Micro-behaviors and structural properties of knowledge networks: toward a 'one size fits one' cluster policy

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ABSTRACT

The economic returns of cluster policies have been recently called into question. Based on a "one size fits all" approach consisting in boosting R&D collaborations and reinforcing network density, 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 build knowledge relationships can give rise to emerging structures with different properties, which imply different innovation and renewal capacities. The simulation results are discussed in a micro-macro perspective, and motivate suggestions to reorient cluster policy guidelines towards more targeted public-funded incentives for R&D collaboration.

1. Introduction

During the two last decades, 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, Gómez Uranga, and Etxebarria 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 cluster policy-makers. 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, Mayer, and Mayneris 2011; Brakman and Marrewijk 2013).

Nevertheless, such skepticism is not sufficient to reject as a whole the network-based incentives that nurture many cluster policy guidelines (Woolthuis, Lankhuizen, and Gilsing 2005; Boschma 2008; Nishimura and Okamuro 2011; McCann and Ortega-Argilés 2013; Vicente 2014). As a matter of fact, the policy transposition of academic conclusions has somehow stopped in the halfway. Policy-makers have focused on cluster relational density, and have put aside researches stressing on more complex structural properties. Using basics of network theories from economics (Jackson and Wolinsky 1996), sociology (Burt 1992; Granovetter 2005) and physics (Barabási and Albert 1999; Brede and Vries 2009), these researches have captured the role of particular micro-founded structural properties of clusters, such as 'small worlds' (Fleming, King, and Juda 2007; Breschi and Lenzi 2015), triadic closure (Balland, Suire, and Vicente 2013; Ter Wal 2014), network centralization and connectedness (Owen-Smith and Powell 2004; Cantner and Graf 2006; Casper 2007; Vicente, Balland, and Brossard 2011) or network assortativity (Crespo, Suire, and Vicente 2014). However, policy-makers have ignored these recent advances when designing their policies. They have aimed at increasing relational thickness of clusters in a 'one size fits all' scheme (Tödtling and Trippl 2005). In doing so, these policies have been suspected to reinforce dysfunctioning structures or to sclerose emerging ones, with risks of crowding-out effects and misallocation of public resources (Duranton 2011).

Structural properties of networks emerge over time through the cumulative aggregation of individual decisions to create (or not) knowledge relationships. Thus, expecting a higher return of cluster policies in the future requires a better understanding of the micro-motives for knowledge collaborations in clusters. Consequently, the aim of the paper is to 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 to link network structural evolution to simple individual relational rules. This provides 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 is structured 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 benefit 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 (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, Kogut, and Shan 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, Rivkin, and Fleming 2006).

These literatures have both contributed to a growing number of cluster analyses. They show 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; Giuliani and Bell 2005; Boschma and ter Wal 2007; Casper 2007). It has joined the so-called *relational turn* of economic geography (Bathelt and Glückler 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 analyses of clusters can provide useful methods to assess individual performance with regard to the position into networks. In economics, as well as in management science, network position of agents has been largely explored as a source of increasing payoffs or long-run performance (Goyal and

Vega-Redondo 2007; Cattani and Ferriani 2008). But these analyses 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, their emerging structural properties may differ, and they are not neutral for cluster 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 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 typified by a high-clustering coefficient, favoring trust in cohesive cliques of interacting actors. As reviewed by Uzzi, Amaral, and Reed-Tsochas (2007), small worlds appear as a regular property of personal (co-authorship and inventors) and organizational (R&D alliances and 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, Amaral, and Reed-Tsochas 2007, 78). Cowan and Jonard (2004) use simulation models to find that knowledge production is maximal when networks exhibit small-world properties. Breschi and Lenzi (2015) use patent data to show that US cities' innovations are positively affected by small-world networks.[2] Moreover, they display robustness across time, as evidenced by Kogut and Walker (2001) and Davis, Yoo, and Baker (2003), according to whom a great amount of transformation is necessary to change a small world into a network of different types.

