The evolution of the French collaborative network of innovation: towards clustering around *competitiveness clusters*' borders?

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Abstract:

In this paper we aim at analyzing the transformation of the French innovation network since the launching of the competitiveness cluster policy. By scanning collaborative projects developed by members of competitiveness clusters, 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 through time. In a second step, we refine those results by pinpointing a dynamics 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 that the evolution of the structure of collaborative innovation networks in France cannot solely be explained by the cluster-policy dynamics.

Keywords: cluster policy, network dynamics, innovation, collaborative projects

Introduction

Since the beginning of 2005, the French government has supported and partially financed collaborative innovative projects involving actors from public research and private firms through an original national cluster initiative: the competitiveness cluster policy ("politique des 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 labelled by at least one of the 71 existing competitiveness clusters and linking clusters' stakeholders (firms and actors of public research) on a given territory[1]. Six years after the implementation of this cluster policy, one may wonder how it influences the French network of innovation.

Clusters and particularly competitiveness clusters are analyzed in a growing literature in economics, management and geography. Some of the existing (empirical) papers aim at characterizing 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 they are targeted at the evaluation of the more or less successful impact of competitiveness clusters on their territories (Chalaye and Massard, 2009). Another category of contributions chooses to look at competitiveness clusters in a more fine- grained way thanks to in-depth case studies of the collaborative behaviors adopted within some of them (Levy and Talbot, 2012; 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 traditionally presented as catalysts 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) neighbours (as it is the case for competitiveness cluster members) is not enough to generate collaborations and to benefit from spillovers (Breschi and Lissoni, 2001; Rondé and Hussler, 2005; Amisse et al., 2011), whereas other papers insist on the potential drawbacks of developing intra-cluster linkages

[1] A competitiveness cluster may be spread over one or several NUTS 2 region(s).

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, 1985).

Facing this lack of consensus, we aim at prolonging these studies and complementing them by offering an original approach of the evolution of the organization of the innovation network developed on the overall French territory. Concretely, the present paper analyses the transformation (from 2005 to 2010) of the French collaborative network of innovation, by scanning collaborative projects labelled by competitiveness clusters. Our main research interest lies first in testing whether the network gets progressively more densely connected, collaborations being stimulated and multiplied over time. Second, we aim at characterizing and understanding in a more fine-grained way the evolution of the structure of the network: if the network gets concentrated, do we observe a tendency for this network to become clustered around some (specific?) competitiveness clusters (collaborations obey in that case a geographical, industrial and or an institutional building logic)? Or, on the contrary, does the network extend on the French territory in a more loosely-coupled way, collaborations being developed with intra- but also extra- competitiveness clusters' members (the cluster policy being in that case less significant in explaining the structuring of the innovation network)?

We mobilize two main methods (social network analysis and econometric modelling) for our empirical study. 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 with the borders of competitiveness clusters. Econometric modelling allows us to estimate the determinants for a given project to be integrated, firstly in the main component of the network, and secondly in the biggest cohesive groups.

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 territorial borders of the competitiveness clusters in the analysis, but rather choosing to test whether the borders of the clusters emerge in the network we build. Moreover, our paper relies on never-used and exhaustive data on collaborative innovative projects labelled by competitiveness clusters 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 i.e. 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 rest of the paper is organized as follows. In a first part we present the theoretical background of the paper i.e. the literature on clusters and innovation networks. Second, we detail the empirical setting of the paper. In a third step we present and discuss the results, before concluding.

1. Innovation networks and clusters: A literature review

1.1. (Competitiveness) 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 catalysts 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 borders of the French competitiveness clusters through time.

However, another part of the literature concomitantly shows that being agglomerated does not automatically generate knowledge exchanges (Breschi and Lissoni, 2001). By refining this idea, more recent papers explain that proximity might be useful (vs useless) to catalyse knowledge exchanges, depending on the very specific steps of the innovation process, and on the nature of the innovation at stake (Suire and Vicente, 2008; Vicente et al., 2011). At the same time, examples of agglomeration of actors which do not generate any effective relationships between them flourished (Vicente, 2005), suggesting that competitiveness clusters are only repositories 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.

