Do birds of a feather flock together? Proximities and inter-clusters network

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Abstract: The present contribution develops on the analysis of clusters in terms of proximities by exploring the issue of distant inter-cluster collaborations. We mobilize different forms of proximity (geographic, cognitive, social) discussed in the literature in order to identify their respective influence on intercluster collaboration by taking the example of French *Pôles de Compétitivité*. Our results echo previous results applied to intra-cluster collaborations since inter-cluster collaboration mostly relies on a form of social capital due to the key roles played by relational and cognitive proximity. Finally, our results exhibit a negative influence of geographic distance on collaboration.

JEL: C45, R12, R58

Keywords: clusters, network analysis, proximities, intercluster collaboration

Introduction

In an era of globalisation of markets, implying important waves of relocation of production to low-wage countries, a paramount issue for numerous policy makers lies in the capacity of national industries to retain or even attract investment from national and international firms. In this perspective, the virtues of activity localisation have been rediscovered (see Cooke, 2008) in such a way that cluster policies have become a central theme of industrial organisation in last decades. Among the literature analysing the innovative performance of clusters or regions, several recent contributions pinpoint the major influence of the characteristics of the networks of actors on knowledge circulation and innovation: the network structure (Cantner *et al.*, 2010) as well as the strength of ties (Fritsch and Kauffeld-Monz, 2010) and knowledge roles and positions assumed by firms (Vicente *et al.*, 2008; Steiner and Ploder, 2008) are hence presented as decisive. Progressively, the notions of gatekeepers, local knowledge brokers, external stars or isolated firms emerged, each of them being characterized by different absorptive capacities and positions in the network of the cluster (Giuliani and Bell, 2005) and having different roles to play for territorial innovation dynamics.

Most of those contributions focus on intra-region or intra-cluster networks of firms, neglecting the impact on innovation the social embeddedness of the region or the cluster itself may have. However, at the same time, the literature concludes that an important factor underlying the dominance and resilience of clusters lies in their respective capacity to build up ties with their environment (Bell and Albu, 1999; Coenen *et al.*, 2004; Suire and Vicente, 2009a and 2009b), to develop "global pipelines" (borrowing Bathelt *et al.* (2004)'s terminology) in order to benefit from knowledge transfers, and more precisely to access external knowledge (Bathelt *et al.*, 2004; Coenen *et al.*, 2004; Giuliani and Bell, 2005). Unfortunately, nothing is said on the identity of the partner to build pipelines with. Should clusters tie up with other actors/organisations regardless of their characteristics or do/should they preferentially tie up with specific partners? Indeed, although extensive, the discussion on global pipelines has been restricted to the ecology of knowledge at the cluster level through a focus on knowledge internal circulation and knowledge provision from external sources. But, paradoxically, the idea that clusters themselves may be part of an ecology of knowledge at the national level, meaning that clusters themselves might provide knowledge to other organisations (and other clusters) has been poorly explored. This is all the more strange that this idea is at the core of numerous public policies around Europe (DTI, 1998; French Ministry of Economy, Employment and Finance, 2009). Hence, the French cluster policy (the so-called “Pôles de compétitivité” policy), which constitutes the empirical context of this paper, precisely goes in this direction, as since 2007 the government has strongly encouraged the development of collaborative research projects involving different clusters. If forging ties with external partners is decisive to stimulate the innovative dynamisms of clusters, it seems crucial to understand the way ties are formed and to identify the driving forces of this networking phenomenon. In turn, investigating the determinants of tie building among clusters is a first analytical step toward an explanation of the dynamics of inter-cluster network formation.

The literature on knowledge networks and inter-firm collaborations insists on the crucial role played by homophily and proximity in the selection process of partners for innovation. But this literature mostly analyses spontaneous, opportunistic collaborative network formation. In the present case, inter-cluster cooperation is strongly sponsored by the French Government, as clusters have been clearly notified that the likelihood of their innovative projects being financed significantly increases for collaborative projects involving several clusters. So what about network formation when ties are strongly government-supported? Do collaborative networks which are partially imposed emerge in similar conditions to spontaneous ones? Is tie formation driven by similar forces? Do proximities still play a role, or are other explanatory factors at stake? This question sounds even more accurate as France hosts a large number of appointed clusters (71 so-called *Pôles de Compétitivité*) characterized by various structural configurations (Hussler *et al.*, 2010), spread on the whole national territory, some of them being involved in similar industries and playing therefore potentially competing roles at the national level. Agreeing to cooperate with other clusters might thus be seen for a given cluster as a strategy to share complementary assets, as a way to increase its probability to see its collaborative research program funded, but it also constitutes a threat by opening up its strategic knowledge bases to potential competitors.

In such a context who collaborates with whom? Which are the clusters which decide to create collaborative links with one another? Do clusters tie up with other clusters regardless of their characteristics or do they preferentially tie up with others based on proximity criteria? If they do, what type of proximity is favoured ? The remainder of this paper aims to assess the relative importance of the different types of proximity (geographic, social, organizational and sectoral) on the capacity of clusters to bind with others, and to assess whether clusters replicate at the national scale behaviours adopted by firms at a regional scale in terms of partner selection process.

To do so, and contrary to most existing studies tackling the issue of the relationships between clusters and their environment which are limited to the simultaneous analysis of a few cases, we run an empirical study on the relational behaviours adopted by the exhaustive population of French *Pôles de Compétitivité*, and test whether sharing similar characteristics can be presented as a factor favouring inter-cluster link formation. Finally, the contribution of this paper is twofold. It investigates the determinants of technological network formation by focusing on a specific type of collaborations (namely sponsored formal collaborations) and by selecting an original level of analysis (namely the inter-cluster level).

The remainder of the paper is organized as follows. Section 1 is devoted to a literature review on proximities and their potential impact on tie formation. In a second section we specify the empirical setting and methodological choices adopted. Section 3 presents and discusses the results, while Section 4 concludes.