2.2. *Network hierarchy*

Recently, other properties have been put ahead to study the long-run performance of clusters. Small-world approaches, based on random graph models (Erdõs 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 has stressed on the hierarchical structure of knowledge relationships in industrial districts (Storper and Harisson 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 a centralization index to assess the innovative capabilities of clusters (Cantner and Graf 2006; Graf 2011; Crespo, Suire, and Vicente 2015). 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 network's degree distribution. This scale-free property reflects a core/periphery structure in which the core is composed of a set of high-degree organizations – the hubs – and a periphery or more loosely connected ones[3] – the spokes (Borgatti and Everett 1999). If all organizations in a particular cluster have a 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 (Ter Wal and Boschma 2011; Crespo, Suire, and Vicente 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, Jeong, and Barabási 2000; Brede and 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 relocation of one of the leading regional companies, can compromise the cluster long-run sustainability, as evidenced by Vicente, Balland, and Brossard (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 interact with others that have a similar degree, while disassortative networks are featured by a negative degree correlation, implying more heterophilic social interactions (Watts 2004; Rivera, Soderstrom, and Uzzi 2010). Therefore, network 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). On the other side, these effects of structural homophily can provoke 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, Polodiro, and Mitchell 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). 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, Suire, and Vicente (2015) 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 of the micro-motives for organizations to join (or not) networks and build (or not) knowledge relationships. Economic literature on networks generally converges on the idea that agents expect shared surpluses from the construction of ties (Jackson and Wolinsky 1996; Dutta and Mutuswami 1997). In innovation studies, these shared surpluses are related to the fact that organizations form 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 capacity constraints on links (Goyal and Vega-Redondo 2007), 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).

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 with 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 (Appold 2005; Romanelli and Khessina 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. 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 is not just "being on the right place", but also "being 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, those getting the control of standards and larger installed bases (Farrell and Saloner 1986; Arthur 1989). Moreover, interactions with leading organizations may be the source of status for new entrants (Balland, Belso-Martínez, and Morrison 2015). Finally, it is also consistent with the relational behavior of spin-offs that tend to connect to their often highly connected parent's company (Buenstorf and Fornahl 2009; Vicente, Balland, and Brossard 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 with new entrants, they are the 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 leads to hierarchical networks: more central nodes become more attractive for new entrants, while peripheral nodes receive little attention. As time goes, these differences are reinforced, and network hierarchy increases. Concerning degree correlation, the structural consequences of preferential 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. On the 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, Schreyögg, and Koch 2009), knowledge networks evolve not only through entries and exits, but also through the propensity of organizations to change their partners' portfolio (Powell, Koput, and Smith-Doerr 1996). Ties rewiring indicates the capability to disrupt and recreates knowledge relationships. Disruption of ties and creation of new ones are driven by cognitive and strategic purposes. They occur 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 2015). Triadic closure implies that an organization with links to two other organizations increases the probability for these two organizations to create 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 intermediation rents for agents (Goyal and Vega-Redondo 2007), and a particular influence and control of the knowledge flows in networks (Ahuja 2000; Baum, McEvily, and Rowley 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, Bell, and Tracey 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. Organizations connect to neighbors of their neighbors, creating dense and cohesive groups, but few between-group links are created. As a consequence, beyond a certain threshold, the whole network connectivity can be reduced (Watts and Strogatz 1998; Gulati, Sytch, and Tatarynowicz 2012). On the 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, that is, a lower path length, thanks to the multiplication 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 in 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 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. On the contrary, with bridging, highly connected organizations will try to find new partners in the periphery and conversely, increasing the disassortativity of the network.

Based on the previous discussion, and in contrast to the (sometimes excessively beatific) view of knowledge networks in many cluster policy guidelines, an increase in 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 are expected to be more efficient in the long run. Table 1 summarizes the expected consequences relational micro-motives on the clusters structural properties. If we set apart entry and rewiring mechanisms, the topological forms of clusters would be possible to anticipate. On the 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 build 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

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

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. On the contrary, when the current population is close to the maximum threshold, new opportunities become scarce, the competition is too fierce and the entry barriers become too high. 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 nonparametric rule consisting in removing nodes 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.

Table 1. Structural consequences of relational mechanisms.

	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

4.2. *Relational mechanisms*

As described in Section 3, organizations in networks are not definitively fixed on a 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 at different moments in time. On the one hand, when organizations enter, they chose their partner either by preferential or by 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 by closure (cluster structuring mechanisms).