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 a., 2003; Boari and Lipparini, 1999) or in horticulture in the French region Anjou (Société d'Horticulture d'Angers et du département du 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. Furthermore, collaborative projects existing in competitiveness clusters are compelled to involve public and private actors of R&D. But academia and firms might suffer from cognitive distance when working together, thus limiting their willingness to collaborate with one another, despite the value of the knowledge they may co-create (Dasgupta and David, 1994; Van de Ven and Johnson, 2005).

Thus, to help competitiveness clusters become efficient innovative project catalysts ("machines à projets" for Fen Chong and Pallez, 2010) and to effectively stimulate innovation networks enrolling public and private partners, the French government(s) created governance structures in each competitiveness cluster, (the latter being) in charge of supporting the networking activities of the members of competitiveness clusters. Recent empirical studies conclude on the role of knowledge/network brokers (Hamza-Sfaxi et al., 2011) played by such structures and on their decisive role in stimulating collective innovation (Chabault and Martineau, 2011) thanks to various strategies (Bocquet and Mothe, 2011). Hence, if networks do not spontaneously emerge within the borders of competitiveness clusters, they might develop thanks to the intervention of those governance structures.

1.2. Innovation networks: locked in (competitiveness) clusters?

At the same time, an excess of homophily (Nooteboom, 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 (Wang et al., 2010). Indeed, such behaviours 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), which could in turn question the resilience of clusters (Suire and Vicente, 2009). An important stream of literature discussed the importance of accessing external sources of knowledge through the development of so-called "knowledge pipelines" (Bathelt et al., 2004; Owen-Smith et Powell, 2004; Maskell et al., 2006; Bathelt and Gräf, 2008; Moodysson, 2008) 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 make it possible to build cognitive complementarities between actors (Boschma and Iammarino, 2009; Suire and Vicente, 2009), and to take advantage of weak ties (Granovetter, 1985) 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 a network of competitiveness clusters, ie to develop innovation networks outside their borders (Hussler et al., 2010; Grandclement, 2011). Some competitiveness clusters thus progressively become responsible for identifying, interpreting, absorbing, and translating pieces of knowledge for other competitiveness clusters (as already shown at the firm level, by Owen-Smith and Powell, 2004; Giuliani and Bell, 2005; Iammarino and McCann, 2006; Morrison, 2008). However, existing case studies on the relational behaviours in and of competitiveness cluster(s) (Levy and Talbot, 2012; 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 different collaborative profiles.

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

1.3. Networking rationales: beyond the (competitiveness) cluster explanation?

Do we observe a clustering of innovation networks around the borders of the competitiveness clusters? The preceding literature review shows a lack of consensus on the effect a cluster policy might generate on the morphology of the national innovation network. We thus want to complement the existing literature by analysing the transformation of collaborative networks of innovation in France, since the launching of the French competitiveness policy. We are interested in understanding how collaborations for innovation organize and evolve in space, and in investigating the logic 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 analysing the role of the competitiveness cluster policy in structuring the innovation network.

More concretely, we aim first at testing whether or not we observe a densification of the French innovation network over the last 5 years, this densification being either explained by the competitiveness cluster policy and/or by individual and proximity motives. In a second step, we propose 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 borders of the competitiveness clusters and is rather determined by individual, structural or proximity arguments. Finally, the hypotheses we want to test are the following:

Hypothesis 1: The density of the French innovation network has increased since the launching of the competitiveness cluster policy

Hypothesis 2: The French innovation network got clustered since the launching of the competitiveness cluster policy

Hypothesis 3: The borders of the competitiveness clusters shape the clustering of the French innovation network.

Following the presentation above of the theoretical background), the next section details the empirical setting selected for the study.

2. Empirical setting

2.1. Data and variables

2.1.1 The FUI database

To proxy the French innovation network we rely on data on collaborative projects funded by the "*Fonds Unique Interministériel*" (FUI). The FUI is the financial instrument associated to the competitiveness cluster policy. Twice a year, the FUI organizes calls for proposals devoted to supporting R&D collaborative projects entailing firms and research institutions from at least one French competitiveness cluster. Since 2005 the FUI has launched 13 rounds of calls for proposals and financed more than 1150 collaborative projects for a total amount of more than two billion euros. This accounts for 60% of the global amount of funding allocated to collaborative projects developed in competitiveness clusters, FUI being thus the main funding instrument of the French cluster policy[2]. Our database covers the 2005-2010 period and includes 779 "FUI" projects, involving 5756 actors/organisations[3]. Data on FUI projects consist in the names, the natures and the addresses of the organisations involved in the project, the amount of public funding each organization was allocated 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. Indeed, to be eligible to FUI funds, R&D projects have first to be labelled by at least one competitiveness cluster (in our database, a quarter of the projects have being labelled by more than one competitiveness cluster as shown in table A1 in Appendix).