Proximities and inter-cluster network formation

According to Mc Pherson *et al.* (2001), "similarity breeds connection" (p.415) and homophily (ie homogeneity of actors) "strongly shapes networks by influencing the opportunity structure for contacts" (p.429). The recent literature on proximity (Boschma, 2005; Bouba-Olga and Grossetti, 2008; Hussler and Rondé, 2005, 2007) builds on similar ideas. Proximity explains the contexts in which individuals or organisations meet and get connected: a priori, a contact between proximate actors occurs at a higher rate than among distant ones, whatever the meaning of proximity. Indeed, proximity is not only a question of geography even if it might include and interact with it. This section precisely aims to scan and discuss the insights provided by this literature on the impact of proximities on collaborative ties building.

Geographic proximity and tie formation:

Geographic proximity corresponds to the physical distance separating two entities. It may be expressed in absolute terms by being quantified as the number of kilometres between them or in relative terms since it depends on various factors: the topography or the quality and density of transportation networks. It might be binary too since agents may consider being far from or close to specific agents or resources. An actor (individual or organization) is more likely to have contact with those who are geographically closer than those who are distant, as he is more likely to meet them by accident, and also since building contacts with them is less expensive than collaborating at a distance (due to lower coordination and transportation costs).

Asheim *et al.* (2007), Bathelt and Schuldt (2008b) and Wickham and Vecchi (2008) raise a first line of criticism towards those assumptions by underlining the fact that interactions may occur at a distance thanks to the possibility raised by low-cost transportation means, professional fairs or ICT. This argument is in line with the literature dealing with virtual communities of practice and for which the combination of different types of proximity (cognitive, social and, sometimes, organized) allow those communities to be freed from physical collocation (see the survey of Amin and Roberts, 2008). Going one step further, temporary geographic proximity might be created between permanently distant partners. Contrasting with permanent geographic proximity, temporary geographic proximity refers to finite periods during which partners share common places: professional fairs, meetings or visits (Bathelt and Schuldt, 2008a; Rychen and Zimmermann, 2008; Torre, 2008). It contributes to the construction of proximities by favouring face-to-face contacts and, in this sense, temporarily replicates the buzz to be found among geographically concentrated organisations (Bathelt and Schuldt, 2008b).

Finally the specific impact of permanent geographic proximity on collaborative tie building remains unclear. Applied to inter-cluster network formation, what sounds worth stressing is that clusters are spread on the whole national territory. Some of them are located within the same region (for instance, the Ile de France Region hosts 6 *Pôles de compétitivité*), meaning that permanent geographical proximity exists between them, whereas other clusters are located in different parts of the country but are active in the same industry (one counts four clusters in the automobile industry for instance), temporary proximity (during industrial fairs) being thus also observable among French clusters. In such a context, specifying the exact impact of permanent geographic proximity of inter-cluster cooperation sounds stimulating.

Organized proximity and innovative collaborations

Organized proximity was first introduced as a complement to geographic proximity. It reflects the capacity of individuals to interact (Rallet and Torre, 2005) by reference to the organized character of human activities (Torre, 2009). It relies on two distinct logics: the logic of belonging and the logic of similarity. The logic of belonging corresponds to the fact that belonging to the same organization or network of relationships leads entities to share common rules and routines, which facilitates their first interaction (Bogenrieder and Nooteboom, 2004; Dyer and Singh, 1998). This common belonging acts as a signal drawing a sharp distinction with the others since both parties know that they share common characteristics. Regarding the logic of similarity, it allows them to share a common set of material and cognitive resources (Bouba-Olga and Grossetti, 2008). All those factors make the interactions easier by saving on costs associated to negotiation of common objectives and to the building of a common language. In a comparative study of the Silicon Valley and of the French Silicon Sentier, Vicente (2002; 2005) points to the combination of both types of logics as a key for the success and resilience of a cluster. The Silicon Valley manages to combine both logics: the logic of belonging acts as a "brand", thus signalling some characteristics of firms of the cluster, while the logic of similarity triggers network effects by favouring interactions among members. The French Silicon Sentier only relied on the logic of belonging. As a result, firms didn't engage in interactions and the cluster did not survive the crash of the Internet Bubble in 2001. Globally, both logics sound useful to catalyse collaborative tie building.

Although providing useful insights for the explanation of the dynamics of innovation, this first distinction between the logics of belonging and of similarity might be considered as too rough and faces difficulties in accounting for the subtleties of their underlying factors. Thus, following Boschma (2005), we use another definition of organized proximity (by restricting it to the belonging to a common organizational arrangement) and introduce four additional forms of proximity. We specify hereafter their respective potential impact on collaboration building.

Institutional proximity and tie formation

Institutional proximity has been introduced by Kirat and Lung (1999) and accounts for the faculty of entities (firms, research institutions, individuals…) to comply to a common set of habits, rules and routines, representations and values (Edquist and Johnson, 1997; Carrincazeaux *et al.*, 2008). Institutional proximity plays a key role in facilitating the circulation of tacit knowledge (Gertler, 2003). The construction of shared representations and values often requires frequent interactions and the embeddedness of actors in local networks that are facilitated by geographical closeness (Gertler *et al.*, 2000; Gertler, 2001). This explains why institutions are hard to reproduce in distinct geographic locations and also why institutional proximity is commonly deemed equivalent to geographic proximity, the position we also choose to follow in the present paper.

Cultural proximity and tie formation

Cultural proximity is understood as the existence of similarities in the patterns of thought, feelings, behaviours and symbols and allows entities to share common routines and interpretations of given situations (Wilkof *et al.*, 1995; Knoben and Oerlemans, 2006). The existence of cultural similarities contributes to the diffusion of knowledge (Hussler, 2004) by facilitating interactions (Lundvall, 1988), to prevent opportunistic behaviours due to the existence of common norms and values (Harrison, 1992). Cultural proximity works at different levels (Gertler, 1995). At an aggregate level, the existence of cultural similarities is critical for actors (mostly multinational ones) to understand the characteristics and needs of a target market in order to address it in the best way. At a microlevel, it constitutes an important factor affecting the quality and effectiveness of collaborations between partners as well as the success of mergers and acquisitions. As our data are restricted to the French case, we do not include cultural proximity in our analysis of inter-cluster network formation.

