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Simulating micro behaviours and structural properties of knowledge networks: toward a "one size fits one" cluster policy

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Abstract
The economic return of cluster policies has been recently called into question. Essentially based on a "one size fits all" approach consisting in boosting R&D collaborations and reinforcing network density in regions, cluster policies are suspected to have failed in reaching their objectives. The paper proposes to go back to the micro foundations of clusters in order to disentangle the links between the long run performance of clusters and their structural properties. We use a simple agent-based model to shed light on how individual motives to shape knowledge relationships can give rise to emerging structures with different properties, which imply different innovation and renewal capabilities. The simulation results are discussed in a micro-macro perspective, and the findings suggest reorienting cluster policy guidelines towards more targeted public-funded incentives for R&D collaboration.

Key-words: cluster policy, networks, micro-behaviours, structural properties, agent-based model
JEL-codes: B52, O32, R12, Z13

1. Introduction

During the last twenty years, Regional science and Economic geography, as well as Management Science and Economic Sociology, have underlined the role of clusters in the innovative capabilities of regions. While interacting little at the beginning, these researches rapidly converge on the critical role of knowledge exchanges, collaborations and networks, in the formation and development of clusters (Saxenian, 1990; Audretsch and Feldman, 1996; Cooke *et al*., 1997; Porter, 1998; Breschi and Lissoni, 2001). Consequently, during the 2000s, increasing local knowledge collaborations and densifying networks have progressively become the central focus of cluster policy guidelines and the main objective for policy makers supporting cluster development. But later in the 2010s, in hindsight, scholars started to question the economic return of these policies. Some of them have shown a growing skepticism regarding the real contribution of network-based cluster policies to innovative outputs and regional growth (Duranton, 2011; Martin *et al*., 2011; Brakman and Marrewijk, 2013).

Nevertheless, such skepticism is not sufficient to reject as a whole the network failure argument that crosses the design of many cluster policy guidelines (Woolthuis *et al*., 2005; Boschma,

2008; Nishimira and Okamuro, 2011; McCann and Ortega-Argilés, 2013; Vicente, 2014). As a matter of fact, the policy transposition of academic conclusions has maybe somehow stopped in the halfway. Policy makers have focused on cluster relational density, and have put aside the development of cluster researches stressing on more complex structural properties for long run cluster performance. Using basics of network theories (ter Wal and Boschma, 2009), these researches have captured the role of particular structural properties, such as "small worlds" (Fleming *et al*., 2007; Breschi and Lenzi, 2014), triadic closure (Balland *et al*., 2013, ter Wal, 2014), network centralization and connectedness (Owen-Smith and Powell, 2004; Cantner and Graf, 2006; Casper, 2007; Vicente *et al*., 2011), or network assortativity (Crespo *et al.*, 2014). However, policy makers have ignored these recent advances when designing there policies. They have aimed at increasing relational thickness of clusters, and excessively applied a "one size fits all" scheme (Tödtling and Trippl, 2005). In doing that, these policies are suspected to reinforce dysfunctioning structures or to sclerose emerging ones, with some risks of crowding-out effects and a misallocation of public resources (Duranton, 2011).

Considering that structural properties of networks emerge over time through the cumulative aggregation of individual decisions to create (or not) knowledge relationships, our goal is to show that expecting a higher return of cluster policies in the future requires a better understanding on the micro-motives for knowledge collaborations in clusters. Nevertheless, beyond the challenge of mapping efficient networks structural properties, the implementation of more targeted collaborative incentives is constrained by the fact that we have scarce knowledge on the articulation between the micro and macro levels in networks.

This paper aims to fill this gap. We analyze how different motivations behind partners' selection result in networks with different structural properties. To do so, following Axelrod (2007), we propose to capture micro-macro aggregation processes by an agent-based-model. It allows us linking network structural evolution to simple individual relational rules. Since we focus on the topological forms of networks, agents are only typified by their relational behaviors, excluding other individual attributes. As the propensity to shape knowledge relationships also depends on cognitive and institutional features (Boschma, 2005; Balland, 2012), our approach is in a sense limited. But our goal in this contribution is to isolate the structural dimension. It constitutes a first step towards more sophisticated analysis. At this stage, our goal is to provide new insights on the types of collaborations policy-makers should incentive to make emerge not only networks, but networks with the structural properties that have been identified to matter for cluster long run dynamics. The remaining of the paper goes as follows. In section 2 we review the main network properties that the literature has identified as important for cluster performance. In section 3, we discuss the micro-motives to enter a cluster and interact with others, as well as the expected consequences on the cluster structural properties. In section 4 we explain the simulation model we have developed to capture the structural patterns of clusters, while section 5 discusses the implications of the findings in a policy-oriented perspective.

2. Structural properties of knowledge networks and cluster long run dynamics

Literature on economic geography has largely admitted that the benefits regions draw from the geographical concentration of innovative activities are due to the existence of voluntary knowledge relationships and networks development rather than to the geographical bound of knowledge spillovers that would be limited by the tacit dimension of knowledge (Breschi and Lissoni, 2001, Boschma, 2005). In innovation studies as well, literature provides empirical evidences of the positive effects of network embeddedness on the firm's innovative capabilities

(Walker *et al*., 1997). Considering the complex dimension of knowledge creation and promotion on markets, firms innovate through recombination processes between separated pieces of existing knowledge (Fleming and Sorenson, 2001), and for that purpose create and maintain collaborations, for which sometimes geographical proximity matters (Sorenson *et al*., 2006).

These literatures have both contributed to a growing number of cluster analyses over the world and technological fields, showing that boosting firm's innovative capabilities was not just a matter of being on the right place, but also of being on the right network. Thus, the adoption of a network perspective to study clusters has become quite popular in the last decade (Owen-Smith and Powell, 2004; Guiliani and Bell, 2005; Boschma and ter Wal, 2007; Casper, 2007). It has joined the so-called *relational turn* of economic geography (Bathelt and Glücker, 2003), and the broader movement towards research on *complex systems* that has reached innovation studies (Frenken, 2006), and economic geography as well (Martin and Sunley, 2007).

Mixing the micro-level (the individual incentives to create or not knowledge relationships and select partners) and the macro-level (the resulting network structures), network-based analysis of clusters can provide useful methods to assess individual performance with regard to the position into networks. But they can also provide useful means to measure the aggregate performance of a cluster as a whole with regard to its structural properties. As a matter of fact, the main findings in the literature clearly show that if networks matter for innovation in clusters, not all structures are equivalent (Uzzi and Spiro, 2005; Fleming *et al*., 2007). The emerging structural properties of knowledge networks in clusters may differ and are not neutral for their long run performance.