2.1.2. Additional data

We choose to enrich the raw database and handle more exhaustive information on collaborative projects and to gather additional data and build new descriptive variables; in order to provide a more comprehensive understanding of the rationales at stake in the network of innovative projects. To do so, we rely on two out of the three main arguments explaining the organization and evolution of a collaborative network presented in the literature: the individual characteristics of the innovative projects on the one hand, and the proximities that might exist between projects on the other hand.[4] Among the individual characteristics of the projects we choose to distinguish between variables accounting for the internal resources of projects and variables describing the sectoral and geographical environment of the projects (see Table A2 in Appendix).

- *Internal resources*

We consider that the nature, diversity and number of actors involved in a given project may be of importance to explain the likelihood for this project to be connected to another project.

[2] Other important contributors do finance those collaborative projects: the National Research Agency (ANR), innovation agencies such as OSEO or local public authorities. Nevertheless FUi is the only source of financing exclusively dedicated to the competitiveness clusters, ANR or OSEO fund innovative projects of other types also.

[3] We gather the exhaustive population of projects funded by FUI from round 2 to round 9 (out of the 13 rounds of calls for proposals organised by the FUI since 2005). Regarding the actors/ organisations involved, they are defined at the plant level in the private sector. Organisations from the public sector are either laboratories or university departments or public research organisations as a whole. This lack of homogeneity in the aggregation level of organizations motivates our choice to build a project-based network (rather than an actor-based one, see below).

[4] We choose not to consider the structure of previous collaborations in the paper as it is not relevant to explain our collaborative dynamics. Indeed, we analyse the networks of projects and not the network of actors. Nodes of the networks are different in each period, each project being developed during a specific and limited period of time.

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.

In addition, we gather information on the nature of the financial and institutional support each project has benefited from. We include a variable accounting for the total amount of funding received, the part of FUI funds in the total amount of funding obtained and a last one, scoring 1 when the project has been labelled by more than one competitiveness cluster.

- *Industry at stake*

Regarding the dominant technology and industry at stake in a given project, we include a variable testifying either to the dominant involvement of 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 main part 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 about the identity of the steering institution in charge of the project.

- *Geographical scope*

Projects labelled 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 the project partners cannot find a specific competence within the competitiveness cluster territory, they might go and look for a partner in a different region. To test whether the likelihood of connection for a given project is a function of the geographical closeness of the actors of this project, we choose to include a variable describing the geographical spread of the project partners. We distinguish three cases for this variable. Project partners can be located (i) in the same region or in two contiguous regions, (ii) in two non-contiguous regions, (iii) in three or more regions.

In addition, we include a variable accounting for the geographical location of the competiveness clusters which labelled the project. Concretely we distinguish mono-regionally labelled projects (labelled by one or several competitiveness cluster(s) from the same region) from multi-regionally labelled projects[5]. Among the multi-regionally labelled projects, we differentiate projects involving competitiveness clusters located in neighbouring regions from those involving competitiveness clusters from distant regions.

After presenting the data, we detail in the next section the methodology adopted for our analysis.

2.2. Methodology

To assess and explain the evolution of the shape of the French innovation network, we run a two-step network analysis combined with an 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 (organizations) who are common to two different FUI projects. We choose to link projects rather than actors so as to favour an analysis of the characteristics of projects as determinants of the collaborative behaviours. Couples of projects (or nodes of the network) are thus disconnected, if they have been conducted by completely different partners (organizations). It is worth highlighting that actors and projects display a natural bipartite structure (Guillaume and Latapy, 2006). Their network can thus be analysed 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 in 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.

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

[5] Multi-regionally labelled projects gather two sorts of projects: projects labelled by different competitiveness clusters located in different regions or projects labelled by a competitiveness cluster spread over several regions.
[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 proposals allows us to build three periods of a similar average size.

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, 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 modelling 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 provide 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 order to highlight their relational logic (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 logic and thus become able to highlight some of the underlying mechanisms that explain the innovation network shape. More precisely, we assume that some

[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 with random connections between nodes. We concentrate on the partitioning associated with the highest Q value.

