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The evolution of the French collaborative network of innovation: towards clustering?

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Abstract

Since the beginning of 2005, the French government supports collaborative innovative projects involving actors of public and private research through the competitiveness cluster policy (pôles de compétitivité). By these projects we aim to offer an original approach of the impact of the cluster policy on the organization and the intensity of innovation network (on the overall French territory). Concretely, the present paper analyses the evolution (from 2005 to 2010) of the French collaborative network of innovation, by scanning collaborative projects funded by the FUI. Our main research interest lies in testing whether the network progressively gets connected, concentrated, clustered around some (specific?)

competitiveness clusters or if, on the contrary, it extends on the French territory, actors building collaborations with intra but also extra- competitiveness clusters? members and becoming more loosely-coupled to one another. We are also interested in analyzing the existence/creation/disappearance of innovative cohesive groups within the overall network. We privilege a social network analysis for our empirical study. It enables us to calculate and follow the evolution of indicators depicting at the same time the structure and spread of the network, and the respective positions of nodes within the network. An its allow us to characterize the impact (if any) of the competitiveness cluster policy on the organization and the intensity of innovation on the French territory.

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The evolution of the French collaborative network of innovation: towards clustering?

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preliminary draft

Introduction

Since the beginning of 2005, the French government supports collaborative innovative projects involving actors of public and private research through the competitiveness cluster policy (pôles de compétitivité). Those competitiveness clusters are defined as "*a joint theme-based initiative for a given geographic area ie as an initiative on a given territory that brings together companies, research centres and educational institutions in order to develop synergies and cooperative efforts targeted at one (or more) given market(s)…clusters using then synergies and innovative joint projects to give their members a chance to be national and international leaders in their fields*" (www.competitivite.gouv.fr). Those synergies and cooperative efforts are materialized by collaborative projects linking clusters' stakeholders (firms and actors of the public research) and partially financially supported by the French government through the intervention of the "Fonds Unique Interministériel" (FUI)[1].

6 years after the implementation of this cluster policy, one may wonder whether it really stimulates networks of innovation. Clusters and more particularly, competitiveness clusters are already largely analyzed in a vast literature in economics, management and geography. Some of existing (empirical) papers aim at the characterization of ideal-types of clusters (Hussler et al., 2010; Gordon and Mc Cann, 1999; Markusen, 1996), at analyzing the relations between clusters (Hussler et al., 2011), or are targeted at the evaluation of the more or less successful impact of clusters on their territory (Chalaye and Massard, 2009), whereas other (more theoretical) works are rather interested in explaining the clusters' life cycle (Suire and Vicente, 2009). Another category of contributions chooses to look at clusters in a more fine-grained way thanks to in-depth case studies of the collaborative behaviors adopted within

[1]The FUI ("Fonds Unique Interministeriel ») is a governmental fund dedicated at financing R&D collaborative projects that entail firms and research institutions from at least one French competitiveness cluster.

some specific competitiveness clusters (Levy and Talbot, 2010; Amisse and Muller, 2010; Hamza et al., 2011). However, the literature remains unclear on the potential effects of cluster policies on the structure and geography of collaborative networks. On the one hand, homophily and proximities are presented as catalyzors of knowledge exchanges and collaborations (Mc Pherson et al., 2001; Boschma, 2005; Bouba-Olga and Grossetti, 2008), agglomeration of actors and clusters being therefore interesting to stimulate innovative collaborations (and generating “local buzz”). But on the other hand, an abundant literature also stresses that being (geographical and industrial) neighbors (as it is the case for cluster members) is not enough to generate collaborations and to benefit from spillovers (Lissoni et Breschi, 2001; Rondé et Hussler, 2005; Amisse et al., 2011), whereas other papers insist on the potential drawbacks of developing intra-cluster linkages exclusively (on the need for global pipelines, cf. Bathelt et al., 2004; Coenen et al., 2004; Giuliani and Bell, 2005; on the worth of weak ties, cf. Burt, 1992; Granovetter, 1982).

Facing this lack of consensus, we aim to prolong these studies and complement them by offering an original approach of the organization and the intensity of innovation network (on the overall French territory). Concretely, the present paper analyses the evolution (from 2005 to 2010) of the French collaborative network of innovation, by scanning collaborative projects funded by the FUI. Our main research interest lies in testing whether the network progressively gets connected, concentrated, clustered around some (specific?) competitiveness clusters or if, on the contrary, it extends on the French territory, actors building collaborations with intra but also extra- competitiveness clusters’ members and becoming more loosely-coupled to one another. We are also interested in analyzing the existence/creation/disappearance of innovative cohesive groups (Coleman, 1988) within the overall network.

We mobilize two main methods (social network analysis and econometric modeling) for our empirical study. The originality of our approach is to focus on the project as the key level to analyze the innovation network. Social network analysis enables us to calculate indicators depicting at the same time the structure and spread of the network, and the respective positions of projects within the network. In a first step, we propose to study the dynamics of the global network, focusing on the evolution of its structure in terms of density and connectivity. In a second step, we adopt a more fine-grained analysis and scan the biggest cohesive groups within the French innovation networks in order to investigate their main features, their rationales of emergence and to compare their shapes to competitiveness clusters' borders. Econometric modeling allows us to estimate the influence of the characteristics of projects on the propensity to be integrated, firstly in the main component of the network, and secondly in the biggest cohesive groups.

The rest of the paper is organized as follows. In a first part we present the theoretical background of the paper ie the literature on clusters and innovation networks. Second, we detail the empirical setting of the paper. In a third step we expose and discuss the results, before concluding.

1. The organization of innovation networks and its evolution: towards clustering? A literature review

1.1. Clusters as potential fertile grounds for innovation network building

According to Porter (1998), a cluster can be defined as « *an interconnected web of focal firms, suppliers, supporting institutions, related-industry firms and customers* ». As agglomerations of related actors (Mc Cann and Folta, 2009), clusters can be seen as fertile grounds for innovation network building. Indeed, a huge literature tends to present homophily and proximity as catalyzors of knowledge exchanges (Mc Pherson, et al., 2001; Boschma, 2005; Bouba-Olga and Grossetti, 2008). In this literature, "similarity breeds connection" as it is a good way to limit misunderstanding (thanks to similar knowledge bases, in the case of cognitive proximity), to adapt to one another (through face to face contacts, in the case of geographical proximity) or to be able to absorb external knowledge (thanks to proximate technological competences). As a consequence one should observe a clustering of the innovation network within the French competitiveness clusters' borders through time.

