionally combines a strong hierarchy between the different firms involved in the supply chain with a systemic production process organized around a hub and spoke network architecture. As pointed by Wink (2010), the industry was until the end of 1980s typified by close links with the military industry implying strong confidentiality requirements and a high share of internal R&D. Diversification was low and the high capital intensity was at the origin of strong entry barriers, together with the government regulation. After this period, the industry met new challenges leading to salient structural changes. On the one side, the aircraft industry started to blur its own sectoral frontiers by looking for partners outside its engineering-based value chain. The main incumbents built relationships with nature, informatics and material sciences in order to find solutions for the weight reduction of airplanes and to improve their eco-efficiency. On the other side, the space industry started to develop civilian applications and strongly diversify its partners' portfolio for that purpose, in particular in the transversal domain of embedded systems. These structural changes have given birth to new industries, such as GNSS (Global Navigation Satellite Systems), drones, and other related industries.

3.2. Cluster policy guideline: a two-stage selection process

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 eleven "globally-oriented clusters", and fifty three "national clusters"). The aim of the national policy consists in fostering innovation by selecting a set of 2-dimension vectors of regions and technological domains that are eligible for receiving grants for R&D collaborative projects. *Aerospace Valley* is 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 for 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 dealt with, 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. Collaborative incentives for 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 acquire 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 guideline has not been 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 persisting constraint is 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 attend a project has been relaxed in an early stage. 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 to the national grants with projects certified by more than one cluster governance structure. This change aimed at finding a better "cluster policy mix" between inward and outward collaborative incentives, as

suggested by Morrison *et al*. (2013). Second, in order 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 have 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 the 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* have recently provided strong incentives toward industrial diversification, in order to better overlap mature and emerging markets.

4. Data collection and methodology

Characterizing networks in clusters using public-funded R&D collaborative projects requires particular caution 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 national list of selected projects. They concern the FUI and ANR programs, both being the main national programs aiming at restoring incentives to collaborate on knowledge. These data include project scientific abstracts, and information about the consortium members (location, institutional form, size). If the collection of projects does not suffer from limitations, that is not the case for the project members. Indeed, an extensive effort of 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. When contradictory information remained, e-mails to academics and engineers were sent and the answers enabled us to reach a sufficient fine-grained extraction.

Over the period, 248 projects were 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 (under 100 employees), 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; Levy and Talbot, 2015; Crespo *et al.*, 2016), as well as in the context of larger networks at the European level (Breschi and Cusmano, 2004; Breschi *et al.*, 2009; Balland *et al.* 2013; Kang and Hwang, 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 of one type of node (the organizations) connected to another type of node (the projects). In this type of networks, there is no link 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 Breschi and Cusmano (2004) 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, in order to capture the structure of innovative activity in clusters. *1-mode* networks are drawn from a square matrix and are composed of a set of nodes representing organizations and a set of ties representing knowledge flows between them. This methodology has proven its reliability to identify critical organizations in knowledge dissemination at the micro-level, and salient structural properties at the meso-level. Nevertheless, as pointed by Robins and Alexander (2004), this network-based analysis is not exempt of biases 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 biases can occur (Uzzi and Spiro, 2005). Most of them 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 (Breschi and Cusmano, 2004). They can give rise to misleading interpretation in the actual role of organizations in knowledge dissemination. To give an example, let us consider an organization that is affiliated to a 15-member consortium, and only to this one. It will have a high degree centrality, while, as shown by Bernela and 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, each affiliating only 3 partners. Its degree centrality will be less significant due to a thinner relationships 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 differs, as it is typically the case in that analysis in which the consortia go from 2 to 32 organizations (see *table 1* above). Therefore, methodologies are required to correct this bias. The idea is to better apprehend the skeleton of the network by capturing the actual influence of nodes. For instance, Breschi and Cusmano (2004), in their network analysis built from European collaborative programs, suggest using 1-mode "star" networks instead of considering consortia as fully-connected cliques. They consider each consortium as a sub-network only connecting prime contractor to participants. Vicente *et al.* (2011) use an alternate method based on the diamond of Robins and Alexander (2004). A diamond appears when two organizations connected to a project are also connected to another project. Both allow limiting these biases and offering the means to study the backbone of networks, without the noise introduced by the heterogeneous size of R&D 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 and 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). 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 (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 to better capture 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 would correct the bias as well as consider groups' behaviors, without compromising the possibility to analyze nodes' position in networks. To do so, we use the so-called "network of places" approach early developed in sociology by Pizarro (2007) and now operational for large dataset-based empirical analysis with the R-module *"Places: Structural Equivalence Analysis for Two-mode Networks"*. 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 as 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 $i \epsilon I$, $P_i = \{c_j \in C : i_i \in c_j\}$. 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 also be 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, each of them 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.