[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 the Appendix.

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 logic 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 explanatory 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 to the same cohesive groups. To go 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 projects belonging to competitiveness clusters located in the same region are presented as region–dominated cohesive groups.
- Institutional proximity: being labelled 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 labelled by the same competitiveness cluster.
- 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.

We have motivated the empirical material. We turn now to the presentation and discussion of the results in the next section.

3. Results

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

Looking at Table 1 hereafter and Figure A1 in Appendix, 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 project on average) to 1610 in period 2 (average of 5.2 actors per project) and 1214 in period 3 (5.05 actors per project on average). The network of actors thus first grew before stabilizing itself 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 (even 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 that 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. Hypothesis 1 is thus confirmed.

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

Interestingly enough, the number of isolated projects has been divided by 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. However, even if the number of projects directly or 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 (resp. 33 and 55) projects (cf. Figure A2 in Appendix for details on the size of the cohesive groups in the 3 periods).

Insert Table 2: Descriptive Statistics on cohesive groups

Looking at the descriptive statistics on cohesive groups (see Table 2), it is worth noticing 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 decreased initially from 46 projects to 33 but then started rising up to 55. Put differently, those figures show that the proportion of collaborative projects developed by "isolated" organizations decreases, suggesting a form of coherence in terms of innovative projects management. All those elements support Hypothesis 2.

When we scan the average size of cohesive groups, we can see that it rises from 3.71 projects per cohesive group on average in period 1 to 6 projects in period 3. Comparing this average size to the average number of projects labelled by each competitiveness cluster over 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 double that of the average number of projects labelled by each competitiveness cluster. This suggests that cohesive groups and the borders of the competitiveness clusters do not coincide. So, at this stage, we cannot validate our third hypothesis.

Moreover, the very limited average size of cohesive groups testifies that the French innovation network is composed of a large number of cohesive groups of a small size, as confirmed by the distribution of cohesive groups by size, provided in Figure A2 in Appendix. In other words all connected projects are not connected to the same number of projects. Faced with such a skewed distribution, we propose to distinguish between small cohesive groups up to 11 projects and main cohesive groups with 12 projects and more (see Table A3 in Appendix for a justification of this threshold), and to investigate in the next paragraph the determinants for a given collaborative project to be connected to more or less numerous projects.

3.3. Staying 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 small versus large cohesive group) are presented in Table 3 and expressed in odds ratio. This ratio indicates the relative variation of the dependent 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 have 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.

Looking at the impact of the internal resources of projects, we confirm that bigger projects in terms of total funding are more likely to be connected to others. For the number of actors, we can notice that small projects with less than 5 actors have a very low probability to be connected to the giant component. 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. Projects labelled by several competitiveness clusters do benefit from a positive yet non-significant effect on their connectedness. Interestingly, involving a large proportion of SMEs decreases the likelihood to be part of the giant component. This means that SMEs have difficulties to be concomitantly involved in several projects.

With regards to the industry at stake, we notice the influence of technology and diversity on the probability to be included in the giant component. Projects run by high tech manufacturing firms are more connected than those run 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. We also show that projects supported by the Defence Procurement Agency (DGA) or the steering institution of territorial planning (DATAR) are more linked to the other projects, whereas on the contrary, projects supported by the agency for agricultural development (DGPAAT) are more scarcely linked to other innovative projects, which could be explained by their specific activity.

Lastly, concerning the geographical scope, projects labelled by competitiveness clusters from neighbouring regions are also more likely to be connected to other projects, which confirms the importance of geographic proximity on the structure of networks. But there is no influence of the location of partners on the probability to be connected.

Insert Table 3: The determinants of connectedness: logit estimates

Models 2 and 3: belonging to a small cohesive group 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.

Bigger projects in terms of total funding but also in terms of number of actors show a higher probability to be part of main cohesive groups. Other internal resources do not exhibit significant differences between small and big cohesive groups. Furthermore, being labelled 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.

High tech projects are more frequently part of major cohesive groups whereas projects supported by the DGPAAT seem to be doomed to belong to cohesive groups of a smaller size. If industrial specialization in high technology favours interconnections between projects, industrial diversity does not impact the type of cohesive groups the projects are part of.