However, another part of the literature concomitantly shows that being agglomerated does not automatically generate knowledge exchanges (Breschi and Lissoni, 2001). Refining this idea, more recent papers explain that proximity might be useful (vs useless) to catalyze knowledge exchanges, depending on the very specific steps of the innovation process, and on the nature of the innovation at stake (Suire et Vicente, 2008; Balland *et al.*, 2010). At the same time, examples of cumulative location of actors which do not generate any effective relationships between them flourished (Vicente, 2005), suggesting that competitiveness clusters are only repository of potential networks, and that spillovers are not "in the air" but require actual structures of interactions to take place and generate the so-called "local buzz" (Bathelt et al., 2004). Intra-cluster networks are finally not that automatic and spontaneous.

To help competitiveness clusters in becoming efficient project catalyzors ("machines à projets" for Fen Chong and Pallez, 2010) and to effectively stimulating innovation networks (what is not always sufficiently done according to DIACT, 2008), governance structures have been created in France to try and support the networking activities of competitiveness clusters' members. Recent empirical studies conclude on the role of knowledge/network broker (Hamza-Sfaxi et al., 2011) played by such structures and on their decisive role in stimulating collective innovation (Chabault et Martineau, 2011) thanks to various strategies (Bocquet and Mothe, 2011). Hence, if networks do not spontaneously emerge within clusters, they might develop thanks to those governance structures' intervention.

1.2. Innovation networks: locked in clusters?

At the same time, an excess of homophily (Noteboom, 2000) and a collaborative strategy exclusively targeted at developing intra-cluster networks of innovation do not seem to be the panacea to accelerate innovative dynamism. Indeed, such behaviors might generate lock-in effects (clusters' members exchanging knowledge with actors very similar to themselves and therefore risking to be trapped in a homogenous way of thinking) or over-embeddedness (Uzzi, 1997), what could in turn question the resilience of clusters (Suire and Vicente, 2009). An important stream of literature has discussed the importance of accessing external sources of knowledge through the development of so-called "knowledge pipelines" (Bathelt et al. 2004; Owen-Smith and Powell, 2004; Maskell et al., 2006) to catalyse clusters' performance. Those pipelines, by offering the opportunity to tap into external pools of knowledge, allow clusters to be fuelled with new knowledge, thus enhancing their innovativeness and growth. By opening their borders, clusters allow the building of cognitive complementarities between actors (Boschma and Iammarino, 2009; Suire and Vicente, 2009), allow to take advantage out of weak ties (Granovetter, 1982) and structural holes (Burt, 1992) ie of non redundant links with distant partners. Thus one observes a recent tendency of competitiveness clusters to get involved in networks of clusters ie to develop innovation networks outside their borders (Hussler et al., 2010; Grandclement, 2011). Some competitiveness clusters finally progressively become responsible for identifying, interpreting, absorbing, and translating pieces of knowledge to other clusters (as already shown at the firm level, by Owen-Smith and Powell, 2004; Giuliani and Bell, 2005; Iammarino and McCann, 2006; Morrison, 2008).

In such a context, innovation networks would not only be catalysed inside competitiveness clusters borders but could also extend outside the cluster, what finally questions the effective evolution of the morphology of the French innovation network.

1.3. Networking rationales: beyond the cluster explanation?

Do we observe a clustering of innovation networks around the competitiveness clusters' borders? The question sounds even more accurate that existing case studies on the relational behaviours in and of competitiveness cluster(s) (Levy and Talbot, 2010; Amisse and Muller, 2010; Hamza-Sfaxi et al., 2011b; Grandclement, 2011) show a form of idiosyncrasy in the shape of innovation networks generated by competitiveness clusters, each of them adopting quite a different collaborative profile. Going one step further, a couple of empirical papers conclude that some clusters, such as the mechanical one in Brescia (Lissoni, 2001) or the district around packaging activities in Northern Italy (Boari *et al.* 2003; Boari et Lipparini, 1999) or in horticulture in the French region Anjou (Société d'Horticulture d'Angers et du département de Maine-et-Loire. 2000) are really flourishing clusters despite their limited networking activity, suggesting therefore that clusters do not necessarily stimulate innovation networks at all.

The idea then becomes to investigate whether (or not) some competitiveness clusters (which ones?) progressively emerge as a networking community in the overall French innovation network, or whether the dynamics of the network is disconnected from the clusters' borders policy. We thus want to complement existing literature by analyzing how collaborations for innovation organize and evolve in space, and by investigating the logics that underlies their organization. To contribute to this topical issue, we rely on previous results according to which three main arguments might explain the organization and evolution of a collaborative network (Balland, 2009): the structure of previous collaborations, individual characteristics and proximity. We complement them by analyzing the role of the cluster policy in structuring the innovation network and finally test whether the innovation network building is driven (or constrained) by the French competitiveness clusters' borders or whether it rather seems determined by individual, structural or proximity motives.

We dissociate ourselves from existing literature, first of all as we study collaborative projects funded on the whole French territory (and not only in some specific clusters), without accounting a priori for the clusters' territorial borders in the analysis, but rather choosing to test whether the clusters' borders emerge in the network we build. Moreover, our paper relies on never-used and exhaustive data on all the collaborative innovative projects financed by the FUI since 2005, which allow us to run a longitudinal study of collaborations over a 5-year period and to account for its dynamics. Third, we adopt a project-based view ie we investigate networks of collaborative projects instead of networks of collaborating actors. Choosing the project level of analysis allows us to provide a richer explanation of the determinants of collaborations in innovation, including variables on the actors and the technology at stake, but also testing "proximity-based" arguments.

The theoretical background and the originality of the paper being presented, the next section details the empirical setting selected for the study.

2. Empirical setting

2.1. Data and variables

To proxy the French innovation network we rely on data on collaborative projects labelled and funded by the French FUI ("Fonds Unique Interministeriel"). The FUI is a governmental fund dedicated at financing the most promising R&D collaborative projects that entail firms and research institutions from at least one French competitiveness cluster[2]. Data on FUI projects gather information on nine calls for proposals covering the 2005-2010 period. They consist in the name, the nature and the address of the organizations being involved on the project[3], the amount of public funding each organization got for the project, a summary of the scientific content of the project, and the name(s) of the competitiveness cluster(s), which have labelled the project.

