Learning and Structural Properties in Small Firms' Networks: A Computational Agent-Based Model

Luca Iandoli
Dept. of Business and Managerial Engineering, University of Naples Federico II
Piazzale Tecchio 80, 80125, Naples, Italy
fax: +390817682154, phone: +390817682935, e-mail: iandoli@unina.it

Elio Marchione
Dept. of Business and Managerial Engineering, University of Naples Federico II
Piazzale Tecchio 80, 80125, Naples, Italy
Phone: +390817682935, fax: +390817682154, e-mail: eliomarchione@katamail.com

Cristina Ponsiglione
Dept. of Business and Managerial Engineering, University of Naples Federico II
Piazzale Tecchio 80, 80125, Naples, Italy
Phone: +390817682956, fax: +390817682154, e-mail: ponsigli@unina.it

Giuseppe Zollo
Dept. of Business and Managerial Engineering, University of Naples Federico II
Piazzale Tecchio 80, 80125, Naples, Italy
Phone: +390817682483, fax: +390817682154, e-mail: giuzollo@unina.it

Abstract

This paper explores how structural properties of small firms' networks emerge from the ways firms exchange knowledge. In particular we are interested in analysing if and under which conditions the need for knowledge exchange within a set of co-located small firms is able to generate a more or less stable structure of links among firms. We focus on a specific kind of small firms' networks called Industrial Districts (IDs). One of the peculiar characteristics of IDs is flexible specialization: small firms specialize in given phases of the production processes and join up production chains in a flexible and dynamic way depending on market opportunities. Consequently, knowledge exchange is mainly related to the matching of complementary know-how and competencies. To explore the relationship between the exchange of complementary knowledge assets and network structure we developed a computational model of an ID. The results obtained through computer simulations of the model show that the exchange of complementary knowledge assets is able to generate stable networks and that, even with different conditions, such networks evolve toward a hub and spoke configuration with a few firms becoming key actors in the network.

JEL classification codes: L14, M15
Keywords: small firms' networks, knowledge exchange, computational agent-based model

1. Industrial Districts as Complex Inter-organizational Networks

The notion of an Industrial District (ID) was introduced by Alfred Marshall in 1919; he identified within the concept of external economies a crucial factor of competitiveness for local systems of specialized small and medium sized enterprises. Becattini (1979) identified the ID as an elementary and autonomous unit of analysis. In the relevant literature flourishing in the '70s and '80s (Aydalot 1986; Becattini 1989; Brusco 1982; Camagni 1989; Rullani 1992) IDs are characterized by two central properties:

- ID's structure is based on a dense and strong network of relationships among autonomous and heterogeneous actors (firms, families, local institutions);
- ID's competitiveness is the result of the co-evolution of district's productive organization and local formal and informal institutions.

Piore and Sabel (1984) emphasized that the ID model is an example of a production model characterized by flexible specialization and by the capability to compete with large integrated enterprises. This approach focuses on transactions related to productive interdependence of district's firms rather than on ID's informal coordination mechanisms such as values and culture. However, the transactional approach (Coase 1937; Williamson 1975) has shown to be inadequate to explain the complex nature of the embedded inter-organization and social processes characterizing small firms' clusters (Uzzi 1996). Instead ID's development is based on a strong relation between production and social systems, spontaneous and informal transactions, sharing norms, frameworks of references, cultural rules, reciprocity and trust. In order to study the structure, the nature and the dynamics of relations that evolve inside IDs, it is necessary to design a more appropriate theoretical approach that enables to take into account the importance of institutional factors (norms, values, culture, routines).

The social network perspective, though acknowledging the relevance of transaction economics, emphasizes the cultural and institutional basis of inter-firms' relationships (Granovetter 1985; Powell 1991). According to this perspective, the ID is framed as a social network including firms, the latter are embedded in a social context and they strictly influence their business performances and their behaviour (Inkpen and Tsang 2005). A key characteristic of social-organizational networks is the privileged access to knowledge resources for members of the network (Podolny and Page 1998); specific and rare knowledge resources are created thanks to the strong capability of network's actors to exchange and combine knowledge assets.