Concerning the geography of the project, being labelled by clusters from non-contiguous regions increases the likelihood for a given project to be part of cohesive groups of a small size. But there is no significant effect of the location of partners on the probability for a given project to belong to small vs big cohesive groups.

To sum up, individual characteristics of projects do explain part of the shape of the French innovation network. More precisely, our results confirm the decisive influence of internal resources on the likelihood for a project to be linked to other projects. Projects with few partners and low levels of funding have a lower probability to be connected to other projects. 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.
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 to be 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 events. We also show 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.
Regarding the impact of geography, we find that projects sponsored by competitiveness clusters spread on non contiguous regions are less connected to one another: indeed, collaboration and negotiation with the structure of a distant competitiveness cluster to get labelled might be more complicated and time-consuming for partners, which limits their capacity to be involved in several projects at the same time. On the contrary, the involvement of project team members that are more or less spread on the French territory never proves significant in our regressions, suggesting that the location of the project team members does not explain the structuring of the innovation network.
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? The next step aims at refining our understanding of the determinants of the links between collaborative projects. To do so, we choose to concentrate on main cohesive groups gathering 12 or more projects, ie on 19 main cohesive groups (respectively 6, 8 and 5 for period 1, 2 and 3) and scan their characteristics so as to identify some (if any) logic in their configurations.

3.4. Identifying relational rationales at stake in major cohesive groups

Despite a huge intra-cohesive group heterogeneity, it is possible, by scanning the data, to propose a typology of the building logic of those main cohesive groups (see Table 4 below). 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 labelled by different competitiveness clusters in a given cohesive group, suggesting that cohesive groups do not coincide with the borders of competitiveness clusters. 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 labelled 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.

We can also pinpoint cohesive groups concentrated on a limited number of regions (one or two maximum), and for which more than 50% of the projects have been labelled by competitiveness clusters from 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 remaining cohesive groups for which geography matters are spread on different competitiveness clusters, but concentrated in one region, meaning that their relational rationales mostly rely 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.

insert Table 4: A typology of the rationales of cohesive groups

Finally, even if the networks that we studied were built using a project based level of analysis, the links between projects are calculated through the existence of common actors participating in 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/or in different sectors of activity. Interestingly, 3 out of those 4 focal actors are large public research organisations. Two explanations might be provided to such a result: either public research organisations act as intermediaries between different regions and/or different types of organizations (cf. for instance Morisson, 2008 or Levy et al., 2012); or the cohesive group under consideration accounts for the innovative

projects portfolio of this focal actor, who then becomes the pilot of the whole cohesive group (as shown by Lévy and Talbot (2012) in the "Aerospace Valley" competitiveness cluster).
Finally, as only 6 out of our 19 cohesive groups coincide with the borders of competitiveness clusters, we reject Hypothesis 3.

4. Conclusion

In this paper we aim at analysing 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 show that this network gets denser and more connected. In a second step, we refine those results by pinpointing a dynamics 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 logic 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(s) they are members of. The evolution of the structure of collaborative networks of innovation in France cannot solely be explained by the cluster-policy dynamics.
While the objective of this paper was not to assess the impact of the competitiveness cluster policy (this initiative being still rather young and data and feedbacks remaining scarce to reach reliable conclusions and to provide an exhaustive evaluation), we however provide first evidence of the complex interactions underlying the way the French innovation network gets organized and structured. Governmental involvement in a deliberate clustering policy and the action of local governance structures only account for part of the innovation network evolution. Other dynamics, based on more traditional collaborative complementarities also matter. Indeed, we observe that the structuring of innovative communities is also explained either by industrial dynamics or geographical dynamics, or both. Those results sound congruent with recent conclusions on the importance for innovation of complementarities between local/non local relations and inter/intra industry relations (Vicente et al., 2011).
Finally, our results undermine the role of the competitiveness cluster policy on the organizing of the French innovation network. This conclusion sounds all the more robust as we base our

analysis on FUI data (ie on information on collaborative projects launched by members of competitiveness clusters exclusively) and we however do not exhibit any strong clustering of the network around the borders of the competitiveness clusters.

In such a context, further work could consist in analysing 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 short, much remains to be done to deepen our understanding of the evolution of the French innovation network.