Our database includes 779 "FUI" projects, involving 5756 actors/organizations. A quarter of the FUI projects have being labelled by more than one competitiveness cluster (see table A1 in annexe). Indeed, if collaborative projects funded by the FUI might involve actors from a single competitiveness cluster, it is worth noticing that since 2007, the DIACT -the State institution in charge of the management of the *Pôles de compétitivité* program- provides tendering parties with strong incentives for designing inter-cluster collaborative projects, by underlining for instance the positive impact of an involvement of several clusters on the probability for a given project to become labelled and financed by the FUI. It sounds therefore quite interesting to see that this cluster policy measure has had a direct impact on the number

[2] Different financing sources of collaborative projects may be enumerated: Fonds Unique Interministeriel; OSEO, a network of regional innovation agencies; Regional and Departmental councils and ANR (National Research Agency). A hierarchy of financing sources according to the economic significance and the scale of project has formed: most significant projects are more likely to be financed by the Fonds Unique Interministeriel, while smaller projects are financed by OSEO and Regional councils (Amisse and Muller, 2010). To be eligible to FUI funds, R&D projects have to be labelled by at least one competitiveness cluster.

[3] Concerning the private sector, organizations are defined at the plant level. Organizations from the public sector are either laboratories or university departments or public research organisms as a whole. This lack of homogeneity in organizations' aggregation level motivates our choice to build a project-based network (rather than an actor-based one).

of co-labelled projects. Our purpose is now to see whether it has generated any change in the geographical shape of the collaborative network.

To enrich the raw database and handle more exhaustive information on collaborative projects, we gather additional data and build new descriptive variables (see Table A2 in Annex). To do so, we rely on previous results according to which three main arguments might explain the organization and evolution of a collaborative network (Balland, 2009): the structure of previous collaborations, individual characteristics and proximity. In the present paper the structure of previous collaborations is not relevant to explain the collaborative dynamics. Indeed, we analyse the networks of projects and not the one of actors. Thus nodes of the networks are different in each period, each project being developed during a specific limited period of time. Therefore, to understand the rationales at stake in the network of innovative projects, we exclusively rely on two out of the three types of potential determinants presented in the literature: the individual characteristics of the innovative projects studied on the one hand, and the proximities that might exist between projects on the other hand.

We thus first built explanatory variables accounting for the individual characteristics of projects, more precisely describing the actors, the industry, the geography and the time period at stake (see table A2 in annex).

We consider that the nature, diversity and number of actors involved on a given project may be of importance to explain likelihood for this project to be connected to another project. We thus create variables accounting for the size of the project (number of actors), the proportion of SMEs involved, and the involvement of public actors. Regarding the dominant technology and industry at stake in a given project, we include a variable testifying either the dominant involvement of a manufacturing industries in the project or/and the decisive presence of actors from Knowledge Intensive Business Services (KIBS). To identify the dominant industry of a given project, we choose to adopt on original indicator, based on fine-grained funding data, rather than computing the number of actors of each category involved in a given project. Concretely, we consider that a project is a manufacturing industry-dominated (resp. KIBS) one, if the majority of public funding associated to the project has been given to manufacturing (resp. service industry) firms. We also decide to estimate the industrial variety of a project by calculating an entropy index (estimating the number of different industries represented in a given project). In addition, we gather information on the institutional support each project has benefited from. We thus include a variable accounting for the part of FUI funds in the total amount of funding obtained, another one precising the identity of the ministry in charge of the project and a third one accounting for the involvement of more than one competitiveness cluster in the project.

Projects labeled by competitiveness clusters are supposed to gather regional actors collaborating on a common research question. However, collaborative teams are not constrained by regional barriers: if a research team cannot find a specific competence on the competitiveness cluster territory, the firm might go and look for a partner in a different region. To test whether the likelihood of connection for a given project is function of the geographical closeness of this project's actors, we choose to include a variable describing the geographical scope of the project. Concretely we distinguish mono-regional projects (labeled by one or several competitiveness cluster(s) from the same region) from multi-regional projects[4]. Among the multi-regional projects we differentiate projects involving actors from competitiveness clusters located in neighboring regions from those involving partners located in competitiveness clusters from distant regions.

Lastly, as actors may accumulate collaborative experiences through time what might lead them to be more inter-connected as time goes by, due to a form of confidence among them, we integrate variables about the time period (and call for proposal of the project).

The main database being presented, the next section details the methodology adopted for our analysis.

2.2. Methodology

To assess the evolution of the shape and the intensity of the French innovation network, we run a two-step network analysis combined with econometric estimation.

In a first step, we build and characterize the French innovation network. Nodes of the innovation network represent projects funded by the FUI and ties account for actors (partners) which are common to two different FUI projects[5]. We choose to link projects rather than actors so as to favour an analysis of the characteristics of projects as determinants of the

[4] Multi-regional projects gather two sorts of projects: projects labeled by different competitiveness clusters located in different regions or projects labeled by competitiveness clusters spread on several regions.

[5] It is worth to highlight that actors and projects display a natural bipartite structure (Guillaume et Latapy, 2007). Their network can thus be analyzed either as a set of projects (where two projects are linked if at least one actor is involved in both of them), or as a set of actors linked to one another if they take part to at least one common project. The impact of the preceding choice on the morphology of the network is non trivial. More precisely, if we consider the second case (networks of actors) it assumes that all the actors of a given project are linked to one another in a similar way. As a consequence, the cliquishness of the network is very sensitive to the size of projects (in terms of number of actors involved). To avoid such problems, we choose to build a network of projects in the present paper.

collaborative behaviours. Couples of projects (or nodes of the network) are thus disconnected, if they have been conducted by completely different partners (organizations).

To account for any evolution of the network, we decide to break up the period of analysis into 3 sub-periods, each of them regrouping data on 3 calls for proposals launched by FUI[6]. We finally build 3 distinct relational matrices, one for each sub-period, and calculate indicators traditionally used in social network analysis. It enables us to follow the evolution of indicators depicting the structure and the spread of the network.