4.2.1. *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. On the contrary, when an organization connects by preferential attachment, existing organizations 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 the k_i, the more likely the organization i to receive a new tie:

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}.$$

4.2.2. *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 rebuild with a new partner 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 holes to connect disconnected parts in the network, we model bridging ties by randomly choosing a partner 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]

4.2.3. *Structural measures*

Through simulation 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 and density[6]), Section 2 discussed important properties for clusters.

The first ones relate to small-world 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

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

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 nodes in the network g. Then, the higher the value of $R(g)$ measure, the higher the connectivity of the network. Following Breschi and Lenzi (2015), 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, Suire, and Vicente (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.

Finally, we measure network assortativity as the degree correlation of the network (DC(g)). Following Crespo, Suire, and Vicente (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. The entrants connect either by preferential or by 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 by 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 a micro-level and the feature of the network structure at a 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 a random distribution of these ties.
- Load capacity of the network M of 500 organizations.
- Speed of convergence r at 0.1.
- α parameter from 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 $\lambda = 0.05$
- 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

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

However, this convergence occurs with different entry/exit turnover depending on the value of the β and λ parameters (Figure 2). Without ties rewiring ($\lambda = 0$), the population stabilizes once the maximum threshold is reached. In contrast, when rewiring is introduced ($\lambda > 0$), 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 an increasing but a smaller number of disconnect components. Exits by isolation increase, and they are again compensated by the population dynamics rule.

4.5.2. Relational mechanisms and network density

Concerning network density (Figure 3(b)), the relational mechanisms at rewire seem to play more significantly than relational mechanisms at entry. While the effect of entry (α) on density is weak, density increases with β, that is, the dominance of closure over bridging. The amount of change in density is only explained by the fact that at each step the amount of rewiring strategies is higher