Cognitive proximity and tie formation

Cognitive proximity corresponds to the existence of overlaps in mental categories and in cognitive frames (Wuyts *et al.* 2005). It constitutes a key factor for the diffusion of knowledge since cognitively proximate entities are more likely to exploit a given piece of information and of knowledge. It follows a positive relationship between cognitive proximity and absorptive capacity (Nooteboom, 2000). It contributes to solving coordination issues in collaborations since entities enjoy a higher capacity to foresee their partners' behaviour. From an industrial point of view, cognitive proximity has often been proxied by measures of technological or sectoral proximity (see Wuyts *et al.*, 2005; Rondé and Hussler, 2005). By and large, it corresponds to cognitive proximity except that technological or sectoral proximity refers to the extent to which entities can learn from each other while the former refers to the extent to which they can efficiently communicate (Knoben and Oerlemans, 2006).

If cognitive proximity might catalyse mutual learning and should therefore be decisive when selecting an innovative partner, excessive cognitive proximity might also be detrimental in two respects. First, it might contribute to prevent partners from innovating by keeping them from undergoing a process of creative abrasion propitious for knowledge creation (Leonard Barton, 1995). Hence, several contributions highlight the positive effect of complementarities in cognitive bases for the success of a cluster (Boschma and Iammarino, 2009; Suire and Vicente, 2009a). Second, it raises knowledge appropriability issues by increasing risks of unplanned and undesired knowledge spillovers. In the specific case of clusters, excessive cognitive proximity combined with geographical promiscuity may paradoxically give rise to a climate of mistrust since they increase risks of uncontrolled knowledge outflows (Suire and Vicente, 2009a). Lastly, cognitively proximate clusters might consider themselves as potential direct competitors, which might limit their willingness to collaborate with similar partners from the industrial viewpoint.

Social proximity and tie formation

Social proximity corresponds to the capacity of actors to belong to the same relational space. It refers to the specific literature and tools designed for social network analysis. Social proximity has to be considered as a consequence of other forms of proximity since tying with similar partners involves lower costs than with dissimilar ones (McPherson *et al.*, 2001). Central to this literature is the concept of embeddedness (Granovetter, 1985) in two respects: structural and relational (cf. Powell *et al.*, 1996; Moran, 2005). Structural embeddedness corresponds to the capacity of actors to build up a complex network of relationships depending not only on the amount of personal ties but also on the relational characteristics of their acquaintances (Nahapiet and Ghoshal, 1998). The level of an actor's structural embeddedness is related to measures of centrality (eg. degree) and of connectivity (eg. same cohesive subgroup in the network). Relational embeddedness rather accounts for an entity's capacity to build up a network of acquaintances he can trust for providing access to high quality, fine grained information and knowledge (Gulati, 1998). This often entails the building up of strong ties characterized by high levels of trust between both partners. In this last respect, the notion of social proximity overlaps with at least one of the other aforementioned forms of proximity: institutional, cultural and cognitive. Even though closely related, they entail differentiated impact on the innovation capacity of firms: while structural embeddedness has a stronger positive impact in explaining performance for routine tasks, relational embeddedness plays a stronger role for performance in innovation-oriented tasks (Moran, 2005). But, at the same time, structural and relational over-embeddedness may be detrimental to firm performance due to risks of lock-in in suboptimal trajectories (Rowley *et al.*, 2000).

Applied to inter-cluster collaboration, those arguments suggest that once it is connected to any other cluster, a given cluster becomes part of an inter-cluster network offering the opportunity to collaborate with other members of the network. Indeed, according to the Social Capital theory, sharing a mutual acquaintance increases the probability of an unconnected couple of clusters to form a tie as it favours trust. Conversely, Burt (1992) argues that filling a structural hole (ie bridging two unconnected communities) is of greater interest, as it allows an actor to access new and more diversified knowledge sources. As French clusters might be competitors (several clusters being active in the same industries), one might find a limited effect of relational proximity in our specific case of inter-cluster networks, some clusters choosing not to share their strategic acquaintances with other (competing) clusters.

Based on those theoretical arguments, the next section specifies the empirical setting adopted to assess the respective influence of the different forms of proximity (cognitive, social and geographical) on inter-cluster collaborative behaviours.

Empirical setting

Measuring collaborations: the inter-cluster collaborative network

The dependent variable is the existence of links between pairs of clusters within the network of cooperation of French clusters. To build this network a link is assigned between any two clusters that have developed together a collaborative project labelled and funded by the French FUI ("Fonds Unique Interministeriel »). The FUI is a governmental fund dedicated to financing the most promising R&D collaborative projects that entail firms and research institutions from at least one French cluster[i]. If collaborative projects might involve actors from a single cluster exclusively, 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. Again, we concentrate here on a specific type of network formation, in the sense that developing ties through FUI-funded cooperative innovative projects is a government-sponsored behaviour and not necessarily a spontaneous decision driven by firms or clusters, which motivates our idea to test for their (specific?) determinants.

Data on FUI projects are publicly available on the institutional website presenting the *Pôles de compétitivité* program (www.competitivite.gouv.fr, accessed on March 22, 2010). They gather information on nine rounds of invitations to tender covering the April 2006- October 2009 period. Data consist in the names of the awarded projects and their associated cluster(s). Thus, the network consists of nodes representing clusters and of ties accounting for inter-cluster cooperations on FUI projects. The inter-cluster network includes 68 clusters[ii] involved in the 794 collaborative projects awarded by the FUI. Globally, those 794 projects gave rise to 448 bilateral interactions between clusters, while the number of different ties is 312 (accounting for the fact that some clusters have collaborated more than once with one another). The network displays moderately low average distance (3,29), for an average clustering coefficient of 0,35. Thus, the small world status of the network, evidenced in many cases (Watts, 1999; Cole, 2008; Vicente *et al.*, 2008), does not seem to be valid in the specific case of inter-cluster network. This finding is in line with Bathelt *et al.* (2004) according to whom the construction and the maintaining of inter-cluster pipelines are costly and require the building up of trusted relationships between partners, which in turn necessitates to be selective when forming collaborative ties. The collaboration network (Figure 1) is rather sparse: its density, corresponding to the share of activated links over all potential links, is of only 6,28%. To put it differently, inter-cluster collaboration may still not be considered as a natural and distributed phenomenon among clusters. This limited connectivity might be explained by the fact that formal inter-cluster cooperations, as promoted in the frame of the FUI financing system, may require a drastic shift in the collaboration culture of numerous clusters. Indeed, in an attempt to formalize their dynamics, Amisse and Muller (2010) have shown that clusters tend to alternate phases of dominant formal cooperation and periods during which informal collaborations preferentially occur. The mastering of this strategic tool may require more time for clusters characterized by dominating informal collaborations than for clusters more used to formal cooperations, for instance, within European Framework programs. However, the small gap between the total number of bilateral interactions and the total number of different ties indicates that once involved in collaborations, clusters tend not to interact with exclusively one cluster but do seem to diversify their relationships with several clusters.