In a second step, we identify cohesive groups within the three networks. Using Ucinet (Borgatti et al.), the network is partitioned into mutually exclusive cohesive groups, applying the hierarchical clustering method (Wasserman and Faust, 1994). Cohesive groups gather nodes (ie collaborative projects) into groups so that nodes within a group have comparatively more direct and indirect links with one another than with nodes that are not members of the cohesive group[7]. Applied to our precise case, the density of ties among projects of a single cohesive group is significantly higher than among projects of different cohesive groups. However, this does not necessarily mean that all projects from a given cohesive group do have direct relationships with one another.

In a third step, econometric modeling allows us to investigate the determinants of the network structure. We first run a logit regression in order to identify the determinants of the likelihood for a given project to be included in the giant component of the network (vs the probability for a given project to remain either isolated or tied to a very limited number of other projects) (model 1). This regression helps us in providing preliminary explanations of the intensity of connectedness of a given project. The computations concretely investigate whether the characteristics of the projects explain the probability for those projects to be connected to any other collaborative project. Then, we run a logit regression in order to identify the determinants for a given project to be included in a (small vs big) cohesive group (models 2 and 3). In a last step, we concentrate on the main cohesive groups (ie the biggest ones) in

[6] We adopt a decomposition based on the calls for proposal rather than on the launching year of projects because calls for proposals are not continuous through time, thus leading to some periods of time without any project being launched. Moreover, this decomposition in calls for proposal allows us to have three periods of similar average size.

[7] The quality of the partition is measured through the computation of a modularity index (Q, Girvan and Newman, 2002) comparing the fraction of edges connecting nodes of the same cohesive group in the network with the expected fraction of edges in the same partition but random connections between nodes. We concentrate on the partitioning associated with the highest Q value.

order to highlight their relational logics (the way those innovative communities of projects emerge)[8]. This leads us to concentrate on 19 (main) cohesive groups, each of them gathering 12 projects or more. We scan the nodes (projects) these main cohesive groups are composed of in order to investigate their clustering logics and thus become able to highlight some of the underlying mechanisms that explain the innovation network shape. More precisely, we assume that some projects are more or less likely to be connected to one another (and to belong to the same cohesive group) due to proximity arguments. In order to provide a more comprehensive understanding of the relational logics at stake in cohesive groups of projects, we thus build indicators of proximity to measure similarities/dissimilarities among projects belonging to the same cohesive groups, and to test their explanation power on the more or less cohesive structure of the French innovation network. Concretely, we assume that some projects are more likely to be connected due to:

- First, cognitive proximity between projects: similarity in the knowledge bases required to solve different projects might explain their need to rely on similar research partners (ie to be linked). We thus rely on our indicators on the technology at stake in the projects and on the knowledge bases of the actors involved to measure cognitive proximity between projects belonging of the same cohesive groups. Going into more details, a cohesive group is presented as being dominated by a given type of industry (KIBS, high tech manufacturing, low tech manufacturing) if it gathers more than 50% of projects which are individually dominated by this specific type of industry.
- Second, geographical proximity: again we test whether projects of a given cohesive group do benefit from geographical proximity between their respective actors. Hence, cohesive groups in which more than 50% of the projects are developed by actors belonging to competitiveness clusters located in the same region are presented as region –dominated cohesive groups.
- Institutional proximity: being labeled by the same competitiveness cluster might explain why two different projects share some common partners. We thus investigate whether the number and the identity of the competitiveness clusters involved in a project might explain the inclusion of this project in a specific cohesive group. More precisely, we create the label cluster-dominated cohesive groups to characterize cohesive groups composed of a majority of projects labeled by the same competitiveness cluster.

[8] Concretely, we select a threshold in such a way that it allows us to account for at least 50% of the collaborative projects funded during each period, as shown in table A3 in annex.

- Organizational proximity: a sub-sample of projects might belong to the same cohesive group because they are developed by the same organization. In that specific case, the cohesive group thus accounts for the R&D projects portfolio of a given organization. We therefore identify the most central actor of the cohesive groups (by computing the actor's centrality) and consider that cohesive groups are dominated by a focal actor, when at least 50% of the projects belonging to those given cohesive groups do have the focal actors among their research partners.

The empirical material being motivated, we present and discuss the results in the next section.

3. Results

3.1. The French innovation network through time: analyzing social network statistics

Looking at Graph 1, 2 and 3 (in Annex) and Table 1 hereafter, we first observe a non linear increase in the number of collaborative projects funded by the FUI (the total number of projects going from 230 in period 1 to 240 in period 3 with a pick of 309 in period 2). At the same time the number of actors involved in collaborative projects varied from 1243 in period 1 (corresponding to 5,4 actors per projects on average) to 1610 in period 2 (average of 5,2 actors per projects) and 1214 in period 3 (5,05 actors per projects on average). The network has thus first been growing before stabilizing more recently.

If the collaborative dynamism seems to stabilize both in terms of projects funded and actors involved, what is worth stressing is the concomitant increase in the number of ties linking collaborative projects with one another and the related increase of the average centrality degree of the nodes (climbing from 6,63 to 15,6 in 5 years). Put differently, the network of innovation becomes denser (event still relatively sparse) through time, as confirmed by the indicator of the density of the network (which doubled between period 1 and period 3). This indicates than a given partner tends to collaborate more frequently on different innovative projects in recent years than in 2005. Encouraging competitiveness clusters to organize themselves in networks (as it is done by the new FUI procedure of funds allocation) thus seems to have an impact on the density of the network of innovative projects.