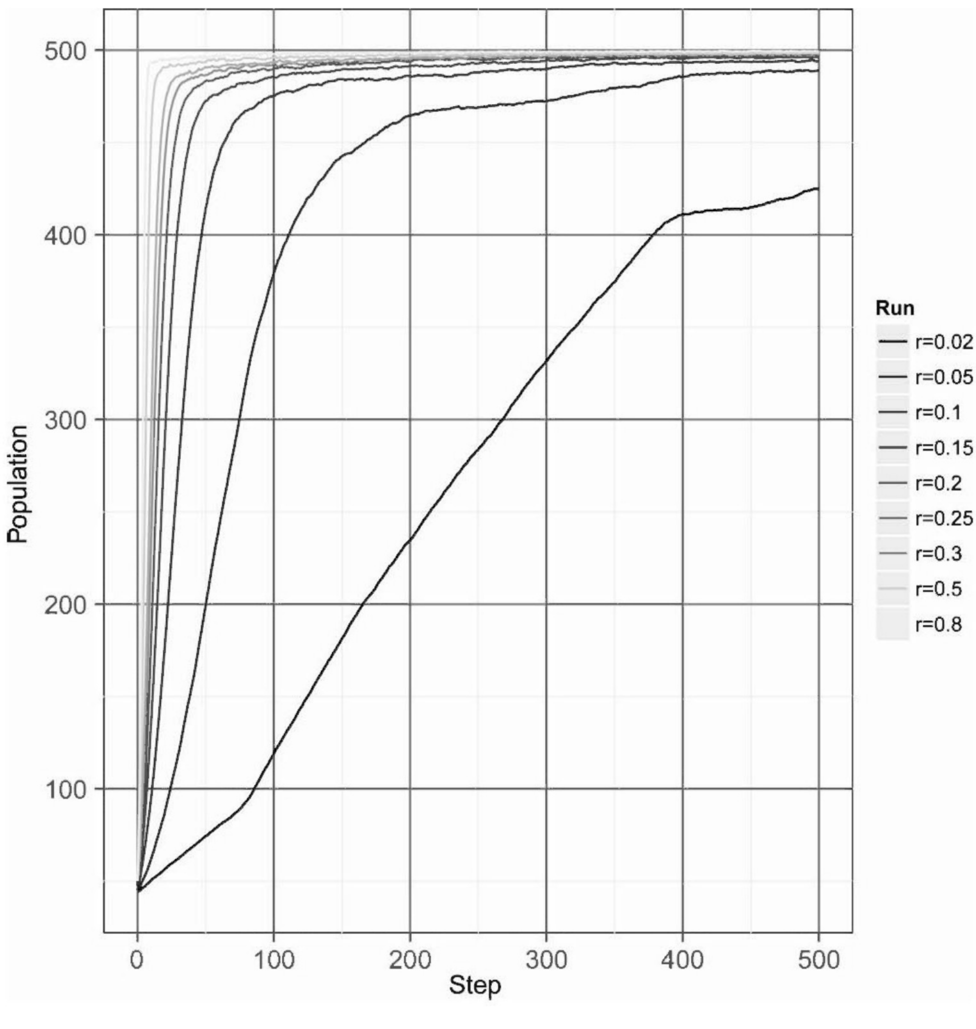

Figure 1. Evolution of the number of organizations across time.

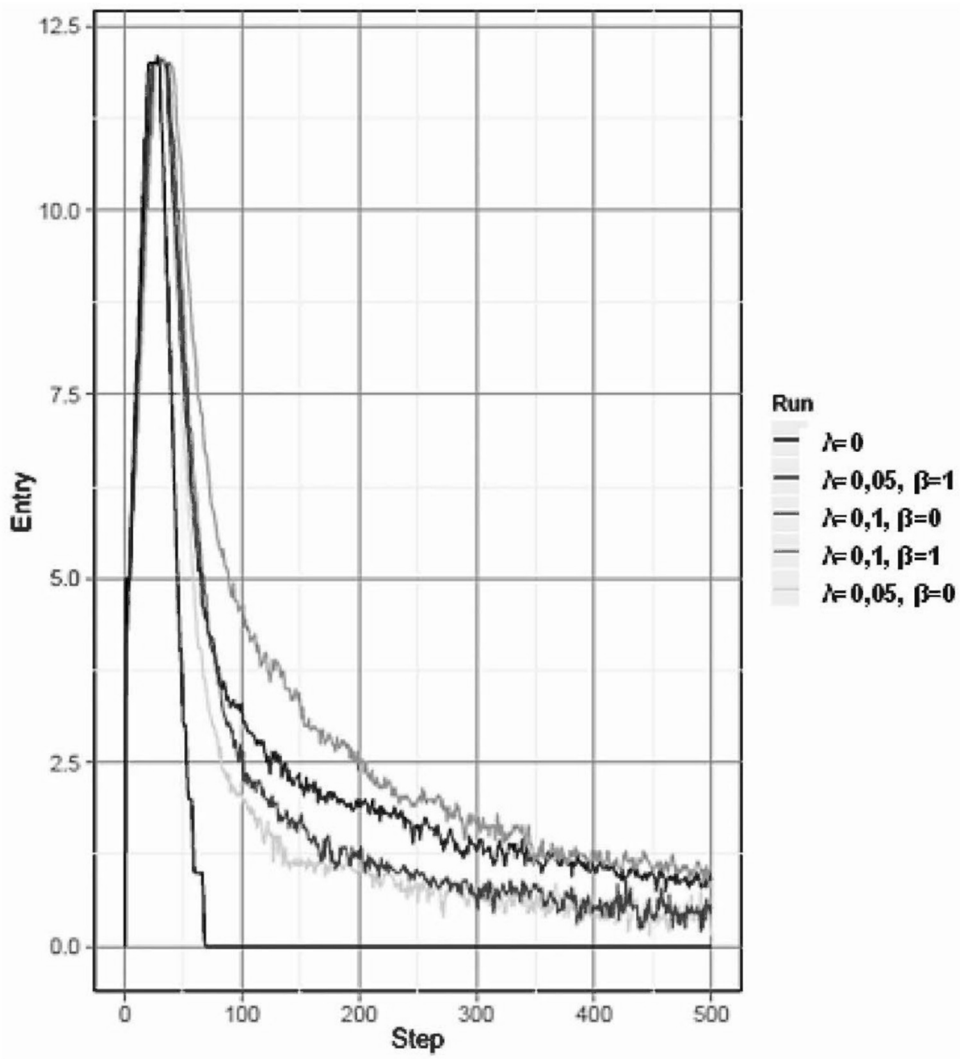

Figure 2. Evolution of entry and exit across time.