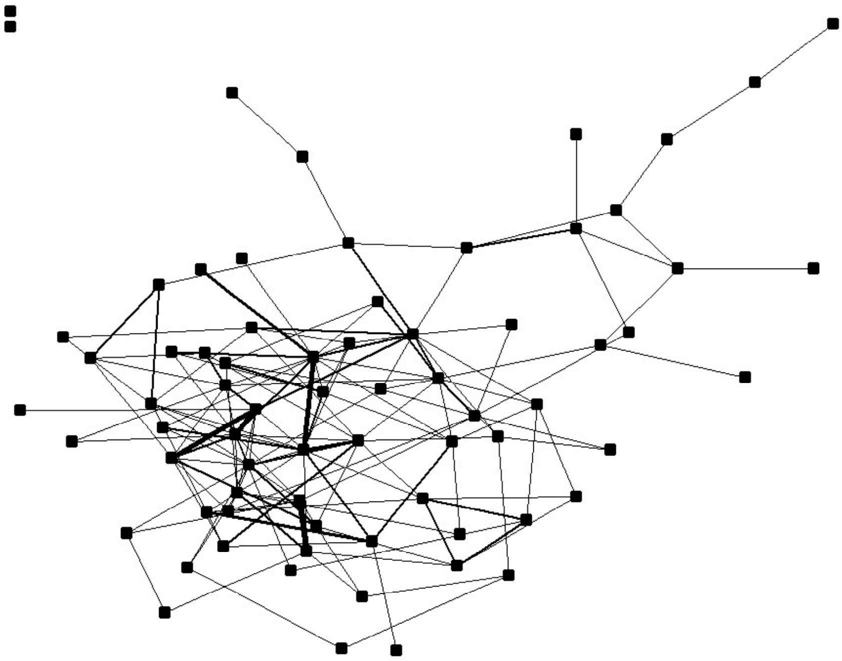

Figure 1: Network of inter-cluster cooperations (thickness of ties is proportional to the number of common projects)

Based on this intercluster network, we build two dependent variables:

- Exist-Link$_{ij}$, scoring 1 if clusters *i* and *j* have collaborated at least once on an FUI funded project during the period, and scores 0 otherwise.
- Streng-Link$_{ij}$, accounting for the strength or intensity of the collaborative link between clusters *i* and *j*. It corresponds to the total number of collaborative projects clusters *i* and *j* have developed together on the period. Looking at Table 1, we find that some pairs of clusters have collaborated up to 8 times on FUI funded projects during the 2006-2009 period, the average number of common projects being however limited as suggested by the descriptive statistics of this variable.

Those two variables allow us to investigate the determinants of the likelihood for a tie to be formed on the one hand, and to highlight the explanatory factors of the likelihood for a tie to be exploited several times (at least more than once) on the other.

Measuring proximities

Geographic distance

The geographic distance (in kilometres) between two clusters is calculated based on the great-circle distance (ie the shortest distance over the earth surface) between the addresses of those clusters headquarters. Concretely, Lat$_i$ being the latitude and Long$_i$ the longitude of the headquarters of cluster *i*, the geographic distance between any two clusters *i* and *j* is computed as followed:

$$\text{Geog-Dist}_{(i,j)}=6366 * \arccos(\cos(\text{Lat}_i)*\cos(\text{Lat}_j)*\cos(\text{Long}_j - \text{Long}_i) + \sin(\text{Lat}_i) * \sin(\text{Lat}_j))$$

If we look at the descriptive statistics of the geographic distance index, one can see that French clusters are geographically spread over the whole French territory (average distance of

680 kilometers), even in the French overseas regions (the maximum distance reaches 9724 kms, since the Qualitropic cluster, focusing on tropical agricultural products, is located in Réunion Island, in the Indian Ocean). In order to have comparable scales for all our explanatory variables, we use the logarithmic value of the kilometric distance in our regressions.

Sectoral (cognitive) proximity

We rely on data provided in the French clusters' scoreboards and published by the public institution in charge of the management of the *Pôles de Compétitivité* policy for building our indicator of sectoral proximity. Indeed, those scoreboards provide information on the main industries firms of a given cluster are active in. For each cluster we have access to the 5 industries[iii] involving the highest proportion of the cluster's workforce. We compute the sectoral proximity index between all pairs of clusters by counting the number of industries both have in common among their respective 5 major industries. For instance, Advancity and Axelera have a sectoral proximity of 2 since they have two main sectors in common: "engineering and technical studies" and "water catchment, treatment and supply", whereas the couple Advancity-Aerospace Valley only scores 1 on the sectoral proximity index since those clusters only have one sector of main activity in common: "engineering and technical studies". Finally, $\text{Sect-Prox}_{i,j}$ ranges from 0 (clusters *i* and *j* do not share any common industry), to 5 (clusters *i* and *j* workforce being involved in 5 out of the the 5 main industries).