2.1. Small worlds

Among this growing literature, the study of the role of small world properties (Watts and Strogatz, 1998) for innovation in clusters has occupied a central position. Small world knowledge networks combine, at the same time, two properties that at first glance might seem contradictory to each other. On the one side, small world networks display a low path length, meaning that knowledge always find short channels to flow between any actors. On the other side, they are also typified by a high clustering coefficient, favoring trust in cohesive cliques of interacting actors. As reviewed by Uzzi *et al*. (2007), small worlds appear as a regular property of personal (co-authorship, inventors) and organizational (R&D alliances, interlocks) networks. Beyond their empirical identification, several researches have argued that small world networks, by mixing cohesiveness in cliques and connectedness between cliques, exhibit high innovative performance[1]. By boosting ideas circulation from one specialized clique to another, cliques *"break out their chambers and mix into new and novel combinations"* (Uzzi *et al*., 2007, p. 78). Cowan and Jonard (2004) use simulation models to find that knowledge production is maximal when networks exhibit small world properties. Breschi and Lenzi (2014) use patent data to show that US cities innovations is positively affected by small world networks[2]. Moreover, they display robustness across time, as evidenced by Kogut and Walker (2001) and Davis *et al*. (2003), according to whom a great amount of transformation is necessary to change a small world into a network of different type.

[1] Other papers have also found positive effects of small worlds on individual performance (Verspagen and Duysters (2004); Uzzi and Spiro (2005), Schilling and Phelps (2007)
[2] However, the work of Fleming *et al*. (2007) fails in finding such evidence

2.2. Network hierarchy

In addition to small world properties of knowledge networks, other properties have been recently put ahead to study the long run performance of clusters. Small world approaches, based on random graph models (Erdös et Renyi, 1959), fail in capturing one of the most important regular structures of real clusters related to the strong hierarchy in the relational capabilities of actors. Former fieldwork analysis have stressed on the hierarchical structure of knowledge relationships in industrial districts (Storper and Harrison, 1991; Markusen, 1996), with the role of hub companies that connects, through spokes, many other actors in the industrial production system. More recent researches have also captured this pattern using centralization index to assess the innovative capabilities of clusters (Cantner and Graf, 2006; Graf, 2011; Crespo *et al*., 2013). Based on the so-called scale-free networks of Barabási and Albert (1999), these works enable to better capture the heterogeneous actual relational capabilities of organizations in clusters, which can be measured by the slope of the degree distribution on the network. This scale-free property reflect a core/periphery structure in which the core is composed by a set of high-degree organizations – the hubs – and a periphery or more loosely connected ones[3] (Borgatti and Everett, 1999). If all organizations in a particular cluster have similar degree, there is no hierarchy and no leading organizations appear. If organizations with high and low degree coexist in the network, the cluster displays a high level of hierarchy and a core/periphery structure. While flat hierarchy can be the sign of an emerging cluster with a scattered structure of burgeoning or small organizations (Audretsch and Feldman, 1996; Klepper, 1996), its growing maturity and effectiveness typically goes with a growing hierarchy, through an ossification process around leading hub-companies (Crespo *et al*., 2014). As a matter of fact, clusters that succeed in establishing themselves as leading places in a particular technological and market domain are those that succeed in defining well-integrated products and winning the battle of standards (Suire and Vicente, 2014). Such an increasing hierarchy in clusters is the sign of a consistent ability for some core-organizations to coordinate complex innovative processes integrating separated pieces of knowledge, and which require a high level of compatibility and interoperability (David and Greenstein, 1990; Moore, 1991; Shapiro and Varian, 1999). Concerning the robustness of hierarchical networks across time, ambivalent effects are underlined in engineering sciences (Albert *et al*., 2000; Brede and de Vries 2009). On the one hand, scale-free networks exhibit strong resistance to perturbations when the core-nodes are not affected. In that case, cohesion and connectivity are both maintained while the most central organizations keep exploiting their position. At the reverse, targeted attacks on hubs can have strong consequences on the whole functioning of networks. The disruption of only few central nodes, for instance the threat of relocation of one of the leading regional companies in a particular cluster, can compromise its long run sustainability, as evidenced by Vicente *et al*. (2011).

2.3. Network assortativity

Since clusters host poorly and highly connected nodes, the question that naturally arises is whether or not highly (poorly) connected nodes tend to interact with other highly (poorly) connected nodes. Network assortativity captures these patterns (Newman, 2002). Assortative networks are those that display a positive degree correlation, meaning a tendency of nodes to

[3] Scale-free networks echo one of the forgotten results of Milgram experiments in small worlds analysis: the role of super-connectors.

interact with others that have similar degree, while disassortative networks are featured by a negative degree correlation, implying more heterophilic structures of social interactions (Watts, 2004, Rivera *et al.*, 2010). Therefore, networks assortativity provides a useful representation of the knowledge pathways between central and peripheral organizations in clusters. The expected effects of network assortativity on clusters performance are partly ambivalent. On the one side, as for high clustering coefficients, structural homophily in clusters reduces uncertainty in collaborative research projects and favors trust in the production of norms and technological standards within the core-component of networks (ter Wal, 2014). But these effects of structural homophily can provoke, on the other side, an excessive redundancy of knowledge flows. The result, for a fixed amount of ties, is a lack of openness of this core-component towards peripheral organizations (Ahuja *et al*., 2009); generally the ones that provide explorative and fresh ideas which need to connect the leading organizations to be turned into future markets (Almeida and Kogut, 1997). Therefore, without a certain degree of disassortativity of knowledge networks, clusters can face conformity and negative lock-in, in particular when markets for mature technologies start to decline. At the reverse, in disassortative networks, core and periphery are better connected. The core is more open, and peripheral organizations holding new and disruptive knowledge can benefit in a larger extent from the well-experienced core-organizations to find opportunities of knowledge combinations for new markets. As evidenced by Crespo *et al*. (2013) for the long run analysis of clusters dynamics in the European mobile phone industry, hierarchical and disassortative knowledge networks match better with clusters able to combine technological performance and structural change capabilities.

To sum up and to go beyond the rather simplistic but well-installed idea that clusters grow in performance with their relational density, we state that the more knowledge networks in clusters are featured by low path length, high clustering[4], high hierarchy and disassortativity, the more clusters will be able to establish themselves as leading places and to adapt and renew over time.

3. The micro-motives of entry and knowledge relationships in clusters

Designing policies that consider structural properties require setting the appropriate collaborative incentives. Thus, they should rely on a good understanding on the micro motives for organizations to join (or not) networks and shape (or not) knowledge relationships. Literature converges on the idea that organizations shape knowledge relationships to gain access to external and complementary pieces of knowledge. But all relationships are not efficient for them. On the one side, organizations, according to their particular model of knowledge promotion, will weigh the expected benefits from external knowledge accessibility with the risks of under-appropriation of their own knowledge (Antonelli, 2006). On the other side, relationships building and maintenance being costly, organizations will limit the extent of their relational space in accordance to their relational capability, which is usually supposed to be partly constrained by their size (Gulati, 1995). Therefore, the aggregative mechanisms of dyadic relationships give rise to networks that evolve according to mechanisms of node entry (or exit) and ties rewiring. The first one will play on the evolving network size (demography), while the second one will play on its evolving structural properties (topology).