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 can help dealing with this question. It consists in discussing the degree-related structural properties of the network of places, in order to discuss whether or not the selection routines meet the policy makers' objectives.

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

Figure 4 here

If we stick to 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 the *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 sizes 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 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 these structural properties in order to have a better understanding of the drivers of these changes. 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). A close method relying on the *k-core* notion has also been implemented by Breschi and Cusmano (2004) to extract in the very large European network of public-funded R&D consortia the areas of the network where interaction among actors is particularly intense. In our case, 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 means 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 means 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 way 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 no place is 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 on *figure 6* that when the higher *p*-values decrease over the period, the "distance" between peaks in the distribution increases, which shows that the blocks with the highest cohesion are less and less closely interconnected 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

Turning these findings into more qualitative readings related to the role of public collaborative incentives on the cluster structural change is a challenging question. 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. The balance between closure and bridging has changed over the period, and organizations seem to have reoriented 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

A first way to assess the changing structural properties of *Aerospace Valley* is to focus on the so-called elite component (Powell *et al.*, 2005) of the 4-cohort networks. The elite component is composed by the places belonging to the two highest *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 regards 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 proportionally present in the elite network than in the entire one in the first two periods, then they start to fill the gap during the third one, and finally succeed in reversing the pattern during the fourth one, with a presence in the elite network slightly superior as regards 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 a 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? A first trivial answer relies on the fact that policy makers have offered stronger incentives to involve SMEs in 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, 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 regards 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 regards big companies. Literature in Geography of Innovation has shown in an early stage that SMEs and big companies to 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 long-established companies differ in their timorousness facing uncertainties and risks in market-oriented researches, the former being steadily less conformist than the latter. 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 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 SMEs enter the elite part of the network, *p* decreases at the same time as 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.

To illustrate this dominant pattern of network evolution in Aerospace Valley, some examples can be provided. When we go in-depth in the database from cohort 1 to cohort 4, we observe the co-attendance of the main big incumbents of space and aircraft industry in several projects. For instance, over the cohort 1, Airbus and Thales are connected together in more than ten central projects focused on the traditional space and aircraft industry. If we add firms such as Snecma or Continental, we also find at least five projects in which the four companies are connected together. If we turn back to the network of places, the cohesive subgraphs identified as the "elite" (the pics) in the first cohort are mainly composed of these organizations. These projects affiliated to the "elite" can be considered as social and cognitive centers of the network, to the extent that they are in the confluence of the research activities, like unmissable "meeting points" in the cluster. If we invest the pics of the fourth cohort, several changes can be observed in the elite part of the network. As a matter of fact, the elite in the network of places consists of more subgraphs (the pics), which are more distant and involve more SMEs. These SMEs, partly marginally involved in the first cohorts and partly involved for the first time, are now connected in many projects but rarely together. At the reverse, they tend to connect unconnected parts of the network. For instance, Magellium and Airod Technologies are both prime contractors of at least three projects but only once together. In these projects different organizations are also involved and disseminated at different points of the network. These projects concern emerging markets such as drones for agriculture, observation devices and consoles for irrigation management and other transversal technologies using satellite positioning. This changing composition of the elite sheds light on how diversification and structural properties of knowledge networks work together, as it confirms the new organizational patterns observed by Wink (2010) in the aerospace industry. It also illustrates but not explains how spinoffs (Magellium, born in 2003, is a spinoff of Thales) matter for the endogenous development of clusters (Hervas-Oliver *et al.,* 2017).