Relational (social) proximity

Our measure of relational proximity relies on cohesive groups that we identify within the network of inter-cluster collaborations. Cohesive groups gather nodes (ie clusters) 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. Applied to our precise case, the density of ties among clusters of a single cohesive group is significantly higher than among clusters of different cohesive groups. This does not necessarily mean that all clusters of a cohesive group do have relationships with each other. The identification of cohesive groups is made by resorting to a method derived from the Newman Girvan procedure (Newman and Girvan, 2004). This method allows us not only to iteratively partition the network into distinct groups but it also allows us to identify the most relevant cut from a structural point of view. More precisely, it consists in the iteration of a two-step process:

- In a first step, the network is partitioned into mutually exclusive cohesive groups. In so doing we apply the method of hierarchical clustering developed by social networks analysts (Wasserman and Faust, 1994) and grouping together nodes similar from a structural standing point. Similarity can be proxied in several, alternative, ways, but the most commonly used proxies are based on geodesic distance between nodes (Borghatti *et al.* 2002) or on betweeness (Newman and Girvan, 2004). Here we rely on geodesic distance to build our groups, which means that two clusters of the same cohesive group are at equivalent social distance to any other French cluster. Finally, relational similarity corresponds to the capacity of entities of a given group to have equivalent access to any other entity of the network (Wasserman and Faust, 1994).
- In a second step, the quality of the partition is measured through the computation of a modularity index 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.

Applying this partitioning procedure to the network allows us to extract 9 groups of various sizes, gathering from 1 up to 25 clusters. French clusters are hence organised around 3 cohesive groups involving most clusters (groups 1 to 3), while the other clusters belong to more peripheral cohesive groups (groups 4 to 9). Annex 2 details the results of the decomposition of the network, by sorting out clusters according to their cohesive group. As shown in Figure 2, some clusters develop only ties with their cohesive group members, whereas others do collaborate with clusters from other cohesive groups: all red diamond-shaped clusters are not exhaustively and exclusively connected to one another. Taking an even more concrete illustrative example, Axelera or Véhicule du Futur (cohesive group 1) are more densely connected with one another than with clusters which do not belong to cohesive group 1. Moreover, if those clusters are interested in collaborating with Aerospace Valley (which is not in the first cohesive group), both of them should go through the same path - the same number of intermediaries clusters - before reaching Aerospace Valley.

Finally, we consider that two clusters belonging to the same cohesive group do benefit from a strong relational proximity ($Rel\text{-}Prox_{i,j}= 1$) whereas clusters in different cohesive groups are considered as having low relational proximity ($Rel\text{-}Prox_{i,j}$ scoring 0 in that case).

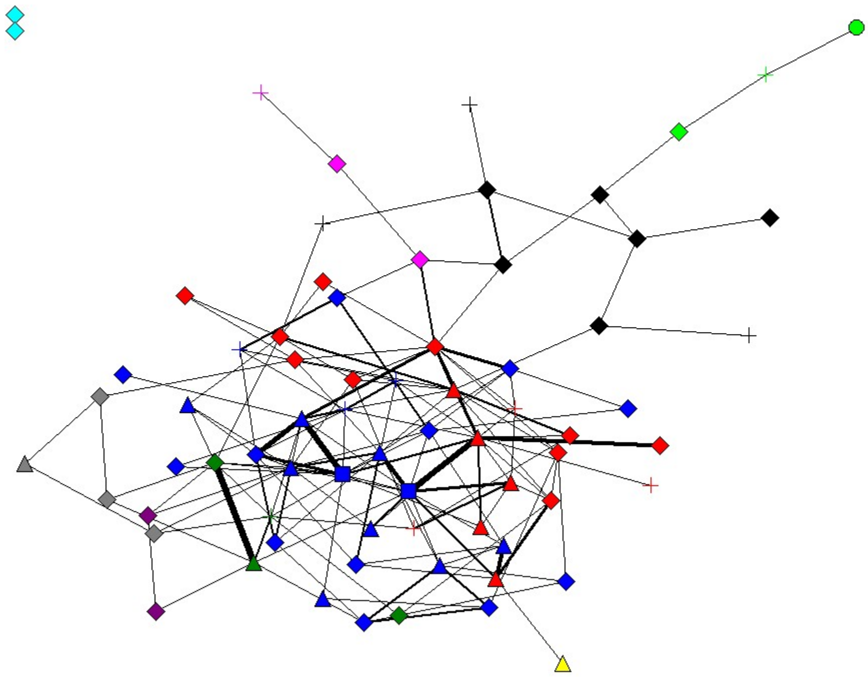

Figure 2: Cohesive-groups within the inter-cluster network (nodes with similar shapes and colours belong to the same cohesive group)

Control variables

Degree centrality

We choose to control the effect of the degree of clusters on their relational behaviours. Degree centrality corresponds to the number of acquaintances an entity enjoys. In our case, it corresponds to the number of different clusters any cluster has collaborated with in the frame of FUI labelled projects.

What we expect is that the more numerous the links formed by a given cluster i, the higher its probability to form a collaborative tie with another cluster j. In that case, cluster i's degree might proxy i's collaborative capacity and experience, its ability to share knowledge with its environment. On the other hand, we also believe that a cluster i looking for collaborative partners is more likely to select a cluster *j* with numerous existing partners. In that case, a cluster *j* with a high centrality degree might be considered as a cluster having strategic knowledge (since everybody wants to collaborate with this specific cluster). Indeed, several contributions have highlighted the complementarity between network position and absorptive capacity (Powell, 1998; Reagans and McEvily, 2003). Lastly, following the argument developed in the social network literature, we also test the assumption according to which central nodes of a network (here highly connected clusters) tend to tie among themselves.

Variable	Min	max	average	standard deviation
Exist-Link	0	1	0,07	0,25
Streng-Link	0	8	0,10	0,46
Geog-Dist	0,2	9724	679,97	1494,18
Sect-Prox	0	4	0,38	0,64
Rel-Prox	0	1	0,22	0,49
Degree	1	14	4,62	3,26
Intern-Struct	1	4	-	-

Table 1: Descriptive statistics of the variables

Table 1 shows that the degree of French clusters ranges from 1 to 14 (the most connected cluster collaborating thus with approximately 1/5 of the total population of French clusters), with an average of less than 5 different ties.