[4] Some authors have shown that thresholds in the small-worldness may exist (Uzzi and Spiro, 2005)

3.1. Nodes entries

Concerning entry, network literature has defined two opposite mechanisms. New entering nodes may connect to existing ones either at random or by preferential attachment (Barabási and Albert, 1999). For nodes following random attachment mechanism, network joining prevails over the position in the structure. New entrants draw their payoffs from the structure belonging and not necessarily from targeted connections. For clusters dynamics, random attachment can be associated to locational cascades (Suire and Vicente, 2009). The motives for entering the regional innovation system rely on the willingness to benefit from the external audience and geographical charisma of the place (Romanelli and Khessina, 2005; Appold, 2005). For randomly-attached organizations, the purpose is not to target particular organizations in clusters, but just to be connected to the right and successful place, and benefit from the positive signal such a location can imply (Frenken *et al*., 2014). Owen-Smith and Powell (2004) have found positive effects of network membership for the biotech cluster in Boston, while centrality has no significant influence. With preferential attachment, the driving force of an organization looking for a partner it is not just to be on the right place, but also to be connected to the right partners. In preferential attachment processes, the attractiveness of an organization increases with its degree. Being connected to highly connected organizations increases new entrants' payoffs. Firstly, they are seen as richer sources of information due to the diversity of their connections. Secondly, connecting leading organizations brings benefits for new entrants, in particular when technological compositeness and compatibility matters for market exploitation. In that case, new entrants find strong incentives to target relationships with leading companies getting the control of standards and larger installed bases (Farrell and Saloner, 1986; Arthur, 1989). Moreover, interactions with leading organizations may be source of status for new entrants (Balland *et al*., 2014). Finally, it is also consistent with the relational behavior of spinoffs that tend to connect to their often highly connected parent's company (Buenstorf and Fornahl, 2009; Vicente *et al*., 2011).

From a structural point of view, both preferential and random attachment increase the connectivity of the network, by creating shortcuts and through the role of super-connectors. Similarly, since these two mechanisms are associated to new entrants, they are source of new relationships, creating new potential triangles but not closing them. Therefore, both of them are expected to favor low clustering. However, the impact of preferential and random attachment differs when we look at the degree distribution (network hierarchy) and the degree correlation (network assortativity). Preferential attachment makes emerge hierarchical networks: more central nodes become more attractive for new entrants, while peripheral nodes receive few attentions. As time goes, these differences are reinforced, and network hierarchy increases. Concerning degree correlation, the structural consequences of preferential attachment and random attachment are different too. With preferential attachment the new entrants, by definition with few relationships, interact with the most connected ones to benefit of their status, influence and large knowledge sources. Thus, they produce disassortatitve networks. Contrary, with random attachment, no leaders come out. All organizations have more or less the same number of relationships. Thus, we expect more assortative structures to emerge.

3.2. Ties rewiring

Even if inter-organizational networks usually display strong path dependency (Gulati, 1998; Sydow *et al*., 2009), knowledge networks evolve not only through entries and exits, but also through the propensity of organizations to change their partners' portfolio (Powell *et al*., 1996).

Ties rewiring indicates the capability to disrupt and recreate knowledge relationships. Disruption of ties and creation of new ones are driven by cognitive and strategic purposes and arise when organizations have exhausted collaborative opportunities and look for new partners to access new cognitive resources or to better secure their network position. The level at which this continuous process of dissolution and creation of knowledge relationships in clusters occurs will also have structural consequences.

From this perspective, following literature on social capital and embeddedness in economic sociology (Coleman, 1988; Burt, 1992; Granovetter, 2005), researches on clusters in regional science have identified two main strategies: closure and bridging (Cassi and Plunket, 2014). Triadic closure implies that an organization with links to two other organizations increases the probability for these two organizations to have a tie between them. Such an argument is grounded on the process of trust construction that grows between two related nodes, because it fosters cooperation and knowledge integration within groups of nodes. Closure in knowledge networks strengthens the mutual monitoring capability of organizations. Indeed, it decreases the possibilities of opportunistic behaviors, and, by increasing trust and conformity, it favors coordination in the mutual design of technological standards (ter Wal, 2014). Bridging relates to more disruptive and entrepreneurial relational behaviors. Organizations are supposed to adopt bridging strategies when they decide to connect unconnected organizations or groups of organizations. Firstly, in cognitive terms, this relational behavior allows organizations accessing to new and non-redundant knowledge and thus new opportunities of knowledge combination (McEvily and Zaheer, 1999). Secondly, in strategic terms, this particular *tertius gaudens* strategy (Burt, 1992) provides for organizations a particular influence and control of the knowledge flows in networks (Ahuja, 2000; Baum *et al*., 2012). In cluster analysis, literature has underlined the role of bridging organizations in the long run dynamics of clusters (ter Wal and Boschma, 2009; Eisingerich *et al*., 2010).

From a structural point of view, bridging and closure relational mechanisms are not neutral. Their effects on small world properties of networks are opposed. On the one hand, closure is, by definition, closing triads and so increasing the clustering coefficient. On the other hand, the focus on close neighbors reduces connectivity. They connect to neighbors of their neighbors creating dense and cohesive groups, but few between-groups links are created. As a consequence, beyond a certain threshold, the whole network connectivity can be reduced. Contrary, with bridging behaviors, organizations look for partners in distant parts of the network. Then, less cohesive groups will emerge, decreasing clustering coefficient, but the whole network will have a better connectivity thanks to the multiplications of shortcuts. The effects of bridging and closure on degree distribution and degree correlation are less clear. Concerning degree distribution, no clear cut expectations may be formulated. The increase or decrease of hierarchy with any of the rewire mechanisms depends on the position of the organization driving the rewire, the type of link that is disrupted, and the position of the new partners towards whom the new relationship is oriented. Similarly, concerning degree correlation many possible cases may exist. However, in this case we expect closure to increase assortativity and bridging to increase disassortativity. We ground our expectations on the assumption that closure represents a tendency to interact with similar peers, while bridging represents a tendency to interact with dissimilar peers. So, with closure, highly connected organizations rewire their relationships towards highly connected ones, and poorly connected organizations rewire their relationships towards poorly connected ones. This will increase assortativity. Contrary, with bridging, highly connected organizations will try to find new partners in the periphery and conversely, increasing the disassortativity of the network.