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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)			
Calls for proposals	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 (nb of closed triplets/ nb of connected triples of nodes)	42.57%	40.72%	60.86%
Average Distance	3.63	3.26	2.79
Diameter	8	9	7

Table 2: Descriptive statistics on cohesive groups

	Period 1	**Period 2**	**Period 3**
Number of cohesive groups	62	61	40
Average number of projects per cohesive group	3,71	5.07	6
Size of the biggest cohesive group	46	33	55
(in % of the total number of projects)	*(20)*	*(11)*	*(23)*
Size of the 2^{nd} biggest cohesive group	28	31	40
(in % of the total number of projects)	*(12)*	*(10)*	*(17)*

Table 3: The determinants of connectedness: logit estimates

Population	Overall population	Giant component	
Dependent variable : belonging to	Giant component	Small cohesive groups	Big cohesive groups
Period : P1 (call for proposals 2 to 4)	*ref.*	*ref.*	*ref.*
P2 (call for proposals 5 to 7)	3.717***	2.822***	0.354***
	(4.16)	(4.27)	(-4.27)
P3 (call for proposals 8 to 10)	5.844***	1.128	0.886
	(4.70)	(0.45)	(-0.45)
Internal resources			
Number of actors : cl2: 5 to 9	*ref.*	*ref.*	*ref.*
cl1: 3 to 4	0.205***	1.503	0.665
	(-5.14)	(1.63)	(-1.63)
cl3: >=10	1.245	0.574*	1.742*
	(0.40)	(-1.95)	(1.95)
SME dominated	0.427***	1.089	0.918
	(-2.93)	(0.44)	(-0.44)
Project dominated by public research	0.708	1.046	0.956
	(-1.14)	(0.21)	(-0.21)
Total funding of the project (in log)	1.487*	0.518***	1.930***
FUI funds dominated	0.960	0.940	1.064
	(-0.14)	(-0.29)	(0.29)
Co-labelled project	1.474	0.628	1.592
	(0.73)	(-1.60)	(1.60)
Industry at stake			
Knowledge Based Intensive Services dominated	0.399***	0.990	1.011
	(-2.62)	(-0.04)	(0.04)
High-tech manufacturing industries dominated	2.530***	0.616**	1.624**
	(2.88)	(-2.45)	(2.45)
Diversity of firm's activities	1.613**	0.882	1.133
	(2.37)	(-1.13)	(1.13)
Steering institution Industry and Services	1.371	1.256	0.796
	(0.92)	(0.79)	(-0.79)
Steering institution Defence Procurement Agency	4.908***	1.023	0.977
	(2.71)	(0.07)	(-0.07)
Steering institution Agriculture	0.347**	4.478***	0.223***
	(-2.49)	(4.07)	(-4.07)
Steering institution Territorial Planning	2.852**	0.912	1.097
	(1.97)	(-0.26)	(0.26)
Geographical scope			
Location of partners: three regions or more	*ref.*	*ref.*	*ref.*
Two non-contiguous regions	0.767	0.675	1.482
	(-0.75)	(-1.53)	(1.53)
Same region or two contiguous regions	1.248	0.896	1.115
	(0.63)	(-0.45)	(0.45)
Location of projects: Mono-region. labelled project	*ref.*	*ref.*	*ref.*
Contiguous regions' labelled project	2.358**	1.264	0.791
	(2.07)	(0.95)	(-0.95)
Non contiguous regions' labelled project	0.546	2.679***	0.373***
	(-1.03)	(2.87)	(-2.87)
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.

Table 4: A typology of cohesive groups' rationales

Number of cohesive groups concerned	KIBS dominated[d]	Manufacturing industry dominated		**Total number of cohesive groups**
		High-tech[e]	Low-tech[f]	
Cluster-dominated[a]	3	3 (1)*		**6 (1)**
Regionally concentrated[b]	3	2 (1)	3 (1)	**8 (2)**
No geographical influence[c]	3 (1)	1	1	**5 (1)**
Total number 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 ie groups in which more than 50% of projects involve the same actor*

APPENDIX

Table A1: The FUI projects through time

Round for project	number of projects: labelled by one cluster.	co-labelled.	total	number of actors in projects: labelled by one cluster.	co-labelled..	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**