The internal structure of clusters

We also choose to control the effect of the structural configuration of clusters on their relational behaviours. Indeed, we assume that the nature, number and dynamism of actors belonging to a given cluster may explain the more or less open nature of the cluster itself. To account for the internal structures of clusters, we also use data from the French cluster scoreboards. More precisely, we select, out of those scoreboards, 14 variables describing the clusters in terms of actors involved (SMEs, establishments of foreign firms, independent firms…), industry at stake, qualification level of the cluster's workforce, size of the cluster (number of employees and of firms), and concentration degree of the cluster (in geographic and sectoral terms). We run a factor analysis on those variables in order to build a typology of the French clusters according to their internal structures. This factor analysis allows us to identify four categories of clusters depending on their respective size, corporate set-up and geographic anchoring Aannex 1 provides detailed classification of clusters). Finally, the Intern-Struct variable is a dummy scoring 1, 2, 3 or 4 depending on the category each cluster belongs to.

Modelling

To investigate the determinants of French inter-cluster network tie formation, we first estimate the likelihood for a couple of clusters to bind as a function of proximities between those clusters and as a function of their respective internal structures and collaborative dynamisms. Concretely, we use the following model (model 1):

$$\Pr(\text{Exist-Link}_{i,j})=f(\text{Geog-Dist}_{ij}, \text{Sect-Prox}_{ij}, \text{Rel-Prox}_{ij}, \text{Degree}_{i}, \text{Degree}_{j}, \text{Intern-Struct}_{i,j})$$

Where $Pr(Exist\text{-}Link_{ij})$ is the probability for cluster i and cluster j to collaborate with one another, Geog-Dist is the geographic distance, Secto-Prox the sectoral proximity, Rel-Prox, the relational proximity, Degree the degree of each cluster, and Intern-Struct, a dichotomous variable representing the structural configuration of each cluster. More precisely, we introduce four dummy variables representing each type of structural configuration.

Our sample of analysis is constituted of 2278 observations corresponding to 2278 pairs of clusters. We consider a non-directed network, as we do not have any information on the history of collaborations (which cluster is at the root of the collaboration and the lead partner). Thus $Exist\text{-}Link_{ij} = Exist\text{-}Link_{ji}$, and the number of pairs= 68*67/2=2278.

As our variable $Exist\text{-}Link_{ij}$ only scores 1 if a link exists or 0 if it does not, we choose to use a logit regression to estimate this first model.

The estimation procedure is the following. In a first econometric step, we estimate a Logit model in which we introduce our explanatory variables step by step. The results (see Annex 3) show that all proximity variables significantly contribute to explain inter-cluster linkage formation. On the contrary and surprisingly, the internal structure of clusters does not impact the likelihood of link formation. Indeed, whatever the structure we consider (types 1, 2, 3 or 4), the likelihood ratio test does not prove significant, suggesting that the four organisational forms of clusters we built do not play any significant role in inter-cluster network building. This result sounds even more interesting as our empirically-based typology of internal structures clearly opposes local clusters - of limited size and being geographically concentrated- of type 4, to major clusters (type 1) or open ones (type 2). Indeed, one could have expected that either type 4 –because of their limited size and therefore limited knowledge bases- or type 1 and 2 – because of their internal openness and larger size increasing the variety of their knowledge bases- would have adopted specific, more or less dynamic, relational behaviours. On the contrary, our findings suggest that the way clusters develop relationships with other clusters is not univocally influenced by the way intracluster linkages are built, size and similarity among clusters' members explaining only the latter relations.

Since the internal structure of clusters is not decisive, the second step of our econometric study consists in investigating whether sharing similar internal characteristics might trigger inter-cluster connections. Thus we build a new dummy variable, Orga-Dist, scoring 0 when two clusters have the same internal structure, and 1 otherwise. The likelihood ratio test validates the introduction of this new similarity variable in the analysis of the likelihood for a pair of clusters to get connected. Concretely, we estimate a new version of model 1:

$$Pr(Exist\text{-}Link_{i,j})=f(Geog\text{-}Dist_{ij}, Org\text{-}Dist_{ij}, Sect\text{-}Prox_{ij}, Rel\text{-}Prox_{ij}, Degree_i, Degree_j,)$$

In a second step, we try and identify the determinants of the intensity of collaboration between each pair of clusters, depending on the same variables according to the following (second) model:

$$Streng\text{-}Link_{ij}= f(Geog\text{-}Dist_{ij}, Org\text{-}Dist_{ij}, Sect\text{-}Prox_{ij}, Rel\text{-}Prox_{ij}, Degree_i, Degree_j)$$

This second model is estimated using several econometric specifications (negative binomial, truncated Tobit, OLS).

The next section provides details on the results.

Results

	MODEL 1	MODEL 2		
Dependent variable	Exist-link$_{ij}$	Streng-Link$_{ij}$		
Estimation method	Logit	OLS	Truncated Tobit	Neg bin
Geog-Dist$_{ij}$	-0,464***	-0,059***	-0,424***	-0,298***
	(0,071)	(0,019)	(0,086)	(0,063)
Sect-Prox$_{ij}$	0,746***	0,158***	0,813***	0,617***
	(0,113)	(0,02)	(0,137)	(0,094)
Org-Dist$_{ij}$	-0,372*	-0,013	-0,473**	-0,337*
	(0,201)	(0,019)	(0,226)	(0,179)
Rel-Prox$_{ij}$	2,089***	0,186***	2,265***	1,728***
	(0,203)	(0,02)	(0,226)	(0,177)
Degree$_i$	0,196***	0,121***	0,227***	0,181***
	(0,031)	(0,02)	(0,037)	(0,026)
Degree$_j$	0,173***	0,147***	0,208***	0,179***
	(0,025)	(0,02)	(0,031)	(0,022)
Constant	-3,161***		-4,461***	-3,74***
	(0,462)		(0,634)	(0,431)
Nb of observation	2211	2211	2211	2211
Adj R2				
Pseudo R2		0,13	0,23	0,24
LR chi2	350,99***		345,44***	326,84***

Table 2: results of regressions - * 10% significance level, ** 5% significance level, * 1% significance level**

The results of the Logit estimation of model 1 show that all the explanatory variables matter at the 1% level, except the Orga-Dist. To put it differently, the probability for a pair of clusters to knit a tie positively depends on their relational, sectoral and geographical proximities. On the contrary, organisational similarity, accounting for the similarity logics among clusters (in terms of size, qualification level of their workforce, geographical and sectoral concentration of their members) does not explain inter-cluster tie formation.