	Entry mechanisms		Ties rewiring mechanisms	
	Preferential attachment	*Random attachment*	*Closure*	*Bridging*
Path length	Low path length	Low path length	Increases	Decreases
Clustering	Low clustering coef.	Low clustering coef.	Increases	Decreases
Degree distribution	high hierarchy	flat hierarchy	Undefined	Undefined
Degree correlation	Negative (disassortativity)	Positive (assortativity)	Increases assortativity	Increases disassortativity

Table 1 – Structural consequences of relational mechanisms

In contrast to the sometimes excessively beatific view of knowledge networks in many cluster policy guidelines, an increase of relational density should not be viewed as a panacea of cluster success. More complex structural properties have to be reached for clusters to establish themselves as leading places. In particular, clusters mixing a certain amount of cohesiveness while shortening knowledge paths, and making core organizations emerge while maintaining channels for non assortative knowledge relations might be expected to be more efficient on the long run. *Table 1* summarizes the expected consequences of micro motives for creating knowledge relationships on the clusters structural properties. If we set apart entry and rewiring mechanisms, the topological forms of clusters would be possible to anticipate. Contrary, considering them together increases complexity. As for many micro-macro processes in social sciences for which the links between social structures and individual behaviors are not directly observable, the use of simulations can be helpful (Axelrod, 2007).

4. The model

To do so, we develop an agent-based model to shed light on how individual motives to shape knowledge relationships can give rise to emerging structures with different properties. In order to design the experiment setting of the micro-macro dynamics of cluster structuring, we model population dynamics and relational mechanisms in the lines of the basic principles previously presented in section 3. In the same vein, we propose simple measures of the structural properties of knowledge networks discussed in section 2. Finally, we run simulations and discuss the findings.

4.1. Population dynamics

To take into account the population evolution, we define a macro-rule that expresses the number of entries per period. The number of entries E in period t is computed by comparing the number of organizations P existing in $t-1$ and a superior threshold M.

$$E_t = rP_{t-1}\left(\frac{1-P_{t-1}}{M}\right)$$

This threshold M is defined as a load capacity of the system and represents the maximal number of organizations that can be in the cluster. When the current population is below this threshold,

the market for technology is not yet saturated and opportunities and niches for new organizations still remain. Contrary, when the current population is close to the maximum threshold, new opportunities becomes scarce, the competition is too fierce and the entry barriers become too high. So no new entries are possible. r is an additional parameter that accounts for the speed of convergence between the population at $t - 1$ and the maximal number of organizations. It ranges between 0 and 1, where 0 means no population growth and 1 instantaneous adjustment. Concerning exit, we define a non-parametric rule consisting in nodes removal when they become isolated. Thus, we assume that without relationships, an organization is not able to get complementary knowledge, loses its capacity to compete and dies.

4.2. Relational mechanisms

As described in section 3, organizations in networks are not definitively fixed on collaborative portfolio. Through time, organizations can decide to create and disrupt relationships to access new cognitive resources or secure their network position. We model the creation of relationships through four different mechanisms working two by two in different moments of time. On the one hand, when organizations enter, they chose their partner either by preferential or random attachment (cluster growth mechanisms). On the other hand, once already in the network, organizations may try to find new partners and connect to them either by bridging or closure (cluster structuring mechanisms).

- *Relationship at entry*

At each step, a number E_t of organizations enter the cluster and connect to one of the previously entered organization. They can connect either by preferential attachment or by random attachment. The selection process is a probabilistic choice defined by the parameter $\alpha \in [0, 1]$. When $\alpha = 0$, organizations exclusively enter the network through preferential attachment, and through random attachment when $\alpha = 1$.

When a new organization enters the network by random attachment, the probability of an existing organization to receive a new relationship is random and uniform. Contrary, when an organization connects by preferential attachment, existing organization with more relationships are more attractive. The probability of existing organizations to receive new ties is not uniformly distributed, but it depends on the degree k of the organization i. The bigger k_i the more likely the organization i to receive a new tie: $\square(k_i) = {k_i}/{\sum_j k_j}$

- *Relationships rewiring*

Additionally, at each step, a certain amount of ties are rewired. This amount is defined as a proportion $\lambda \in [0, 1]$ of the existing nodes. We randomly select the ties to be disrupted and the extreme of the tie that will act as a rewiring agent. This organization destroys the selected tie, and then proceeds to re-build it elsewhere by finding a new partner. In this recreation process, the organization can either reconnect by closure or by bridging. The selection of one or the other mechanism is a probabilistic choice defined by the parameter $\beta \in [0, 1]$. When $\beta = 0$, organizations exclusively rewire by bridging, and by closure for $\beta = 1$. As bridging strategy

consists in spanning structural hole to connect disconnected parts in the network, we consider bridging ties randomly chosen out of the rank-2 neighborhood of the rewiring organization. In contrast, as closure strategy consists in exploiting the information and trust of direct partners to find new ones, we consider that an organization rewiring a relationship by closure will build a new partnership by randomly selecting an organization in his rank-2 neighborhood to whom it is not connected yet[5].

4.3. Structural measures

Through simulations runs, entry mechanisms and relationships rewiring at the individual level will give rise to networks. For each of these networks, we compute a set of relevant structural properties. Beyond the most elementary properties and basic statistics related to the network size (number of organizations, number of ties and thus density[6]), section 2 discussed important properties for clusters.

The first ones relate to small worlds properties. We compute the clustering coefficient of network g as the proportion of fully connected triples over the potential ones. Following Jackson (2008), we look at all situations in which two links emanate from the same node i towards nodes j and k, and we count the number of times the tie jk is also present in the network.

$$Cl(g) = \frac{\sum_{i=1;j\neq i;k\neq j;k\neq i}^{n} g_{ij}g_{ik}g_{jk}}{\sum_{i=1;j\neq i;k\neq j;k\neq i}^{n} g_{ij}g_{ik}}$$

Secondly, we compute reachability. The traditional average path length is not useful when networks have several components due to infinite distances. Instead, we compute a measure of reachability $R(g)$, as a weighted average of $1/d_{jk}$, where d_{jk} is the geodesic distance between organizations j and k, and n the number of node in the network g. Then, the higher the value of $R(g)$ measure, the higher the connectivity of the network. Following Breschi and Lenzi (2014), we compute it as follows:

$$R(g) = \frac{\sum_{j=1}^{n}\sum_{k=1;j\neq k}^{n} 1/d_{jk}}{n}$$

Thirdly, the level of network hierarchy of network g is captured by the degree distribution *(DD(g))*. Following Crespo *et al*. (2014), we compute it as the slope of the relation (in *log-log* scale) between the organization degree k_i and his ranking position k_i*:

$$log(k_i) = log(C) + a\, log(k_i^*),$$

where C is a constant. Thus, $DD(g)=a$, the higher the value of the slope, in absolute terms, the higher the hierarchy of the network.

[5] If this condition cannot be matched, the disrupted relationship is not recreated and the tie definitively dies.

[6] Density of a network refers to the ratio between the existing number of ties and the number of potential ties in a network.

Finally, we measure network assortativity as the degree correlation of the network ($DC(g)$). Following Crespo *et al.* (2014), we compute it as the slope of the relation between the degree of node i (k_i), and the average degree ($\overline{k_i}$) of the nodes in his neighborhood (V_i): $\overline{k_i} = \frac{1}{k_i}\sum_{j \in V_i} k_j$. Thus, the estimated relationship is $\overline{k_i} = D + bk_i$. Where D is a constant, and b our measure of $DC(g)$. If $b>0$ the network is assortative, and if $b<0$ the network is disassortative.