Table 1: Descriptive statistics on the French innovation network and its evolution

	Period 1	Period 2	Period 3
STATISTICS ON THE OVERALL NETWORK (VALUED NETWORK)			
Rounds of invitations to tender	2,3,4	5,6,7	8,9,10
Number of projects (nodes)	230	309	240
Number of ties	1526	3388	3744.
Average centrality degree (normalised degree)	6.63 (0.41)	10.96 (0.59)	15.60 (1.30)
Density (number of actual ties / number or potential ties)	4.58%	5.97%	10.98%
Number of isolates	43	25	18
Number of components (isolated being excluded)	5	4	1
STATISTICS CALCULATED ON THE GIANT COMPONENT (NON-VALUED NETWORK)			
Size (in % of the total number of nodes)	66.9%	89.9%	92%
Clustering coefficient (% of ordered triples in which i-->j and j-->k that are transitive)	42.57%	40.72%	60.86%
Average Distance	3.63	3.26	2.79
Diameter	8	9	7

Interestingly also, the number of isolated projects (or grouping of two or three projects of small isolated groups) has been divided more than 2 and as a corollary the size of the giant component has significantly increased, showing that the network of collaborative projects becomes more and more connected. Even if the number of projects directly of indirectly connected increases, the diameter of the giant component remains stable (we even notice a slight decrease) suggesting that accessibility from one given node in the network to any other one has been improved. Moreover, the network displays moderately low average distance (3,63 in period 1 vs 2,79 in period 3), for an average clustering coefficient of 0,42 (respectively 0.60 in period 3). Thus, the small world status of the network, evidenced in many cases (Watts, 1999; Cole, 2008) is confirmed on our project-based network.

3.2. Identifying cohesive groups to see whether competitiveness clusters emerge

Applying the partitioning procedure described in the previous section allows us to extract 62 (respectively 61 and 40) cohesive groups for period 1 (resp. 2 and 3) of various sizes, gathering from 1 up to 46 (33 and 55) projects (in period 1, 2 and 3 respectively).

Table 2: Descriptive Statistics on cohesive groups

	Period 1	**Period 2**	**Period 3**
Q-prime[9]	0,52	0,49	0,47
Number of cohesive groups	62	61	40
Average size of the cohesive groups	3,71	5.07	6
Size of the biggest cohesive group	46	33	55
(% of the total number of projects)	(20%)	(11%)	(23%)
Size of the 2nd biggest cohesive group	28	31	40
(% of the total number of projects)	(12%)	(10%)	(17%)

What is worth noticing is that the number of cohesive groups has a fairly clear decreasing tendency from 2005 onwards. At the same time, we saw in the previous paragraph, that the network became denser and more clustered through time. The combination of those two observations suggests that the French innovation network becomes more connected due to the development of larger connected communities of projects (the cohesive groups). This tendency is confirmed by the evolution of the size of the giant cohesive group which decreases initially from 46 projects to 33 but then starts rising up to 55. Put differently, those figures show that the proportion of collaborative projects developed by isolated partners decreases, suggesting a form of coherence in terms of innovative projects management.

Scanning the average size of cohesive groups we can see that it rises from 3.71 projects per cohesive groups on average in period 1 to 6 projects in period 3. Comparing this average size to the average number of projects labeled by each competitiveness cluster on the 3 periods (see Table 2 supra) allows us to highlight that if in period 1 the two figures were almost equal, they significantly differ in period 3, where the average size of cohesive groups is almost the double than the average number of projects labeled by each competitiveness cluster. This suggests that cohesive groups and competitiveness clusters' borders do not coincide.

Moreover, the very limited average size of cohesive groups testifies that the French innovation network is composed of lots of cohesive groups of small size, as confirmed by the distribution of cohesive groups by size, provided in annex 2. Put differently all connected projects are not connected to the same number of projects. Faced with such a skewed distribution, we choose to concentrate on cohesive groups gathering 12 or more projects, ie on 19 main cohesive groups (respectively 6 for period 1, 8 for period 2 and 5 for period 3). We focus on those main cohesive groups and try and understand and compare their relational logics in the next paragraph.

[9] Newman and Girvan's modularity Q is the fraction of edges that fall within the partition minus the expected such fraction if the edges were distributed at random, Q has a maximum value of 1-1/m where m is the number of clusters Q prime is a normalized version of this. Note for similarity data we expect all be positive.

3.3. Remaining out of the network and out of the main cohesive groups: preliminary explanations

Results of our logit regressions (on the determinants of the likelihood for a given project to be included in the giant component of the network, or included in a cohesive group) are presented in Table 3 and expressed in odds ratio. This ratio indicates the relative variation of the dependant variable for a unitary variation of the explanatory variable.

Model 1 : belonging to the giant component

We first notice a time effect, more recent projects having a higher probability to be part of the giant component of the network. This appears to confirm the greater involvement of actors in collaborative projects over time. Second, projects involving partners from neighboring regions are also more likely to be connected to other projects, which confirms the importance of geographic proximity on the structure of networks. On the contrary, involving a large proportion of SMEs decreases the likelihood to be part of the giant component, that means than SMEs have difficulties to be concomitantly implicated on several projects. Interestingly, projects run by high tech manufacturing firms are more connected than those handled by knowledge intensive business services firms. Not surprisingly, multi-sector projects have significantly more chances to be connected to other projects than mono-industrial ones. The nature of the project (more or less research-based and more or less diversely funded) does not have any significant influence on the probability for the project to be included in the giant component. Looking at our control variables: we confirm that bigger projects are more likely to be connected to others, and show that projects supported by the Defence Procurement Agency (DGA) or the agency of national and regional development (DATAR) are more linked to the other projects, whereas on the contrary, projects supported by the DGPAAT (agency of agricultural development) are more scarcely linked to other innovative projects, that could be explained by their specific activity. Lastly, projects labeled by several competitiveness clusters do benefit from a positive yet non-significant effect on their connectedness.