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* 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 the shares between single and multi-granted collaborative projects over the period, taking into account that the shares between the organizations affiliated to the *Aerospace Valley* cluster and others affiliated in other clusters remain 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 in 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 network skeleton? *Figure 9* allows understanding this changing pattern

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

during the last period. Indeed, if we consider all the places of the 4-cohort 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. 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 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 over time. For instance, SMEs like M3 Systems and Nexio, involved in R&D consortia since the start of the Aerospace Valley Program, have progressively changed their relational strategies. Mainly involved as simple participants in single-granted projects related to space industry from cohort 1 to cohort 3, these two small companies succeed in entering the core of the network as leading companies coordinating multi-granted projects on the emerging markets on navigation satellite systems. The project GEOTRANS-MD, in which M3 system is involved in cohort 4, has been certified by *Aerospace Valley* but also *Systematic*, the central cluster of Ile de France (Paris) specialized in automation and electronic systems. This project consisted in designing a standard applicable in the framework of the European legislation on the tracking of hazardous materials transport. The project LOCRAY, in which Nexio is involved in cohort 4 as prime contractor, has been certified by *Aerospace Valley* but also by *Systematic* and *Mov'eo*, the main French cluster specialized in new mobility and transport of the future. This project is dedicated to near-field measurements, electromagnetic compatibility and their compliance with EMC standards. Being still involved in local R&D consortia, these two small companies succeeded in acting as geographical gatekeepers (Morrison, 2008: Morrison *et al.*, 2013), becoming central in the knowledge pipelines related to the emerging markets using satellite navigation or electronics as transversal technologies.

7. Conclusion

It is common in the literature to study the impact of cluster policies by capturing the output and input additionality effects. These effects generally require investigating the causality between the design of public incentives and the performance of treated organizations in terms of outputs (patents, exports ...) and inputs (R&D expenses, absorptive capabilities …), compared to non-treated organizations and after the treatment ends. The paper was aiming at dealing with another complementary but too weakly-explored challenge, related to the search for behavioral additionality effects in a particular public-supported cluster. We have investigated how the visible hand of cluster policy makers develops micro-

incentives to shape knowledge networks, and linked the expected and unexpected changes in the macro-structure to the changing position and relational behavior of agents.

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*-mode 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-established oligopolistic companies, to a more democratic, less assortative, and multipolar structure of knowledge flows. The analysis of the evolving composition of places has allowed a better understanding of who the agents of the structural change 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 on the efficient properties of local knowledge networks (Uzzi and Spiro, 2005, Breschi and Lenzi, 2016; Crespo *et al*., 2016), this changing pattern in the *Aerospace Valley* network may involve the possibility of a more adaptive and innovative cluster. More unexpectedly, these findings do not converge with evidence found for geographically and institutionally larger networks. As a matter of fact, papers dealing with European collaborative programs (Framework Programs) tend to observe an ossification of networks and an increasing oligarchic structure of interaction (Breschi and Cusmano, 2004; Kang and Hwang, 2016). The hypothesis that can be made is then based on the nature of incentive schemes. As previously observed by Balland *et al.* (2013), the incentives underlying cluster policies at the regional level are based on exploration logic. The challenge at European level is quite different. Incentives are dominantly oriented towards technological exploitation, and rely on the need to better integrate knowledge to produce dominant design for competitive global markets. Ossification and cohesion within the networks are therefore a coherent objective, even if the risks of lock-ins must be taken into account by the European institutions (Breschi and Malerba, 2009).