4.4. Experiment setting

The simulation protocol is designed as follows: at each step of time, a number E_t of organizations, depending on the distance to the load capacity of the system *M,* enter the network. They connect either by preferential or random attachment according to a probabilistic choice defined by $\alpha \in [0, 1]$. At each step of time, a proportion $\lambda \in [0, 1]$ of ties are disrupted and recreated either by bridging or closure, as a probabilistic choice defined by $\beta \in [0, 1]$. After the rewiring process, the organizations that become isolated exit[7]. We use NetLogo to build the model and run the simulations.

To explore the link between the relational mechanisms at micro-level and the feature of the network structure at macro-level, we run multiple simulations with different parameter settings to explore the whole parameters space:

- Initial conditions: a random network with 50 nodes and 50 ties. When not specified otherwise, the results are based on random initial conditions.
- Load capacity of the network *M* of 500 organizations.
- Speed of convergence *r* at 0.1.
- α parameter form 0 to 1 by 0.1.
- β parameter from 0 to 1 by 0.1.
- λ parameter from 0 to 0.2 by 0.025. If not specified otherwise, the results are presented for a λ = 0.05
- Each simulation runs for 500 steps and then stops. The network measures are computed at this last step.
- Each parameter setting is run 20 times[8]

4.5. Results

- *Relational mechanisms and network growth*

Given the population dynamics rule of the model, when *r>0.05*, the number of organizations in the simulations always converges to *M*. This holds whatever the parameter setting and the initial

[7] Along each simulation step, entry and rewire mechanisms are simultaneously activated, but in a cumulatively unbalanced proportion. On the one side, the number of entries decreases as the population comes close to its maximum threshold (*M*). Therefore, preferential or random attachment mechanisms play only few times in each step. On the other side, the number of rewired links, defined as proportion λ of the existing population, increases when the population comes close to *M*. Consequently, the number of times bridging and closure are activated becomes higher. Since this unbalance is reproduced at each step, the effect of entry mechanisms tends to smooth, while the effect of rewire tends to be enforced.

[8] The results presented are the average values of these 20 runs for each parameter setting

conditions. As expected, the higher the value of *r* the faster the convergence towards the threshold (*Figure 1*).

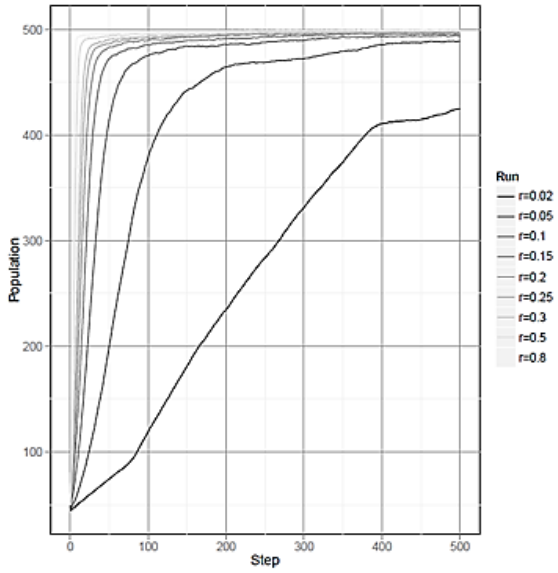


Figure 1 – Evolution of the number of organizations across time

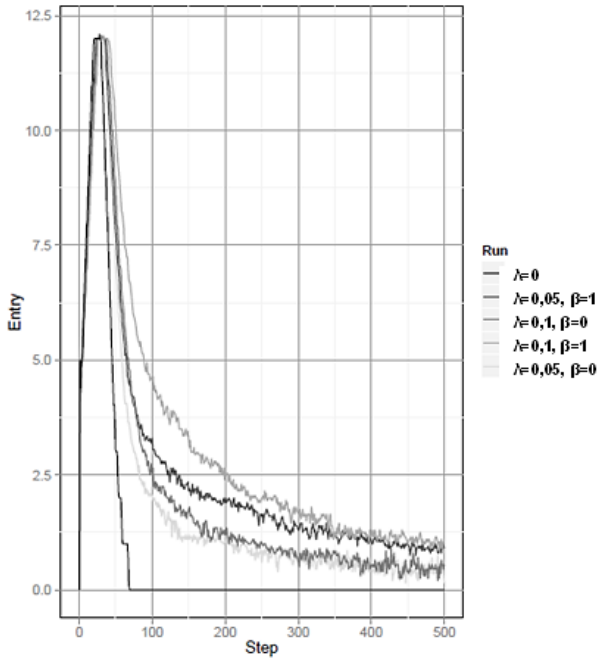
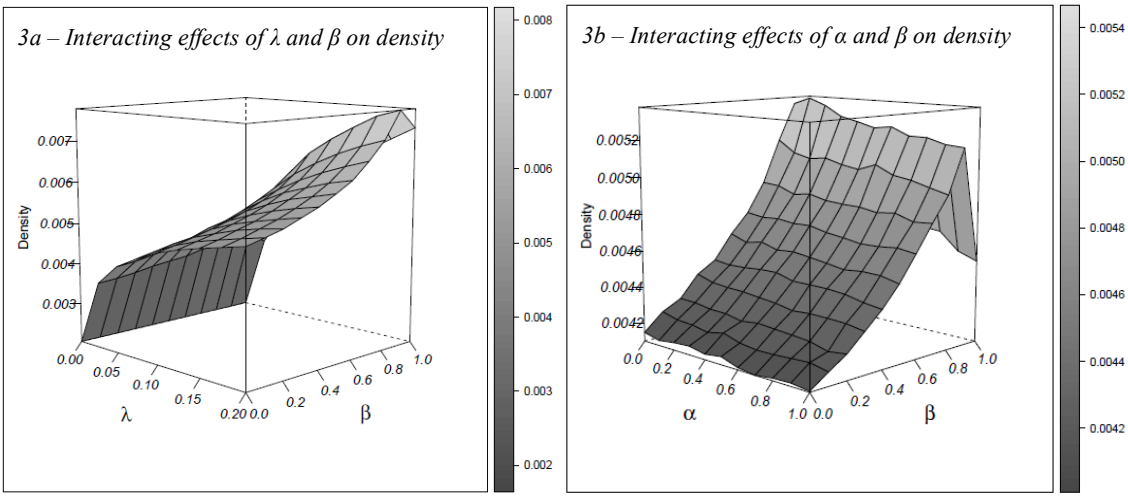


Figure 2 – Evolution of entry and exit across time

However, this convergence occurs with different entry/exit turnover depending on the value of the β and λ parameters (*Figure 2*). Without ties rewiring (λ=0), the population stabilizes once

the maximum threshold is reached. In contrast, when rewiring is introduced (λ>0), the destruction of ties increases the risks of isolation and exit. The exit of nodes being compensated by new entries, the population remains at its superior threshold, but with a higher nodes turnover. This turnover is also affected by β. When closure prevails over bridging (high values of β), the network breaks up in a increasing but smaller number of disconnect components. Exits by isolation increase, and they are again compensated by the population dynamics rule.