Both traditional quantitative methodologies and social network analysis have been employed to find determinants of knowledge exchange in small firms' clusters and in IDs. However, traditional social science methodologies are unable to explain the dynamic emergence of knowledge-based networks in small firms' clusters and of their structural properties from the analysis of the bottom-up interactions of multiple co-located firms. In particular, while research on networks has, widely explored how networks' structural properties influence knowledge flow in clusters (Cowan and Jonard 2004), there is a lack of studies about how and if knowledge exchange can dynamically originate a stable network configuration. The main research questions we aim to answer in this paper are the following:

1) Can local knowledge exchange give rise to a stable network? More specifically, is knowledge complementariness, a recurring characteristic in partnerships in IDs, a sufficient reason to explain the emergence of a stable network?
2) Which are the structural properties of knowledge networks generated by the exchange of complementary knowledge assets?

In the next section we provide a review of previous works about knowledge flows in Industrial Networks. Then we present a computational agent-based model of an ID in which heterogeneous and autonomous agents trade complementary knowledge assets and build network relationships. Finally, results of several computer simulations to answer the above research questions are presented. In conclusion, limitations and potential of the computational approach to the analysis of small firms' clusters as well as implications for research and policy making are discussed.

2. Knowledge Flows in Firms Networks

Firms' networks are locus for innovation and knowledge creation (Podolny and Page 2000). Firms' networks involve "a selected, persistent, and structured set of autonomous firms engaged in creating products or services based on implicit and open-ended contracts to adapt to environmental contingencies and to coordinate and safeguard exchanges" (Jones et al. 1997).

A firms' network is made by a collection of (often small) autonomous actors that pursue repeated and enduring reciprocal exchanges aimed at creating products or services for final markets. The term "structured" in the definition proposed by Jones et al. (1997) means that exchanges among firms are not random but reflect specific coordinated patterns and shared rules for labour division. Repeated, enduring and structured relationships are the main rationale behind the capability of networks to spread and diffuse knowledge among their members. Relationships taking place in small firms' networks are characterized by "embeddedness" (Uzzi 1996). Embeddedness means that social relations affect and shape the economic and productive behaviour of network members; thanks to embeddedness, actors in a network can safeguard their exchanges using implicit and incomplete contracts (Jones et al. 1997). The social embeddedness of ties among firms in a network fosters information transfer and the creation of novel knowledge through trust and reciprocity (Podolny and Page 2000), but can increase the network inertia in regards to innovation and change.

Networks can be also seen as structure providing specific patterns of interactions facilitating transfer, diffusion and creation of knowledge. According to Kogut (2000), a network is itself "knowledge" because it is guided by stable and enduring principles of organization.

From a social network theory perspective, research on networks has widely explored the problem of how structural properties of the (such as density, position of specific nodes, pesence of hubs or of structural holes, presence of cliques, strength of ties) affect the efficiency and efficacy of knowledge exchange as well as learning performance of individual firms and of the network as a whole (Dhanaraj and Parkhe 2006; Cowan and Jonard 2004; Inkpen and Tsang 2005; Podolny and Page 2000; Tsai 2001; Uzzi 1996). By exploiting the concept of scale-free networks developed by Watts and Strogatz (1998), Cowan and Jonard (2004) developed a computational model to analyze the relationship between network architecture and knowledge diffusion performance and, specifically, how network topology influences knowledge sharing performances. In this paper we start from Cowan and Jonard's model, but following the opposite perspective: can local knowledge exchange give rise to a stable network? Is knowledge complementariness between firms a sufficient reason to explain the emergence of a stable network? These questions are particularly relevant for IDs, in which the complementariness of knowledge assets between firms, through flexible specialization, is a major economic explanation for ID emergence (Piore and Sable 1984).

In order to answer these questions in the following we introduce an agentbased model of ID. Agent based models have been largely employed for the analysis of Complex Adaptive Systems, i.e. systems characterized by intense local interaction among heterogeneous agents provided with bounded rationality, absence of central control, and continual adaptation (Arthur et al. 1997). These properties also characterize IDs, as shown by some studies on IDs, firms' clusters and supply chains (Fioretti 2001; Boero and Squazzoni 2001; Strader et al. 1998; Pèli and Nooteboom 1997).