Table 3: The determinants of connectedness: logit estimates

	Overall pop.	Giant component	
	(1)	(2)	(3)
Belonging to	Giant Comp.	Small cohesive groups	Big cohesive groups
Call for proposals 2 to 4	*ref*	*Ref*	*ref*
5 to 7	3.613***	2.817***	0.355***
	(4.09)	(4.31)	(-4.31)
8 to 10	5.661***	1.120	0.893
	(4.65)	(0.42)	(-0.42)
Mono-regional project	*ref*	*Ref*	*Ref*
Contiguous regions' project	2.440**	1.320	0.757
	(2.16)	(1.14)	(-1.14)
Non contiguous regions' project	0.524	2.808***	0.356***
	(-1.10)	(3.05)	(-3.05)
High-tech manufacturing industries	2.429***	0.595***	1.679***
	(2.78)	(-2.64)	(2.64)
Knowledge Based Intensive Services	0.398***	0.979	1.022
	(-2.63)	(-0.09)	(0.09)
SME dominated	0.435***	1.075	0.931
	(-2.89)	(0.37)	(-0.37)
Diversity of companies' activities	1.575**	0.887	1.128
	(2.29)	(-1.10)	(1.10)
Basic Research project	0.710	1.052	0.951
	(-1.13)	(0.24)	(-0.24)
FUI funding greater than 50%	0.969	0.969	1.032
	(-0.11)	(-0.15)	(0.15)
Total funding (in log)	1.529*	0.517***	1.933***
	(1.86)	(-3.76)	(3.76)
Number of partners : 1 to 4 partners	*ref*	*Ref*	*ref*
5 to 9 partners	4.814***	0.710	1.408
	(5.20)	(-1.41)	(1.41)
10 and more partners	5.978***	0.431**	2.322**
	(3.03)	(-2.31)	(2.31)
Co-labeled project	1.455	0.634	1.577
	(0.70)	(-1.57)	(1.57)
Steering institution Industry and Services	1.462	1.283	0.779
	(1.12)	(0.86)	(-0.86)
Steering institution Defence Procurement Agency	5.398***	1.037	0.964
	(2.88)	(0.11)	(-0.11)
Steering institution Agriculture	0.371**	4.731***	0.211***
	(-2.39)	(4.25)	(-4.25)
Steering institution Territorial Planning	2.767*	0.902	1.109
	(1.92)	(-0.29)	(0.29)
Observations	779	679	679
Ll	-204.4	-371.3	-371.3
df_m	18	18	18
Aic	446.8	780.5	780.5
r2_p	0.315	0.142	0.142

Exponentiated coefficients - * p<.10, ** p<.05, *** p<.01 - zvalue in brackets

How to read the table? In model 2, the likelihood for a given project financed during the 5th, 6th or 7th call for proposals to be part of a small cohesive group is 2.82 times higher than its likelihood to be out of any small cohesive group. .

Models 2 and 3: belonging to the giant component and to small cohesive groups vs a big cohesive group

What is worth noticing is that projects launched in the second period exhibit a significantly higher (respectively lower) tendency to be part of small (respectively major) cohesive groups. Involving partners from non contiguous regions increases the likelihood to the part of cohesive groups of small size. If high tech projects are more frequently part of major cohesive groups, the industrial diversity of projects does not impact the type of cohesive groups they are part of. This lack of impact also holds for the nature of the projects considered. Bigger projects show a higher probability to be part of large cohesive groups, whereas projects supported by the DGPAAT seem to be doomed to belong to cohesive groups of smaller size. Lastly, being labeled by more than one competitiveness cluster does not significantly modify the likelihood for a given project to be part of any type of cohesive groups.

To sum up, individual characteristics of projects do explain part of the shape of the French innovation network. More precisely, those first estimations highlight the decisive role played by the technology underlying a collaborative project on the degree of connectedness of this project. Indeed, high tech manufacturing projects appear as more connected (and connected to a large number of projects) than projects developed around services (even knowledge intensive ones). We thus exhibit a form of technological trajectory among collaborative projects funded by the FUI, different high tech projects being linked to one another. On the contrary, in the service sector, collaborations look like one-shot collaborations. We also exhibit that projects related to agriculture are less connected, probably due to the very customized solutions they provide. On the contrary, projects sponsored by the defence procurement agency are well-connected, this result being probably due to the limited number of potential partners in this industry.

Our results also confirm the decisive influence of size on the likelihood for a project to be linked to other projects: size of the projects but also of the project's partners. Indeed, we confirm that projects run by SMEs are more isolated, probably because small firms do not have enough resources to get involved in several innovative projects concomitantly.

Regarding the impact of geography, we find that projects run by distant partners are less connected to one another: indeed, collaboration at distant might be more complicated and time-consuming for partners, what limits their capacity to be involved in several projects at the same time.

But if individual characteristics of projects do explain the probability for a given project to be linked to other projects (through a shared partner), do we observe more links between projects of similar profiles or are projects of a given type linked to projects of various shapes? In a second step, we precisely aim at refining our understanding of the determinants of the links between collaborative projects. To do so, we concentrate on cohesive groups being composed of at least 12 projects (see table A3 in Annex for a justification of this threshold) and scan their characteristics so as to identify some (if any) logics in their configurations.

3.4. Identifying relational rationales at stake in major cohesive groups

The descriptive statistics of the composition of major cohesive groups are provided in Table A4 in Annex. Looking at this annex, we can first emphasize the huge intra-cohesive group heterogeneity. Despite this intra-cohesive group heterogeneity, it is possible, by scanning the data, to propose a typology of those main cohesive groups' building logics (see Table 4, hereafter). First focusing on the role of competitiveness clusters in the dynamics of those cohesive groups, we can notice that all major cohesive groups share a common feature: the inclusion of projects labeled by several competitiveness clusters in a given cohesive group, suggesting that cohesive groups do not coincide with competitiveness clusters borders. Nevertheless, looking into more details, we can find 6 cohesive groups which seem to be dominated by a given competitiveness cluster, as more than 50% of the projects included in those cohesive groups have been labeled by the same competitiveness cluster. The 13 other cohesive groups are spread on various competitiveness clusters, suggesting thus a limited influence of the competitiveness cluster policy on the structuring of innovation networks.

Those statistics also allow us to pinpoint cohesive groups concentrated on a limited number of regions (one or two maximum), and for which more than 50% of the projects involved partners located in the same region. Among those geographically concentrated cohesive groups, we find the cohesive groups that we just mentioned, ie the ones organized around a specific competitiveness cluster. In those cases, the impact of the competitiveness cluster might explain the geographical concentration of the cohesive group. On the contrary, the 8 other cohesive groups for which geography matters are spread on different clusters, but concentrated in one region, meaning that their relational rationales mostly relies on physical proximity rather than on the institutional impetus of the competitiveness cluster policy.

If we now focus on sectoral differences, we can see, that 9 major cohesive groups (out of the 19 we consider) are "KIBS-dominated" (more than 50% of the projects included in those cohesive groups being run by firms in knowledge intensive services). The ten remaining cohesive groups are dominated by manufacturing industries, 6 (respectively 4) of them being mostly active in high-tech (resp. low-tech) industries.