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 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 fewer and fewer conformist collaborative projects, which have then 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 originally 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 role on the network structuring. After a while, they succeeded in positioning themselves in the elite part of the network, without any more public incentives, but with their own growing experience in the attendance at collaborative projects. In terms of cluster policy economic return, this growing experience is the mark of a positive effect of behavioral additionality. We succeed in partially capturing this effect. Indeed, by pushing large firms into collaborating with SMEs, the latter have gained a great deal of experience enabling them to better integrate the ecosystem and in return to succeed in establishing themselves as central actors able to take the leadership of projects. Without this initial impetus from policy makers, these opportunities to reach the elite part of the cluster could not have run for them. This leadership was not the aim of public incentives, so that it clearly results in behavioral additionality effect. However, we only partially shed light on this effect, as it would also require measuring the maintenance of links when funding expires, which remains on the agenda for future research.

But is the growing role of SMEs in the elite network de facto a loss of control by large firms? It may be a misleading question. Given that part of the SMEs result of spinoff process and local labor mobility, social networks of the incumbents' executives are not necessarily as far away as one can imagine. It is difficult to observe such a pattern when using data composed of organizations and not individuals. But one of the perspectives for a near future would be to couple the organizational network to the network of individuals, to see in the line of Audretsch and Lehman (2005) or Hervas-Oliver *et al*. (2017) how these leaders themselves promote the creation of new companies in order to absorb with them the risks of market diversification. Finally, 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.

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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