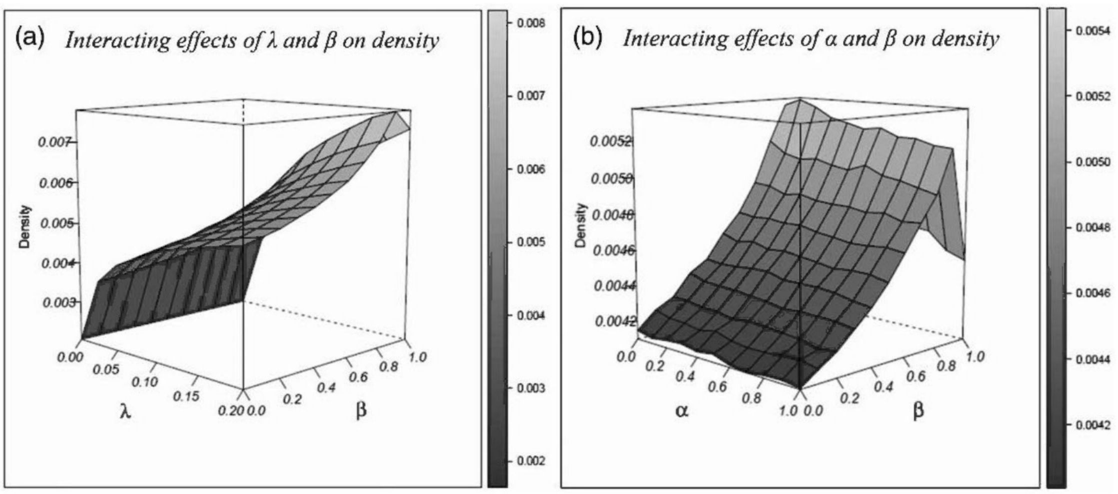

Figure 3. Network density. When $\alpha = 0$, all entries are by preferential attachment; when $\alpha = 1$ all entries are by random. When $\beta = 0$, all rewires are by bridging; when $\beta = 1$ all rewires are by closure.
Note: The axis interpretation holds for the remaining figures.

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 ($\beta < 0.9$). 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 one decreases. This reduces the network density.

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 3(a)).

4.5.3. *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.

Firstly, as expected from the discussion of Section 3, clustering increases with β, that is, when closure prevails over bridging[9] (Figure 4(a)). However, clustering coefficients do not significantly change with the different values of α, balancing between preferential and random attachment. Positive and increasing values of λ (beyond the value *0.05* displayed in Figure 4(a)) do not change these conclusions. Similarly, these results do not change for different population dynamics settings (M and r), or for different initial conditions.[10] When rewiring strategies are not considered ($\lambda = 0$, not displayed here), no triangles can appear and so clustering is 0.

Secondly, results also match, although partially, our expectations concerning reachability (Figure 4 (b)). 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-group 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 in reachability contrasts with the slight decrease in 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

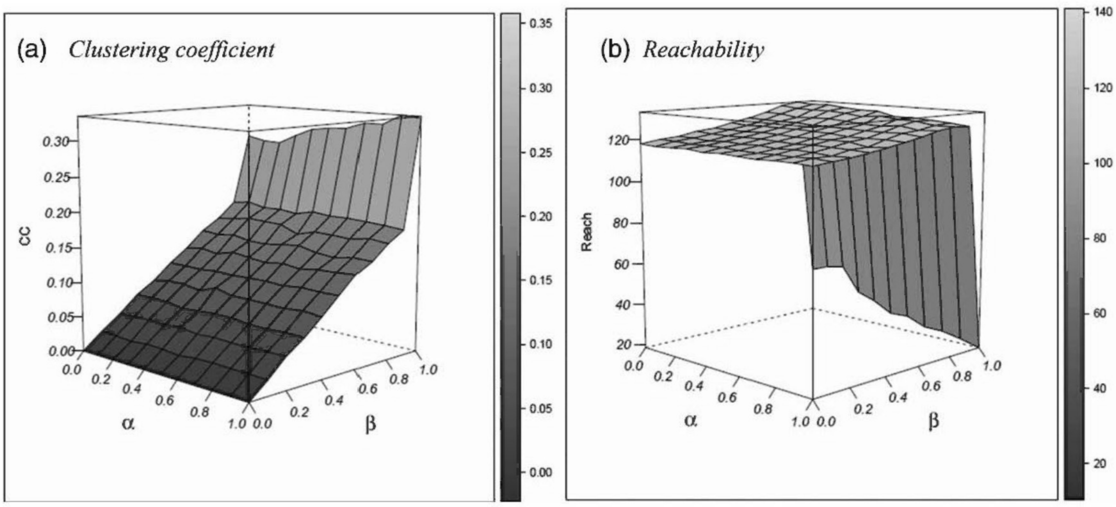

Figure 4. Small-world properties.