Finally, even if the networks that we have studied are built using a project based level of analysis, the links between projects are calculated through the existence of common actors participating to different projects. And if we scan the functioning of the biggest cohesive groups, we can find 4 cohesive groups, in which a focal actor plays a key role in linking together projects involving actors from different locations and and/or in different sectors of activity. Interestingly, 3 out of those 4 focal actors are large public research organisms (PROs). Two explanations might be provided to such a result: either PROs act as intermediaries between different regions and/or different types of organizations (cf. for example Morisson, 2008); or the cohesive group under consideration accounts for the innovative projects portfolio of this focal actor, the latter then becoming the pilot of the whole cohesive group (as shown by Lévy and Talbot (2012) in the Aerospace Valley competitiveness cluster).

Table 4: A preliminary typology of cohesive groups' rationales (number of cohesive groups concerned)

	KIBS dominated	Manufacturing industry dominated		**Total nb of cohesive groups**
		High-tech	Low-tech	
Cluster-dominated	3	3 (1)*		**6 (1)**
Regionally concentrated	3	2 (1)	3 (1)	**8 (2)**
No geographical influence	3 (1)	1	1	**5 (1)**
Total nb of cohesive groups	**9 (1)**	**6 (2)**	**4 (1)**	**19 (4)**

**Figures into brackets indicate the number of cohesive groups dominated by a focal actor*

4. Conclusion

In this paper we aim at analyzing the transformation of collaborative networks of innovation in France since the launching of the French competitiveness cluster policy. By scanning collaborative projects funded by the FUI, we build up the network of innovative projects and characterize its evolution through time. We first exhibit that this network gets denser and more connected. In a second step, we refine those results by pinpointing a dynamic of concentration of the network towards a limited number of innovative communities (proxied by cohesive groups). In a last step we try and investigate the relational logics explaining the emergence of those innovative communities. We find that the borders of innovative communities do not coincide with the territories of competitiveness clusters, suggesting thus, that we do not observe a clustering of the French innovative network around some specific competitiveness clusters: public and private actors, when looking for innovation do not limit their collaborative perimeter to the borders of the competitiveness cluster they are members of. The evolution of the structure of collaborative networks of innovation in France cannot solely be explained by a cluster-policy dynamics. Actually, we observe that the structuring of the innovative communities is also explained either by industrial dynamics or geographical ones, or both. Put differently, despite the governmental involvement in a deliberate clustering policy, the French network of innovation seems to continue to obey to a spontaneous self-organizing dynamics, based on traditional collaborative complementarities. This conclusion sounds even more robust that we base our analysis on FUI data, ie on information on collaborative projects launched by competitiveness clusters' members exclusively. This choice simultaneously constitutes one of the limits of the present study but also its strength: indeed we do not observe any clustering phenomenon around the competitiveness clusters' borders within the network, even when using potentially biases data. In such a context, further work could consist in analyzing the morphology of the innovation network, based on other data sources (such as the ones on more science-based projects funded by the French national research agency). Another idea to improve the paper lies in testing whether we can reach similar conclusions when building an actor-based network. In a word, much remains to be done before providing a definite explanation of the evolution of the French innovation network.

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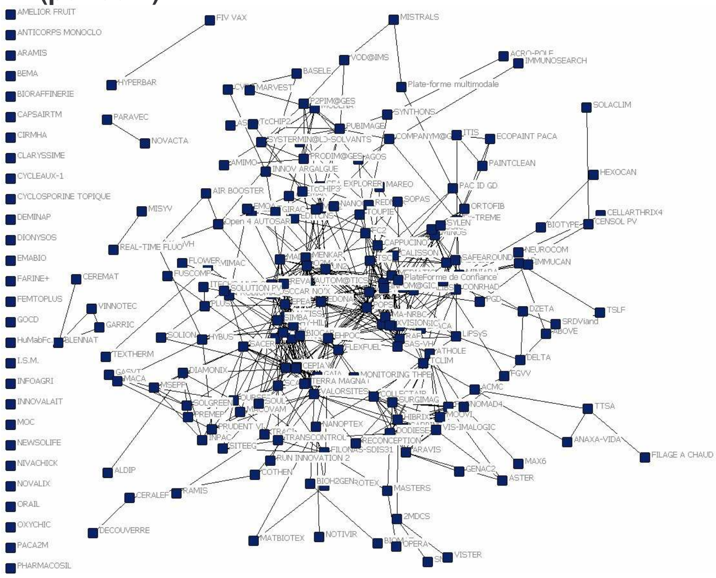
ANNEXES

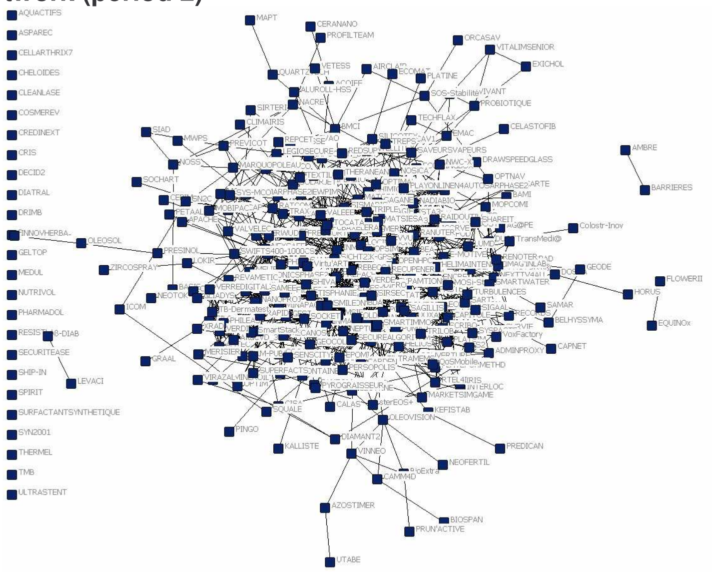
Table A1 : The FUI projects through time

Round for project	number of projects mono-acc.	co-acc.	total	number of actors in projects mono-acc.	co-acc.	total
2	60	1	61	310	7	317
3	97	2	99	783	25	808
4	56	14	70	367	145	512
5	99	21	120	688	188	876
6	68	30	98	509	228	737
7	54	37	91	398	311	709
8	54	38	92	346	353	699
9	39	36	75	298	270	568
10	41	32	73	259	271	530
Total	**568**	**211**	**779**	**3958**	**1798**	**5756**