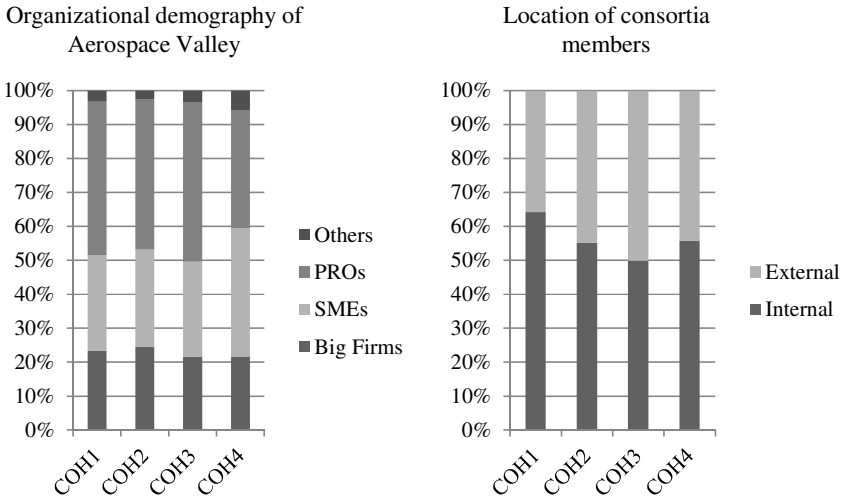

Figure 1: evolving demography of Aerospace Valley network

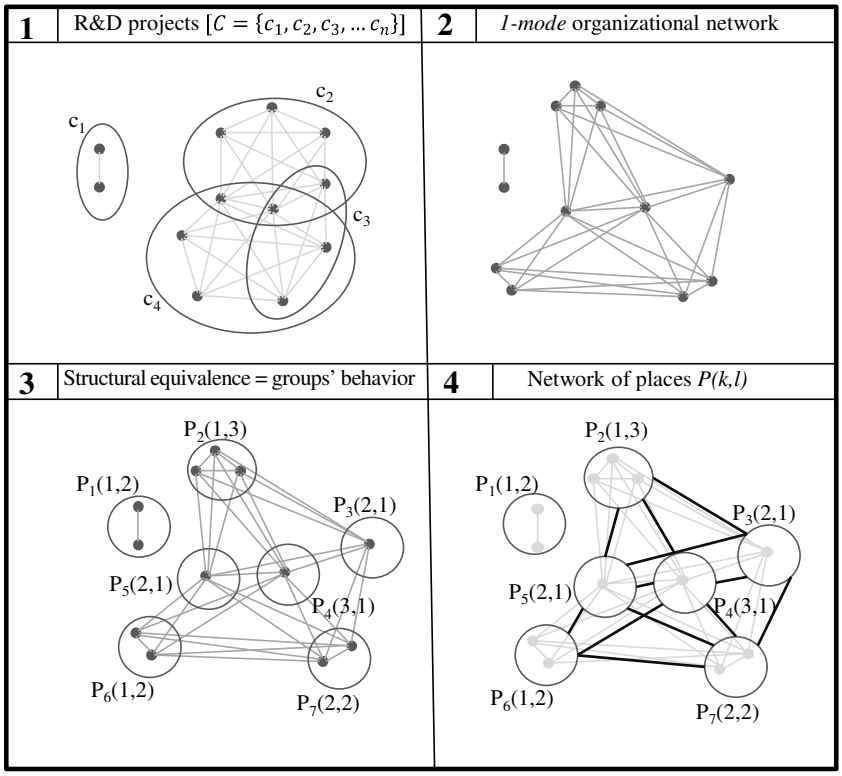

Figure 2: a stylized construction of a network of places

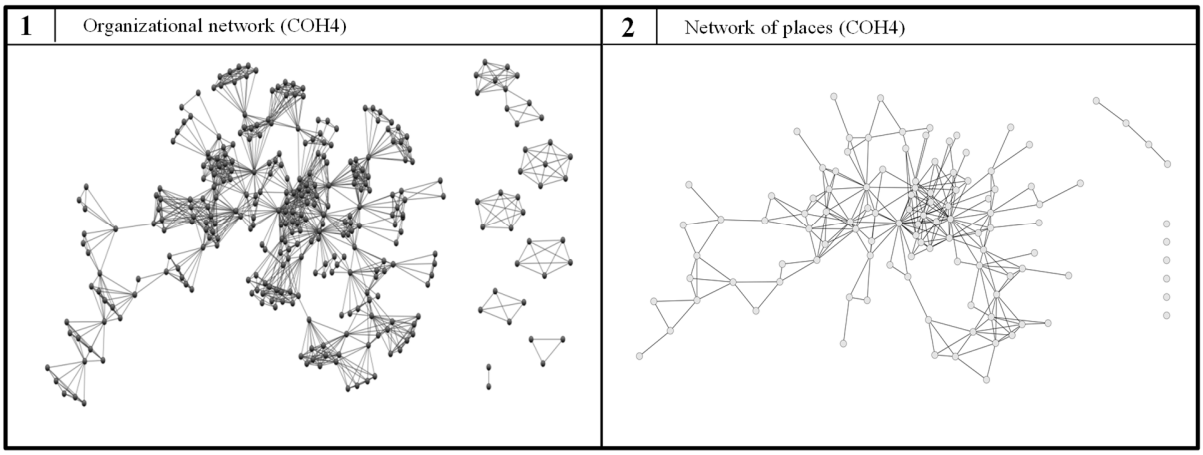

Figure 3: 1-mode network and network of places (Aerospace Valley cluster, cohort#4)