- *Relational mechanisms and network density*



When α=0, all entries are by preferential attachment; When α=1 all entries are by random.
When β=0, all rewires are by bridging; when β=1 all rewires are by closure[9]

Figure 3 – Network density

Concerning network density (*figure 3b*), the relational mechanisms at rewire seems to play more significantly than relational mechanisms at entry. While the effect of entry (α) on density is weak, density increases with β, i.e. the dominance of closure over bridging. Consequently, the amount of change in density is only explained by the fact that at each step the amount of rewiring strategies is higher than the amount of entries. Therefore density increases with the dominance of closure over bridging. With closure, the probability of node exit by isolation increases. However, nodes exit does not imply losing links, since the disrupted link can be recreated by the other organization of the old dyad. The exited node will open the opportunity of connection for newcomers. They will enter the network by adding a new link. As a result, the network has the same number of nodes but more links, and even more since entries by preferential attachment prevails over random connections.

Such a pattern works only under a β threshold (β < 0.9). Above it, only closure is considered in the rewiring mechanisms, and the network splits into several highly cliquished components. Therefore, the more the number of these cliquished components increases, the more the possibility for a disrupted tie to be replaced by a new tie decreases, reducing the network density.

[9] The axis interpretation holds for the remaining figures

The effects of different combinations of α and β on network density are robust across different initial conditions of the networks and different r. Only the amount of rewiring matters, since closure and bridging do not play any role when $\lambda = 0$ (*figure 3a*).

- *Relational mechanisms and small world*

Concerning the small world properties of networks, the simulation results show that clustering and reachability are highly sensitive to micro-behaviors.

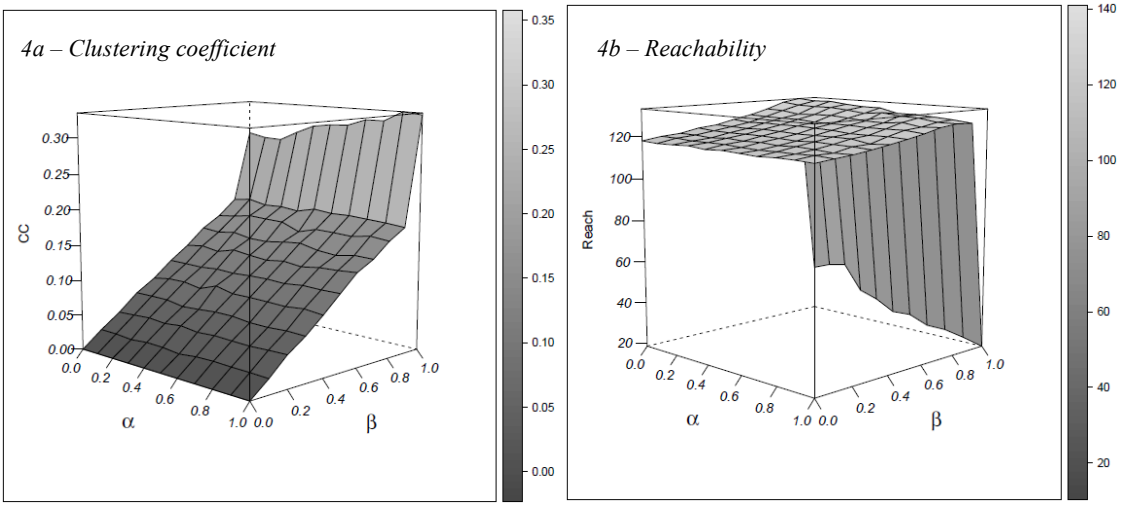


Figure 4 – Small world properties

Firstly, as expected from the discussion of section 3, clustering increases with β, i.e. when closure prevails over bridging[10] (*Figure 4a*). However, clustering coefficients does not significantly changed with the different values of α, balancing the choice between preferential and random attachment. When rewiring strategies are not considered ($\lambda = 0$, not displayed here), no triangles can appear and so clustering is *0*. Positive and increasing values of λ (beyond *0.05* displayed in *Figure 4a*) do not change these conclusions. Similarly, these results do not change for different population dynamics setting (M and r), or for different initial conditions.

Secondly, results also match, even partially, our expectations concerning reachability (*figure 4b*). Firstly, for $0 < \beta < 0.9$, reachability is high, meaning that bridging micro behaviors contribute to the global reachability of the network by creating between-groups shortcuts. When a bridging relationship is created, it increases not only the reachability of the newly connected nodes, but also the reachability of all their neighbors. This slight increase of reachability contrasts with the slight decrease of small world patterns but does not contradict them. Indeed, such a difference can be explained by the fact that small world properties in Watts and Strogatz (1998) are computed from a fixed number of links, while in our model, the number of links depends on the distribution of rewiring strategies. Since the number of links strongly increases with closure behaviors in our simulations (*figure 3a*), it naturally increases the reachability.

[10] When β goes from 0.9 to 1, the increase of clustering coefficient accelerates. Once again, the splitting of the network of several components explains this pattern.

Secondly, in contrast, for (β > 0.9), closure prevails and drastically decreases the number of between-group links and then increases the number of separated network components. As a result, there is a radical cut down in reachability.

- *Relational mechanisms, degree distribution and correlation*

Degree distribution and correlation have also been identified as crucial properties for cluster performance. *Figures 5a* and *5b* show the variation of degree distribution across different combinations of α and β values[11].