simulations (Figure 3(a)), it naturally increases the reachability. Secondly, in contrast, for ($\beta > 0.9$), 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, also observable in Watts and Strogatz (1998).

4.5.4. *Relational mechanisms, degree distribution and correlation*

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

As expected, when there is no rewire ($\lambda = 0$), micro-behaviors at entry by preferential attachment result in more hierarchical structure than random attachment ones (Figure 5(a)). This effect partially remains when rewiring behaviors are introduced (Figure 5(b), with $\lambda = 0.05$). Indeed, the 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 5(b) shows that along the β-axis, as closure dominates over bridging, the network becomes more and more hierarchical.[12]

Figure 5(c) and (d) shows 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 5(c)). When organizations take rewire decisions

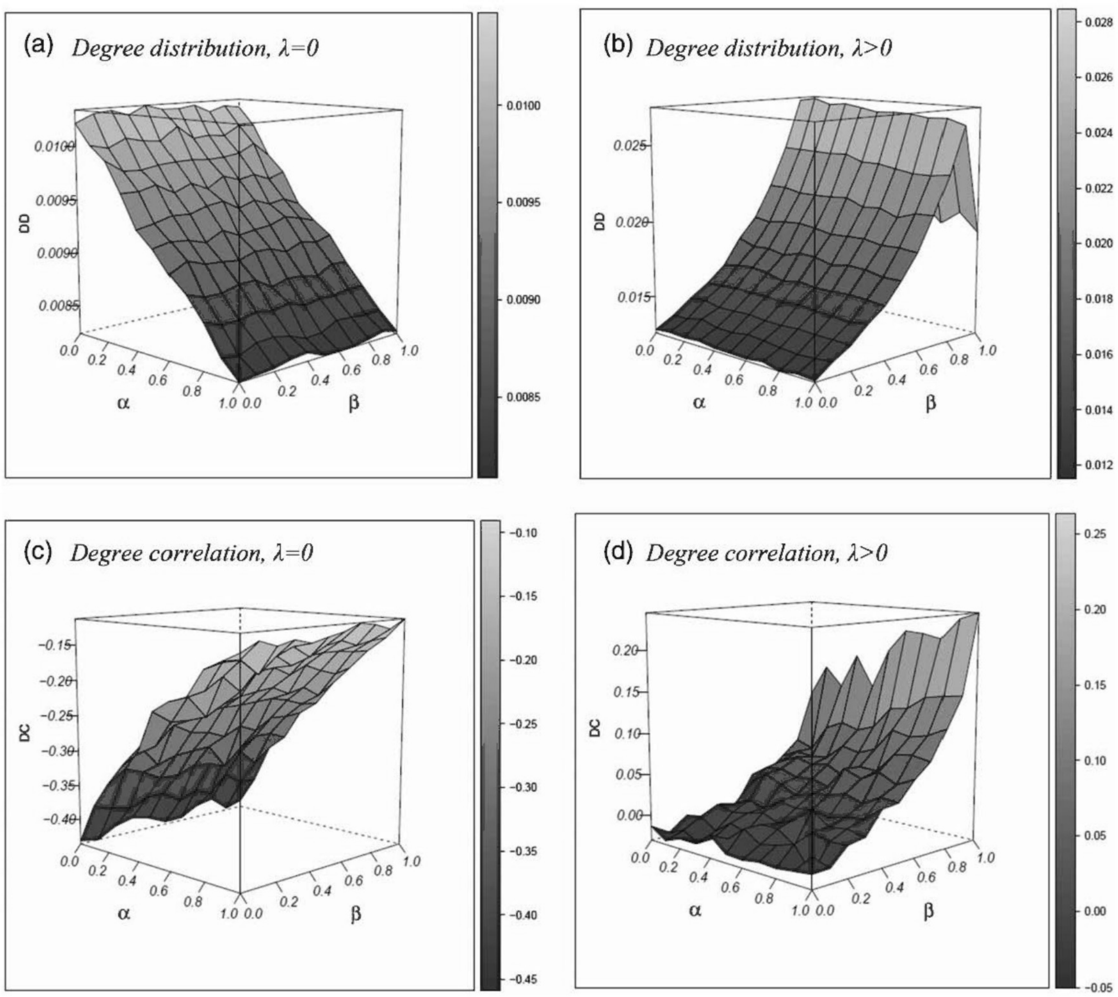

Figure 5. Degree distribution and correlation.

($\lambda > 0$), two main changes appear (Figure 5(d)). 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, that is, 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 parameter settings on the population dynamics (M and r), and different initial conditions of the network.

5. Discussion

Which implications on cluster policy design can we draw from these results? 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). In particular, 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, the simulation results 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 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. This should help the cluster to reach the maturity stage by developing focal points and positive synergies (Menzel and Fornahl 2010). 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 5(b) 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 2015), weakening their ability to produce well-performing dominant design (Crespo, Suire, and Vicente 2015). At the same time, the capacity of clusters to produce tradable technological standard 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 observed in many high-tech clusters and networks (Aoki and Takizawa 2002; Balland, Suire, and Vicente 2013). For that purpose, Figures 5(b), 4(a) and 4(b) 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. This secures the control of knowledge integration around a couple of leading organizations. Additionally, under the same closure threshold, networks' clustering increases and networks' internal reachability remains high. 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 dominant designs on markets.

Secondly, in contrast, when clusters have 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 capabilities of structural change of clusters. They should provide incentives that allow clustered organizations to overlap mature and emerging markets. As a 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 weakens 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 5(b) and (d), under a threshold where networks remain connected, clusters 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 2015), incentives oriented toward connections by preferential attachment and bridging behaviors should be preferred. They will avoid conformism in clusters core component, regenerate it, and favor 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) evidences 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, because 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 