Looking at the control variables ie. the degree centrality of clusters, we find that it positively and significantly influences the probability for a tie to emerge. The more numerous the acquaintances of a given cluster, the higher the probability for this cluster to be connected to any other cluster. Thus, building a first tie by launching a collaborative project with at least one other cluster is positively correlated with developing other collaborative projects (with the same cluster(s) or other(s)), indicating the development of a collaborative ability. Hence, relational skills and abilities in sharing knowledge with a cluster do not seem to be cluster specific: as soon as a cluster has a minimal collaborative experience, it can expand its portfolio of inter-cluster collaborations without too many efforts.

Regarding the factors underlying the intensity and redundancy of inter-cluster linkages (model 2), they remain the same whatever the econometric model selected (Negative Binomial, truncated Tobit and OLS). More precisely we find quite similar results to the ones obtained for the Logit model (model 1). Indeed, the redundancy of a collaborative link between a pair of clusters positively depends on the relational and sectoral proximities of the two clusters and on their degrees. The geographic distance between the clusters at stake also plays a negative role. This last result might be explained by the fact that French "pôles de compétitivité" are not used to collaborating with one another. They need to spend plenty of time to build a common knowledge basis, to delineate common research goals and to establish coordination rules. Geographical proximity may precisely facilitate this coordination step, and also limit the risk of free riding behaviours (which is rather high in first collaborations).

Finally, the determinants of inter-cluster collaborations seem to echo those explaining intracluster partnerships (see Suire and Vicente, 2009a): clusters appear to favour complementarities in the knowledge bases. But such a behaviour might hamper innovativeness due to possibly large overlaps in the bases (Nooteboom, 2000). Lastly the impact of organisational similarity is not straightforward: indeed, this variable does not prove significant when we use negative binomial and OLS regressions, but becomes determinant in the truncated Tobit.

Going one step further and scanning the respective power of the explanatory variables, what is worth pointing out is that relational proximity is the key factor in explaining the intensity of inter-cluster relationships. Indeed if we concentrate on the OLS results for instance, one can see that the estimation coefficient associated to the relational proximity (0,2) is far more important than the one associated to sectoral proximity (0,11) geographical distance (0,00013) or even clusters' degrees. This finding suggests that belonging to the same cohesive group, ie adopting similar relational behaviours strongly influences the likelihood for a given pair of clusters to get connected and to develop repeated connections

It is the not the cluster's effective relational ability (measured by this cluster's degree) which matters more, but the relational similarity it develops with other clusters within the network. In other words, if the degree increases the likelihood to collaborate with any other cluster, the final partner with whom the collaboration is undertaken is not randomly selected. The one privileged, is the cluster with similar relational competences (being involved in similar technologies or located in the geographical vicinity are less important). Hence, sponsored relationships do not lead to the development of go-between behaviours (ie collaborations mixing socially distant clusters), but rather favour intra-cohesive group partnerships. This suggests that sponsored relationships are governed by a specific pattern. It seems to be that clusters use their networks of relations to test collaborative opportunities: they first select their potential partners among their relational neighbours and then think about the type of collaboration that may be undertaken with them in order to benefit from FUI funds. In this context, the major motive to select a given cluster to collaborate with, seem to be the ease to collaborate with this cluster rather than the intrinsic technological competences or knowledge/or access to market this cluster might bring into the collaborative project. This finding is in line with Granovetter's (1985) perception of social capital (see also Rowley *et al.*, 2000; Inkpen and Tsang, 2005; Moran, 2005) according to whom individuals tend to bind relationships with relationally close individuals.

What is also worth stressing is that the determinants of tie formation remain the same whether we try and explain the existence of any given tie between two clusters or the repetition of this tie. There seems to be no specific logic in tie repetition as compared to the logic of first tie formation: clusters do not become more or differently selective once they have to choose, among their collaborative partners, the clusters with which to collaborate again. The major determinant is still the relational proximity between clusters.

Finally, what seems to lead a given cluster to select another cluster to collaborate with, are not the intrinsic knowledge and competences this second cluster holds, but rather the potential access to other pools of competences this second cluster allows.

Conclusion

In this paper we aimed at understanding the determinants of tie building among French clusters. We investigated the relative impact of different types of proximity (geographic, social, organizational and sectoral) on inter-cluster tie formation and tie repetition, running our empirically study on sponsored formal collaborations measured at the cluster level.

We found that relational skills and abilities in sharing knowledge with a cluster do not seem to be cluster specific: as soon as a cluster has a minimal collaborative experience, it can expand its portfolio of inter-cluster collaborations without too many efforts. Moreover, our results show that the existence and the intensity of a collaborative link between a pair of clusters positively depends on the relational proximity and sectoral proximity of the two clusters and on their centrality degrees. It is also negatively influenced by the geographical distance between the clusters at stake. Thus the determinants of inter-cluster collaborations seem to echo those explaining intracluster partnerships.

Going one step further and scanning the respective power of the explanatory variables, we concluded that relational proximity is the key factor in explaining the intensity of inter-cluster relationships: what seems to lead a given cluster to select another cluster to collaborate with, is not the intrinsic knowledge and competences this second cluster holds, but rather the potential access to other pools of competences (ie other clusters) this second cluster allows.

Before providing a definite picture of the French pattern of inter-cluster collaborations much remains to be done. First, we have to bear in mind that the present paper does not assess all the relations developed by clusters. For instance, informal and international relationships are not covered by our relational indicator. However, cooperation might be effective out of the "pôles de compétitivité" system: with non-cluster-member firms, with foreign clusters, etc. Second, our study does not include any dynamics, as we do not analyse inter-cluster collaborations through time but only consider the picture at one given point in time. Scanning data on additional FUI invitations to tender would pave the way for a more evolutionary perspective of the question.