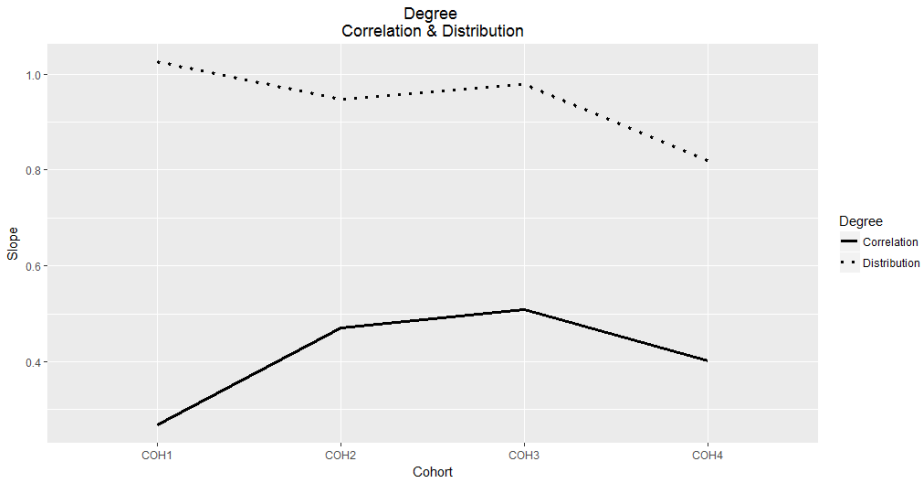

Figure 4: Degree distribution and correlation over time

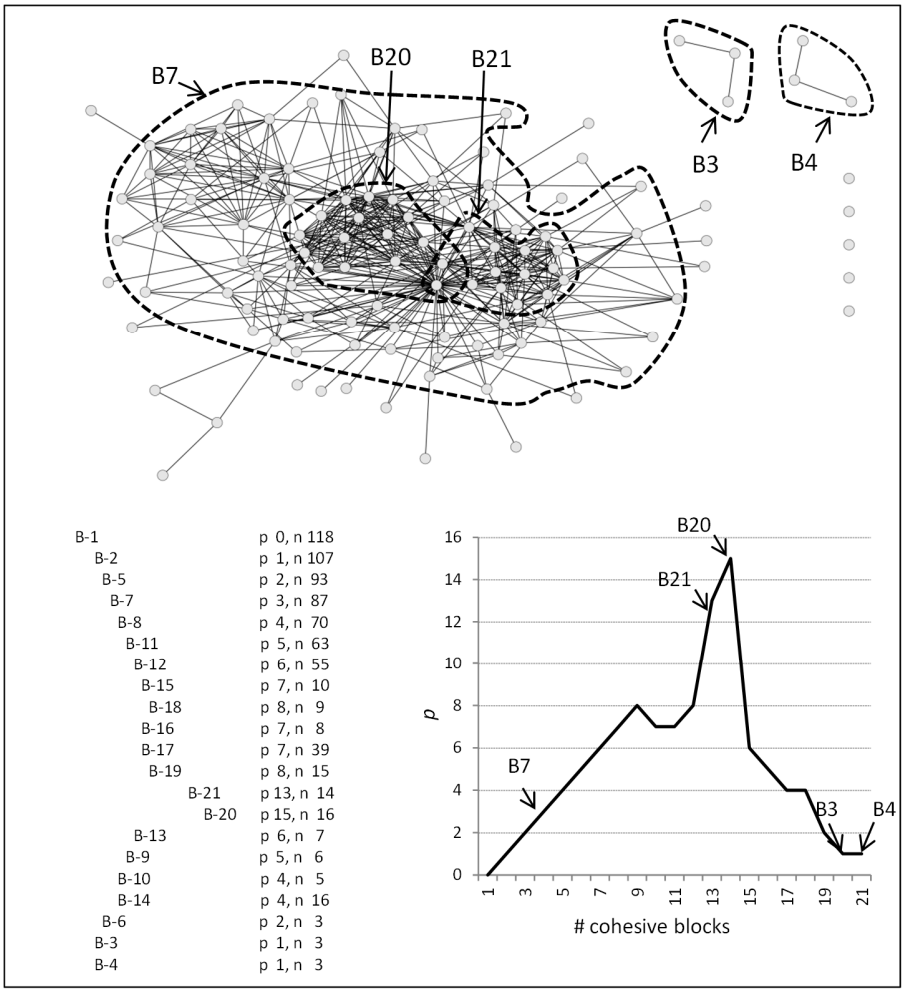

Figure 5: the construction process of the p-cohesive blocks of the cohort 1

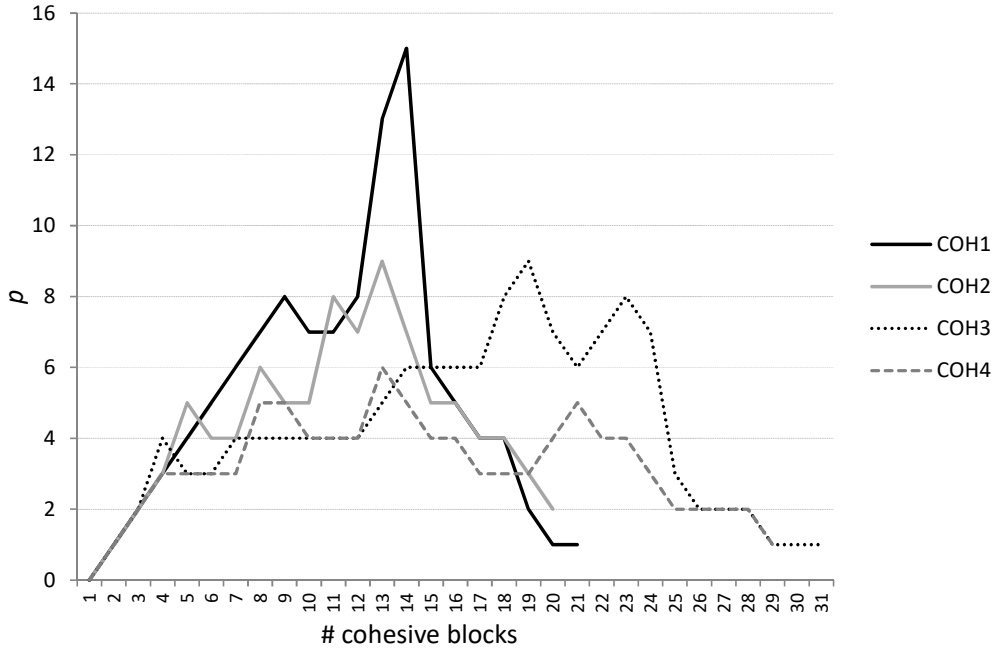

Figure 6: p-cohesive blocks (4 cohorts)