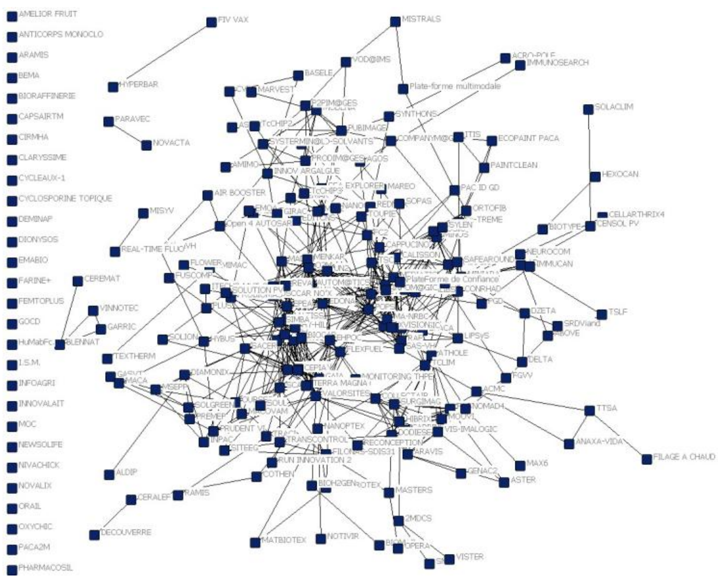
Table A2: Individual characteristics of collaborative projects

Characteristics	Measured by	Details
Time period	Call for proposals	P1: 2 to 4 ; P2: 5 to 7 and P3: 8 to 10
<u>Internal resources</u>		
Actors involved	Number of actors	cl1: 3 to 4 ; cl2: 5 to 9 and cl3: >= 10
	SME dominated	1 if the project includes at least 1/3 of SME's
	Project dominated by public research	1 if funds for public research > 50% of total funds
Funding	Total funding of the project	in log
	FUI funds dominated	1 if FUI funds > 50% of total funds
Competitiveness clusters involved	Co-labelled project	1 if the project has been labelled by more than one competitiveness cluster
<u>Industry at stake</u>		
Firms involved	Knowledge Based Intensive Services dominated	1 if the share of funds collected by service sector firms >=50%
	High-tech manufacturing industries dominated	1 if the share of funds collected by high tech manufacturing sector firms is dominant
	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
Steering institution	Industry and Services Defence Procurement Agency Agriculture Territorial planning	1 if under DGCIS's supervision 1 if under DGA's supervision 1 if under DGPAAT's supervision 1 if under DATAR's supervision
<u>Geographical scope</u>		
Location of partners	Same region or two contiguous regions	1 if partners in a project are located in the same regions or in two contiguous regions
	Two non-contiguous regions	1 if partners in a project are located in two non-contiguous regions
	Three regions or more	1 if partners in a project are located in three regions or more
Location of the project	Mono-regionally labelled project	1 if cluster(s) which has(ve) labelled the project is(are) in the same region
	Contiguous regions' labelled projects	1 if cluster(s) which has(ve) labelled is(are) located in neighboring regions
	Non-contiguous regions' labelled projects	1 if clusters which have labelled are located in distinct and not neighboring regions

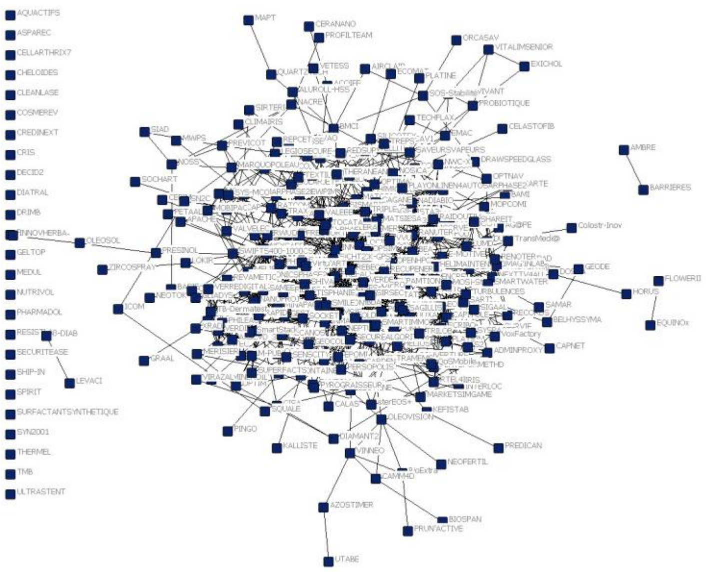
<u>NB</u>: DGCIS, DGA, DGPAAT and DATAR are "delegations", meaning those steering institutions belong to different French ministries. Hence, DGCIS is the delegation in charge of the competitiveness in manufacturing industries and services. DGA is the delegation for the army. DGPAAT is in charge of agricultural policies, agro-industry and territories, whereas DATAR manages regional planning.