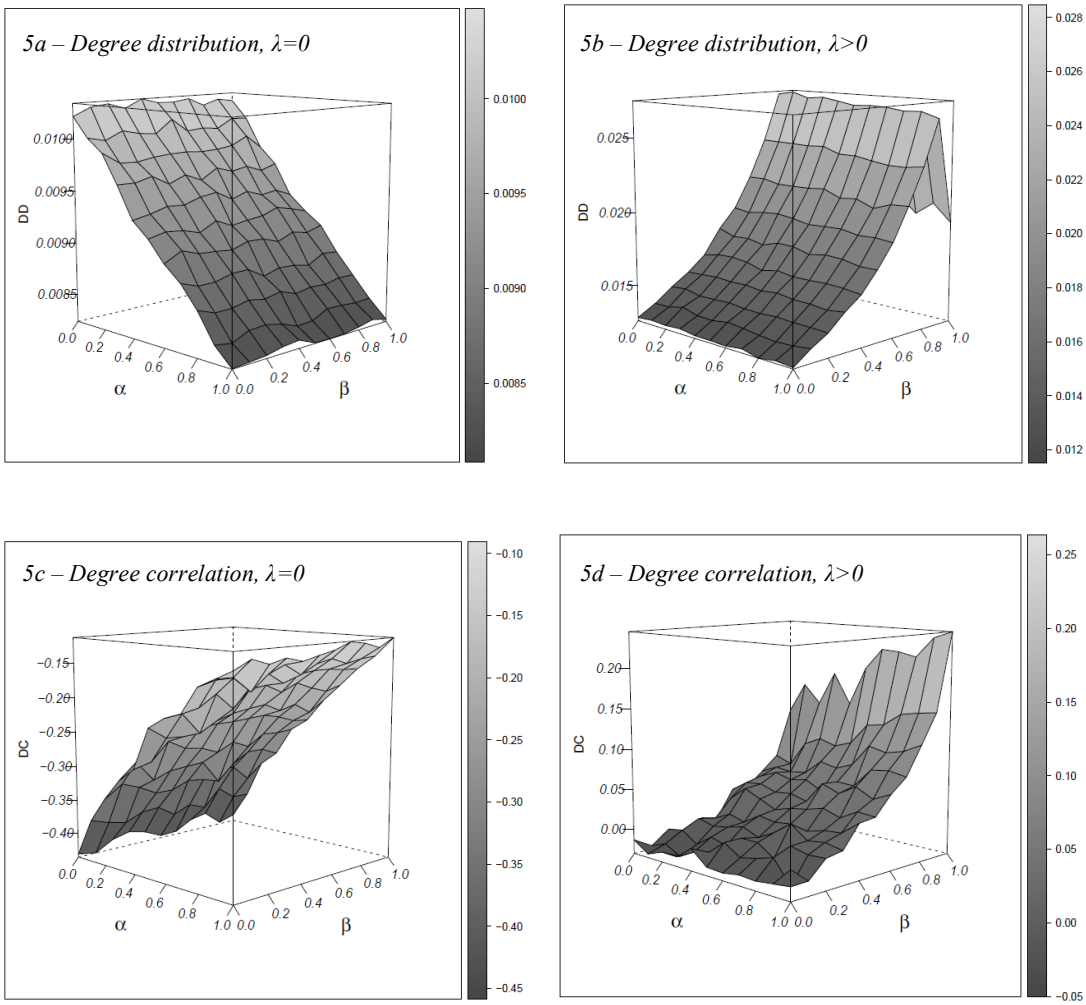


Figure 5 – Degree distribution and correlation

As expected, when there is no rewire ($\lambda=0$), micro-behaviors at entry by preferential attachment result in more hierarchical structure that random attachment ones (*figure 5a*). This effect partially remains when rewiring behaviors are introduced (*figure 5b,* with $\lambda=0.05$). Indeed, the

[11] Degree distribution is computed in absolute terms, so higher (lower) values mean more (less) hierarchical networks

higher frequency of rewire events over entry ones blurs the structural effects of preferential and random attachment mechanisms. However, this does not occur in an even way. When bridging dominates over closure (low β), the entry mechanism becomes irrelevant. But when closure dominates (high β), the effects of entry mechanisms on network hierarchy remain as expected. However, more outstanding is the direct impact of rewiring on degree distribution. *Figure 5b* shows that along the β axis, as closure dominates over bridging, the network becomes more and more hierarchical[12].

Figures 5c and *5d* show how the different relational mechanisms interplay on degree correlation[13]. In case of no rewire ($\lambda=0$), as expected, the emerging structure is more and more disassortative when preferential attachment prevails (*Figure 5c*). When organizations take rewire decisions ($\lambda > 0$), two main changes appear (*Figure 5d*). On the one hand, as with degree distribution, the effects of entry mechanisms slightly erode. On the other hand, there is a shift up of the whole results surface, i.e. network structures become more assortative. Nevertheless, the variations of degree correlation along the axis support our expectations. The network becomes more and more assortative when closure dominates over bridging. The results on degree distribution and degree correlation hold for different parameters settings on the population dynamics (M and r), and different initial conditions of the network.

5. Discussion

Which implications can we draw from these results for innovative clusters? Several aspects may make the organization of clusters significantly different, such as their organizational ecology, their degree of industrial compositeness, their size or their R&D intensity. Here the aim was to stress on their structural dimensions in order to contribute to the literature that tries to link the performance of innovative clusters to their internal structural features (Markusen, 1996; Owen-Smith and Powell, 2004; Broekel and Graf, 2011). And a better understanding of the interplay between relational behaviors and aggregate structures may contribute to improve cluster policy design.

Our findings offer an embryonic but promising perspective for that purpose. As a matter of fact, policy makers have long been limited to support collaborative R&D in clusters for the sole purpose of increasing relational density as a mean to boost their innovative performance. Such a "one size fits all" approach of clusters policies (Tödtling and Trippl, 2005) has been progressively suspected to be counterproductive, engendering crowding-out effects on public expenses and a weak economic return (Duranton, 2011). By connecting micro and macro levels of knowledge networks, our findings suggest incentivizing collaborations in a more surgical manner. Policy makers should orient their action toward targeted distortions of the existing knowledge networks, when these latter do not match the structural properties positively affecting cluster performance and trajectories.

In that respect, our findings will make all the more sense as they are related to the development stages of clusters and to the degree of maturity in their technological and market domains. Indeed, since simulation results show that entry and rewiring mechanisms may play as opposing

[12] As for density and reachability, the effect of β on degree distribution also exhibits a trend reversal when above a very high level of closure, the network splits in several components.

[13] Recall that assortative networks are characterized by positive degree correlation. Disassortative networks are characterized by negative degree correlation.

forces in the formation of clusters structural properties, the design of public incentives has at the same time to rely on the position of clusters in the cycle of markets (Brenner and Schlump, 2011), and to pay attention to the risks of irreversible trap some extreme incentives could produce when networks end up splitting themselves into separated components.

Firstly, we consider immature clusters, when technologies and markets are far from being stabilized. The challenge for these clusters is to ossify the structure of interactions. So, all means to support the emergence of super connectors can be useful to favor the cluster development. The simulation results show that public collaborative incentives have to be oriented toward preferential attachment and closure to help clusters reach the maturity stage. By inciting newcomers to connect to the mostly connected organizations, policy makers will favor the centralization of the knowledge integration process and thus allow clusters better securing the setting of technological standards. *Figure 5b* shows that prevalence of closure (under a certain threshold), favors the emergence of hierarchical structures. If policy makers do not target incentives towards the aim of increasing hierarchy, clusters will display a lack of control of the composite knowledge process (Levy and Talbot, 2014), weakening their ability to produce well-performing dominant design (Crespo et al., 2013). At the same time, the capacity of clusters to produce tradable technological standards needs i) a high level of interoperability and compatibility supported by a high level of cohesion between interacting organizations, and ii) short knowledge paths between them. Both allow increasing the systemic integrity of the collective process of innovation we observed in high-tech clusters and networks (Aoki and Takizawa, 2002; Nooteboom, 2003; Balland et al., 2013).