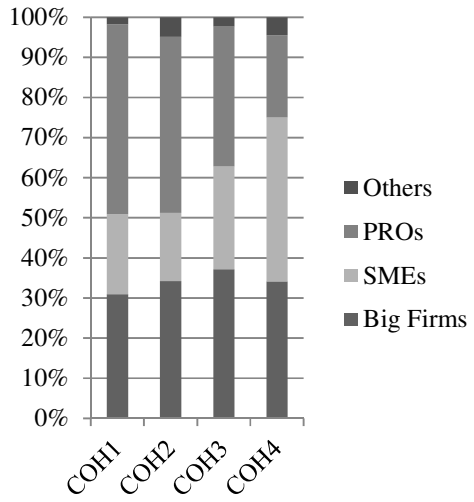

Figure 7: The elite component of the Aerospace Valley network

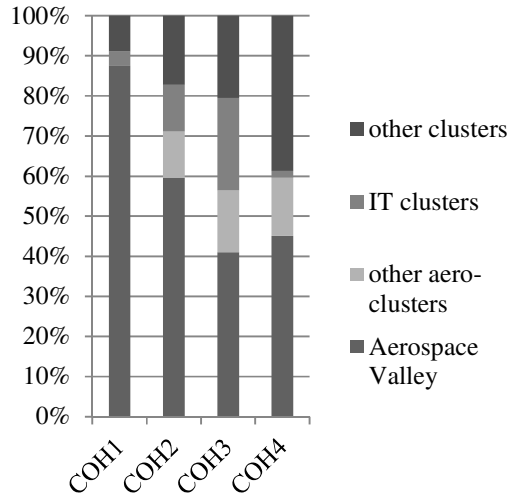

Figure 8: Single & multi-granted projects and diversification

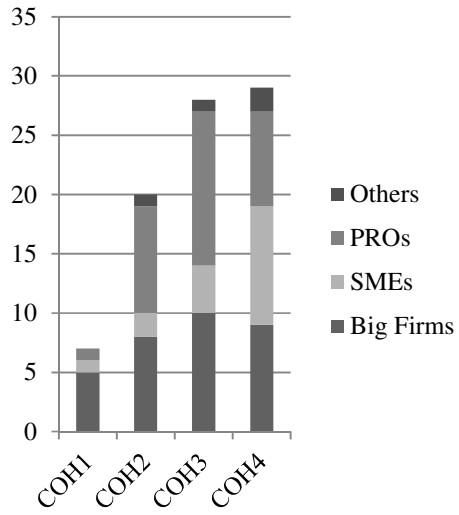

Figure 9: Organizations linking aerospace industry and other technological fields