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Annexes

Annex 1

Type	Main characteristics	Cluster names
1	Clusters involving a large number of members of worldwide origins	Aerospace valley, System@tic
2	Clusters of medium size involving a large proportion of SMEs, a highly qualified manpower which is rather locally implanted	Astech, Axelera, Cancer bio-santé, Cap digital, Capénergies, Finance innovation, Images et réseaux, I-trans, Industries du commerce, Medicen, Mer bretagne, Minalogic, Mobilité, Mov'eo, Solutions communicantes sécurisées, Transactions électroniques sécurisées
3	Clusters of various sizes which are open to foreign firms and have a geographically spread manpower	Arve industries, Cosmetic valley, Elastopole, Emc2, Européen d'innovation fruits et légumes, Fibres grand est, Innoviande, Materalia, Up-tex, Valorial, Véhicule du futur, Viameca
4	Clusters with a reduced size and a limited international dimension	Advancity, Agrimip innovation, Alsace biovalley, Aquimer, Atlantic biotherapies, Céramique, Céréales vallée, Derbi, Elopsys, Eurobiomed, Filière équine, Génie civil Ecoconstruction, Idforcar, Imaginove, Industries et agroressources, Lyon biopole, Lyon truck, MAUD, Mer PACA, Microtechniques, Novalog, Nucléaire bourgogne, Nutrition santé, Optitec, Parfums, Arômes, Pegase, Plastipolis, Prod'innov, Qualimed, Qualitropic, Risques, Route des lasers, S2E2, Sporaltec, Techtera, Tennerdis, Trimatec, Vegepolys, Vitagora, Xylofutur

Annex 1: Typology of clusters' structural configurations.

Annex 2

Group n°	Name of clusters	Size
1	Advancity, Axelera, Capdigital, Cerealesvallee, Derbi, Elastopole, iDforCAR, I-Trans, Lyonbiopôle, Lyon Urban Truck & Bus , Mobilité et Transports Avancés, Mov'eo, Plastipolis, Techtera, Tenerrdis, Trimatec, Up-Tex, Véhicule du futur	18
2	EMC2, Génie civil Ecoconstruction, Mer Bretagne, Mer PACA	4
3	Aerospace Valley, Alsace Biovalley, Arve Industries, ASTech, Atlanpole Biotherapies, Cancer-Bio-Santé, Capenergies, Elopsys, Eurobiomed, Images & Réseaux, Imaginove, Materalia, Medicen Paris Region, Microtechniques, Minalogic, Nucléaire Bourgogne, Optitec, Pegase, Pôle Européen de la Céramique, Route des lasers, S2E2, Solutions Communicantes Sécurisées, System@tic Paris Région, Transactions Electroniques Sécurisées, Viaméca	25
4	Agrimip Innovation, Fibres Grand'Est, InnoViandes, Nutrition Santé Longévité, Pôle Européen d'Innovation Fruits et Légumes, Prod'Innov, Q@LI-MEDiterranée, Vitagora, Xylofutur	9
5	Aquimer, Industries du Commerce, MAUD, Nov@log	4
6	Finance Innovation	1
7	Cosmetic Valley, Industries et Agro-Ressources, PASS	3
8	Enfant, Valorial, Végépolys	3
9	Qualitropic, Risques	2

Annex 2: Cohesive groups of clusters

Annex 3

	MODEL 1.0	MODEL 1.1	MODEL 1.2	MODEL 1.3	MODEL 1.4
Dependant variable	Exist-link$_{ij}$	Exist-link$_{ij}$	Exist-link$_{ij}$	Exist-link$_{ij}$	Exist-link$_{ij}$
Estimation method	Logit	Logit	Logit	Logit	Logit
geog-dist$_{ij}$	-0,464***	-0,468***	-0,466***	-0,47***	-0,47***
	(0,07)	(0,071)	(0,071)	(0,071)	(0,071)
secto-prox$_{ij}$	0,746***	0,76***	0,762***	0,766***	0,765***
	(0,114)	(0,114)	(0,113)	(0,114)	(0,114)
rel-prox$_{ij}$	2,089***	2,075***	2,083***	2,079***	2,076***
	(0,203)	(0,203)	(0,203)	(0,203)	(0,203)
degree$_i$	0,196***	0,187***	0,195***	0,188***	0,181***
	(0,031)	(0,031)	(0,032)	(0,031)	(0,031)
degree$_j$	0,173***	0,168***	0,174***	0,17***	0,162***
	(0,025)	(0,026)	(0,026)	(0,025)	(0,026)

Type 1	/	0,064 (0,31)	/	/	/
Type 2	/	/	-0,154 (0,209)	/	/
Type 3	/	/	/	0,063 (0,226)	/
Type 4	/	/	/	/	-0,286 (0,223)
Cste.	-3,161 (0,461)	-3,289*** (0,461)	-3,3*** (0,459)	-3,318*** (0,464)	-2,99*** (0,512)
Nb of observation	2211	2211	2211	2211	2211
LR chi2	350,99***	351,08***	351,53***	351,06***	352,59***
-2 Log	761, 52	761, 37	760, 87	761, 34	759, 81

Annex 3: Results of regressions including the structural configurations of clusters - * 10% significance level, ** 5% significance level, * 1% significance level**

The likelihood ratio tests are never significant, suggesting that the introduction of variables describing the structural configuration of clusters (Type 1, 2, 3 and 4) does not improve the model's explanatory power.

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[i] Different financing sources of collaborative projects may be enumerated: Fonds Unique Interministeriel; OSEO, a network of regional innovation agencies; Regional and Departmental councils. A hierarchy of financing sources according to the economic significance and the scale of project has formed: the 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). If rather targeted at large and significant projects, FUI funds however constitute the most important source of financing for all the French clusters (Amisse et al. 2010), which supports our idea to use them to build the intercluster collaborative network.

[ii] Two clusters, Filière Equine and Sporaltec, are excluded from the network since they did not collaborate with any other cluster on a FUI project; a third cluster (pôle Enfant) is withdrawn from our analysis since the cluster does not exhaustively fill its annual scoreboard, which impedes us to build its proximity indexes.

[iii] We have the 5 digit industrial class of those 5 industries.