According to the agent-based approach, a possible way of explaining the emergence of macroscopic regularities in social systems is to answer the following question (Epstein and Axtell 1996): "Is it possible to generate observed macro-regularities at the collective level from micro-specifications governing local and de-centralized interactions of autonomous and heterogeneous agents?" A possible way to answer this question is to simulate through a computer model the interaction of autonomous agents provided with bounded rationality within a virtual environment bearing both resources and constraints. In the following section we present an agent based model of a network of firms involved into trading of complementary knowledge.

3. A Computational Model of an Industrial District

Our model is similar to the one proposed by Cowan and Jonard (2004), but it differs for one fundamental reason: the Cowan and Jonard model assumes the topology of the network as a given and assess how structural properties affects information exchange into networks. We instead assume the opposite perspective: given certain kind of information exchange among agents, we want to discover if they are able to set up stable networks and which structural characteristics such networks show.

Cowan and Jonard show that small world networks, i.e. networks in which a few hubs act as shortcuts between many spokes-agents, achieve the best performance in terms of network average knowledge level as well as satisfying results in terms of knowledge diffusion speed. The price to pay is inequality in knowledge distribution: a few agents in the network will become key players by accumulating disproportionately more knowledge than others (the so-called "rich gets richer" phenomenon).

In our model the network topology is not assumed. Instead we allow a set of agents with complementary knowledge assets to trade with each other, while they also establish links among them as soon as a reciprocal exchange of complementary knowledge assets is possible. Our aim is to observe the network dynamics during repeated interactions and check if and under which conditions a stable network emerges. As for any Agent Based model, the simulation has two aims: 1) to explain the occurrence of aggregate regularities on the base of assumptions about individual firms' behaviours; 2) to observe the emergence of possible unexpected consequences.

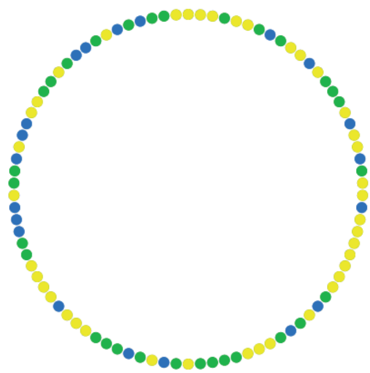
In the following sections we describe the main modelling decisions and the components of the model.

Time & Space

Simulation time is given by an internal clock defining simulation cycles during which the agents interact. The model can be run through several iterations until either equilibrium is achieved or a certain state is reached, depending on the objectives of the simulation.

Firms are represented through a set of agents characterized in terms of behavioural rules. The model has been implemented using NetLogo® software, freely downloadable social simulation software developed by Northwestern University. The model is available and can be run on-line at the following web-site http://ccl.northwestern.edu/netlogo/community/models/cluster. In the NetLogo graphical interface the agents are arranged into a circle where different colours represent certain types of agents (Figure 1).

Figure 1. Graphical Representation of the Cluster through NetLogo Interface



Source: Authors' illustration, NetLogo

A major simplification in the model is that the network is a closed system in which external firms cannot enter. Though this represents a limitation of the model, in stable phases of their existence IDs can be assumed as closed systems because of a low rate of entrants and a high level of embeddedness of existing links.

Agents

Agents in our model represent cluster's firms. To agent j-th is associated a vector of knowledge assets:

$$Kj = [c_{j1}, c_{j2}, \dots, c_{jn}]$$

where each dimension c_{ji} represents the knowledge level achieved by the firm j-th in the i-th asset. Knowledge levels are measured through real positive numbers in the interval [0,100]. In our model we set n=3. Consequently, firms can belong to one out of three classes, depending on their specialization in one of the assets. In our model there are 90 firms of which 30 are final firms (yellow circles) specialized in c1, 40 are direct suppliers firms specialized in c_2 (green circles), and 20 are second level suppliers (blue circles) specialized in c_3. These proportions roughly reflect the firm's distributions in real IDs characterized by flexible specialization.