Figures 5b, 4a and *4b* provide interesting findings for policy design and targeted incentives for knowledge collaborations. Under a certain threshold of closure where networks remain fully connected, hierarchy increases with closure behaviors, securing the control of knowledge integration around a couple of leading organizations. Additionally, under the same closure threshold, networks increase clustering and maintain a high level of internal reachability. Therefore, one of the challenges for cluster policy makers is to go through this window by targeting public collaborative incentives that allow organizations reinforcing their relational cohesion without compromising the overall connectedness of the network and favoring the structuration of a core. Consequently, when clusters just start to structure themselves, policy makers can help them play the battle of places by boosting knowledge relationships. Incentives for collaborations should be oriented towards the development of an attractive core of connected organizations able to drive the coordination process by which a collection of separated pieces of explorative knowledge can be turned into a dominant design on markets.

Secondly, in contrast, when clusters jave reached maturity in their technological domain, the structural properties ensuring performance are different. Then, from the perspective of a surgical cluster policy, the target of incentives will also change. The challenge for policy makers is to favor structural changes capabilities for clusters by providing incentives that allow clustered organizations overlapping mature and emerging markets. As the matter of fact, the risk for mature clusters is that their core-organizations enter a critical phase where growing worldwide competition overshadows local exploration and weaken their ability to reorganize knowledge networks towards new technologies and related markets. This risk will increase if closure behaviors, crucial to secure technological standards during the growing phase, produce too many disconnections between core and peripheral organizations when market maturity arises. As displayed in Figure 5b and 5d, under a threshold where networks remain connected, cluster grow in hierarchy with closure at the same time as they grow in assortativity. These related network patterns show that, when closure behaviors prevail over bridging ones, an increase in

hierarchy goes with a tendency of core-organizations to mutually interact. In particular when random entries prevail over preferential attachments. Consequently, for mature clusters to maintain innovative and structural change capabilities (Boschma, 2014), incentives oriented toward connections by preferential attachment and bridging behaviors should be preferred. They will allow avoiding conformism in clusters core-component, regenerating it, and favoring a better flowing of fresh and explorative ideas from peripheral organizations toward more central and well-experienced ones. Such bridging behaviors in clusters explain why some clusters succeed in overlapping mature markets and related emerging ones, through the process by which core-organizations owning transversal technologies diversify their network portfolio and continuously find opportunities to absorb knowledge from new entrants.

Investigating the renewal of the Silicon Valley during the 1980s, Saxenian (1990) evidenced these findings. She explains how networks restructuring between well-performing organizations of the semi-conductor mature industry and start-ups providing innovative and fast-changing components and applications has led the cluster to develop, and control later in the 1990s, the worldwide computer industry. But this network structural change process is not always self-evident since assortativity generally appears as a natural tendency of growing social networks (Newman, 2002; Watts, 2004). Breaking assortative paths can be done by the support of public collaborative incentives aiming at connecting peripheral and core organizations in clusters. For that, policy makers have to accept higher risks than the ones they take when they reinforce collaborations between previously connected organizations.

In that sense, the archetypal system of calls for collaborative proposal that typifies many clusters policies is highly responsible of these difficulties for policy makers to favor more disassortative structures in clusters. Indeed, public subsidizers that launch these calls are trapped in informational asymmetries vis-à-vis the applicants. They may be tempted to reduce the risk relying on successful pas collaborations to select new collaborative projects. But by increasing network assortativity and reinforcing closure behaviors, they do not appropriately help clusters continuously regenerate themselves. For mature clusters, targeted inducements towards bridging collaborations and more disassortative relational behaviors will be expected engendering higher economic returns.

6. Conclusion

This paper has tried to provide a better understanding of the micro-foundations of clusters, stressing on the links between the relational strategies of agents and the resulting structural properties of knowledge networks. Using a (too) simple model of simulation for that purpose, our findings offer imperfect but promising perspectives to better grasp the reasons why some clusters performs better than others on the long run. In particular, results shed light on the relational behaviors that can give rise to clusters able to establish themselves as a leading place in their technological domain, and to continuously renew themselves by overlapping mature and emerging markets.

In cluster analysis based on small world properties, it has been supported that knowledge networks succeeding in maintaining a high level of closure while decreasing the path length for a better knowledge circulation would be more likely to be able to compete in innovation. Nevertheless, these properties remain discussed (Fleming *et al.*, 2007). Introducing the properties of degree distribution (hierarchy) and correlation (assortativity) allow going one step beyond. They provide interesting insights to disentangle the combined effects of networks

cohesiveness and openness on cluster performance (Eisingerich *et al*., 2010). Indeed, by considering hierarchy of local knowledge networks, our contribution allows linking effective clusters to the process of relational ossification which favors the coordination process between separated organizations, and without which emerging clusters could experience difficulties to cross the chasm between early markets and mass-markets (Moore, 1991, Suire and Vicente, 2014). Cluster entries by preferential attachments also affect such an ossification process; Therefore,they are perfectly adapted to the growing phase of clusters. Rewiring by closure complement this process by improving the systemic integrity generally required in composite technological fields. Nevertheless, once clusters have reached maturity, closure behaviors can hamper their capacity to react and resist to declining markets. Systemic integrity can be turned into systemic conformism during the mature phase of markets, and can weaken the capabilities of structural change of clusters. To remain competitive on the long run, entries by preferential attachments in clusters need to play with more heterophilic relational behaviors in the existing core of leading organizations. These latter have to reorient their relationships portfolio towards peripheral organizations, in order to facilitate new knowledge combinations and the raising of new knowledge towards the core of experienced organizations. Consequently, for clusters having reached maturity, bridging behaviors and the resulting disassortative structures of knowledge interactions will be more suitable with their self-sustaining growth path.

Obviously, this contribution remains an academic exercise, and the attempt of policy implications previously done is not free of limitations. Firstly, for the sake of clarity, the model has only focused on structural mechanisms and has deliberately ignored the cognitive and institutional attributes of organizations. Indeed, at the micro-level, the motives to shape or not knowledge relationships also depend on these attributes. To be improved, further extensions of the model should consider that organizations in clusters also select partners depending on the features of these partners, and disentangle how cognitive and relational characteristics play together in shaping particular structural properties[14]. Secondly, to be tractable for policy design, clusters diagnoses on existing relational structures have to be systematically implemented. Such a task can be costly and not necessarily reliable, due to the difficulties to gather relational data and to capture the market cycles. Nevertheless, by stressing on the necessity to develop targeted and surgical incentives for knowledge collaborations, this study provides a better significance of what network failures in clusters actually are. In that respect, it makes a small step which can help policy makers to expect a better policy return, by taking better informed decisions about the structural consequences of their public-funded networking incentives.

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[14] The same limitation concerns the locational attributes. The model could be extended introducing a distinction between local and non-local nodes in networks in order to study how and for what purpose organizations shape knowledge relationships with local and non-local organizations. See Fijtar and Rodríguez-Pose (2011) and Balland *et al*. (2013).

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