Graph 1 : overall network (period 1)



Graph 2 : overall network (period 2)



Graph 3 : overall network (period 3)

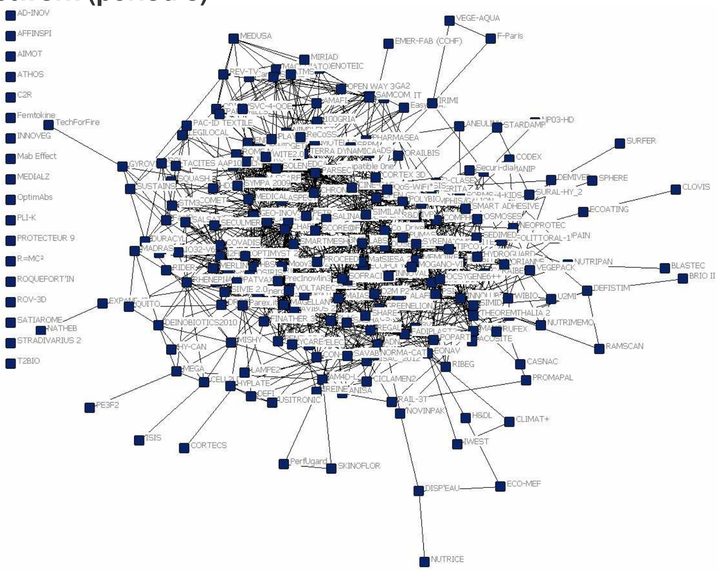
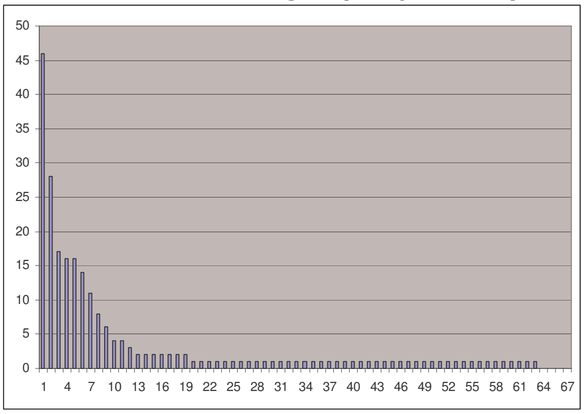


Table A2: Individual characteristics of collaborative projects

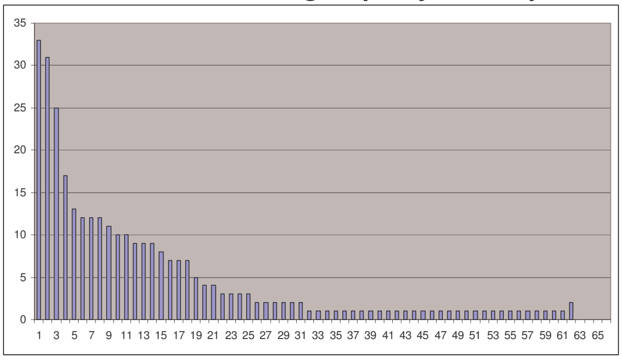
Characteristics	Measured by	Details
Time period	Call for proposals	P1 : 2 to 4 ; P2 : 5 to 7 and P3 : 8 to 10
Actors involved	Number of actors	cl1 : 1 to 4 ; cl2 : 5 to 10 and cl3 : > 10
	SME dominated	1 if the project includes at least 1/3 of SmES
	Project dominated by public research	1 if funds for public research > 50% of total funds
Firms involved	Knowledge Based Intensive Services	1 if the share of funds collected by service sector firms >=50%
	High-tech manufacturing industries	1 if the share of funds collected by high tech manufacturing sector firms is dominant in manufacturing sector
	Diversity of firms' activities	$\sum_{i=1}^{n} p_i * \log(1/p_i)$ with p_i = the share of funds collected by firms active in activity i
Funding	FUI funds dominated	1 if FUI funds > 50% of total funds
	Total funding of the project	in log
Steering institution	Industry and Services	1 if under DGCIS's supervision
	Defence Procurement Agency	1 if under DGA's supervision
	Agriculture	If under DGPAAT's supervision
	Territorial planning	If under DATAR's supervision
Competitiveness clusters involved	Co-labelled project	1 if the project has been labeled by more than one competitiveness cluster
Location of the project	Mono-regional project	1 if cluster(s) which has(ve) labeled the project is(are) in the same region
	Contiguous regions' projects	1 if cluster(s) which has(ve) labeled is(are) located in neighboring regions
	Non-contiguous regions' projects	1 if clusters which have labeled are located in distinct and not neighboring regions

Figure A1 : Distribution of cohesive groups by size in different periods

Distribution of cohesive groups by size in period 1



Distribution of cohesive groups by size in period 2



Distribution of cohesive groups by size in period 3

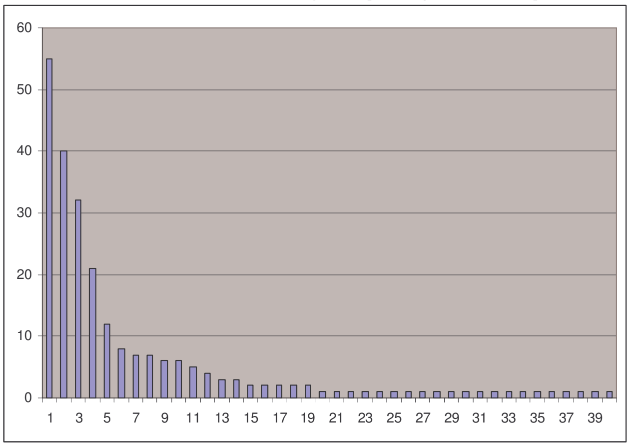


Table A3: Definition of the main cohesive groups

If a « main » cohesive group has a minimum size of	% of projects included in "main" cohesive groups		
	Period 1	Period 2	Period 3
12 projects	**59.56%**	**50,16%**	**66.67%**
11 projetcs	59.56%	53,72%	66.67%
10 projects	59.56%	60,19%	66.67%