Figure A1: the network of projects by period

period 1



period 2



period 3

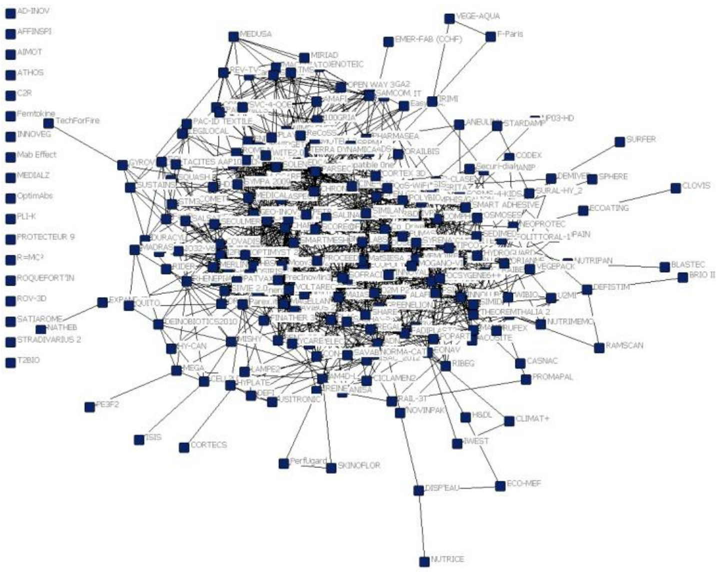
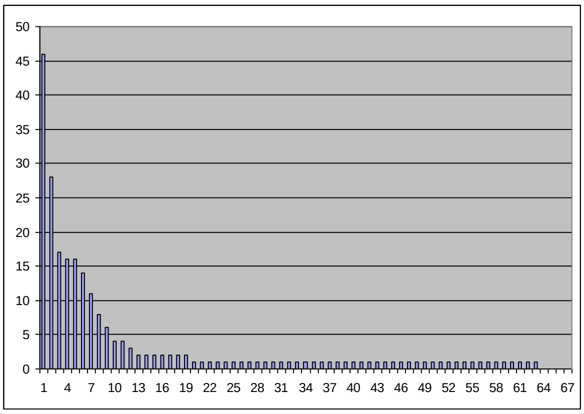
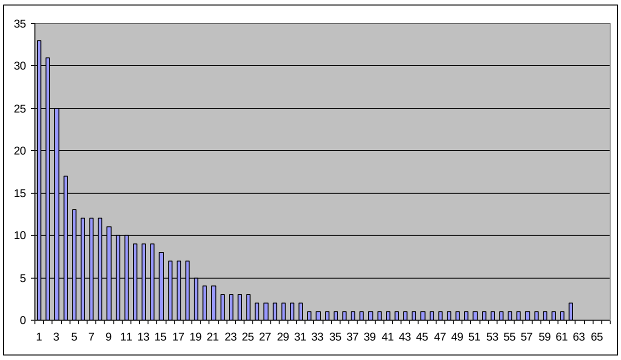


Figure A2: Distribution of cohesive groups by size in different periods

period 1



period 2



period 3

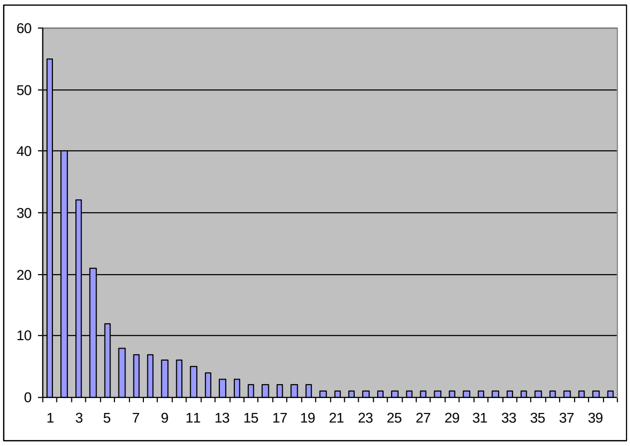


Table A3: Definition of the main cohesive groups

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