cluster 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 past 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 to engender 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 simulation model for that purpose, our findings offer imperfect but promising perspectives to better grasp the reasons why some clusters perform better than others in 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, King, and Juda 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, Bell, and Tracey 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 affect such an ossification process, in particular in the growing phase of clusters. Rewiring by closure complements this process. It improves 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. Thus, it 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, network-brokers matter (Goyal and Vega-Redondo 2007; Buskens and van de Rijt 2008). They will help clusters reaching more disassortative structures of knowledge interactions, which is a crucial condition of their self-sustaining growth path. Therefore, identifying potential knowledge brokers in mature clusters remains one the most important challenges for an expected higher economic return of cluster policies. For that, public collaborative incentives should be based on a robust expertise of the phase of the technological cycle and the related supporting cluster structure. Such an expertise will allow policy-makers being smarter when dealing with incentives for explorative and reinforcing ties, in order to boost together cluster efficiency and renewal capabilities.

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, cluster 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.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work is part of a project granted under the Open Research Area in Europe for the Social Sciences (ORA): *'Territories and technologies in an unstable knowledge economy: An evolutionary framework of regional resilience'*. We would like to thank the ANR (France), NOW (Netherlands), ESRC (UK) and DFG (Germany) for funding this project. This work has also received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement number 320131: SmartSpec-Smart Specialization for Regional Innovation.

Notes

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, King, and Juda (2007) fails in finding such evidence.
3. Scale-free networks echo one of the forgotten results of Milgram experiments in small-world analysis: the role of super-connectors.
4. Some authors have shown that thresholds in the small worldness may exist (Uzzi and Spiro 2005).
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.
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.
9. When β goes from 0.9 to 1, the increase in clustering coefficient accelerates. Once again, the splitting of the network of several components explains this pattern.
10. When rewiring strategies are not considered ($\lambda = 0$, not displayed here), no triangles can appear and so clustering is 0.
11. Degree distribution is computed in absolute terms, so higher (lower) values mean more (less) hierarchical networks.
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 into several components.
13. Recall that assortative networks are characterized by positive degree correlation. Disassortative networks are characterized by negative degree correlation.
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 Fitjar and Rodríguez-Pose (2011) and Balland, Suire, and Vicente (2013).

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