At the beginning of the simulation each firm is assigned a random value in the interval [20, 100] for the knowledge asset the firm is specialized in and the value 10 for the other two assets. Consequently, the knowledge vectors have been assigned as follows:

- Yellow firms → $K = [c_1, c_2, c_3]$ = [20 + random 80, 10, 10]
- Green firms → $K = [c_1, c_2, c_3]$ = [10, 20 + random 80, 10]
- Blue firms → $K = [c_1, c_2, c_3]$ = [10, 10, 20 + random 80]

Each agent is also assigned a certain value of absorptive capacity (AC). Cohen and Levinthal (1989) assume that knowledge spillovers from one firm to another can happen to the extent to which a firm can interiorize and appropriate knowledge. This ability ultimately depends on the firm's absorptive capacity. AC is a function of the knowledge a firm already possesses and is ultimately influenced by factors such as the amount of R&D activities and investments in knowledge assets and human capital. Morrison (2005) points out the path dependency of AC: as companies increase their knowledge stocks they also are more and more aware of their knowledge needs and able to find and connect with relevant external sources of knowledge. In other words, AC involves both internal and external learning. Since AC is a function of existing specific knowledge we associate to each firm a three-dimensional vector A-C = [a-c1, a-c2, a-c3], whose elements, assuming values are in [0,1], represent the AC associated to the i-th knowledge asset. A simple way to model the dependency of a-ci from existing knowledge is to assume a direct proportionality in the following way: a-c1 = c1 / 100, a-c2 = c2 / 100, a-c3 = c3 / 100.

At the beginning of the simulation each agent is given a certain knowledge level depending on its specialization and, consequently, a certain a-ci. During the simulation, knowledge levels can increase or decrease under the influence of learning and obsolescence. In the model learning happens in two possible ways: internal and external. Internal learning is directly influenced by R&D activities or experience (learning by doing) while external learning is due to interactions with external knowledge sources, i.e. other firms in the model (learning by interacting).

Firms are allowed a maximum number of outgoing links L. This is a reasonable assumption since interaction involves transaction costs; in particular, small firms can manage only a limited number of partners at the same time, though they can build relations with many partners during their lifetime. By limiting the number of simultaneous partners we also force firms to choose among possible partnership alternatives.

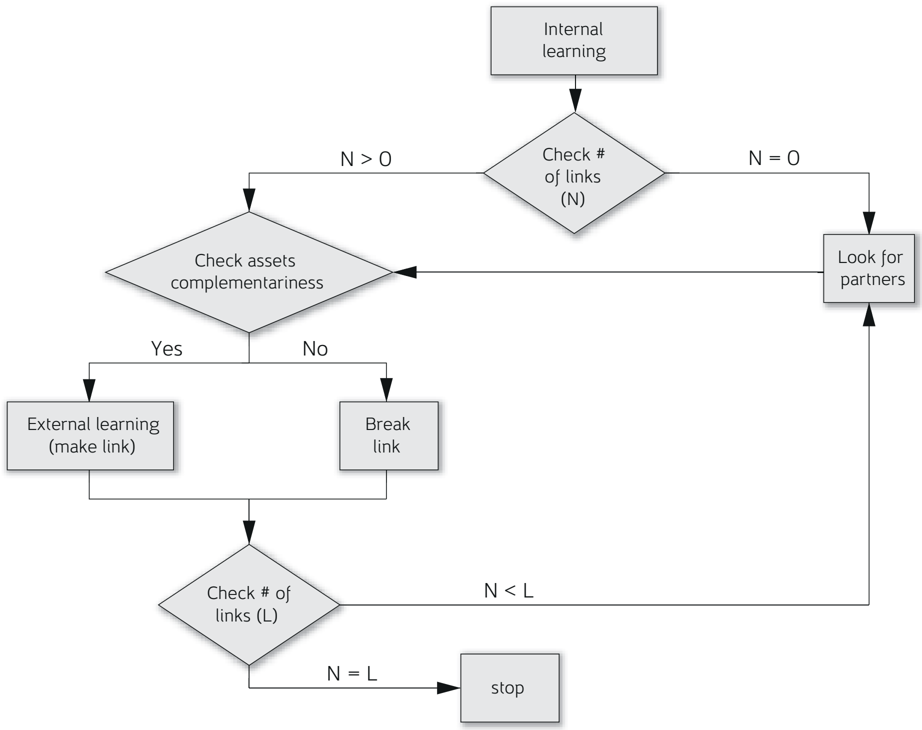
Network Construction

Figure 2 reports a flow chart describing how firms make decisions about building or breaking links in the cluster. All firms contribute to the creation of links among them through the following steps:

1. **Internal learning:** each firm increases the value of the knowledge it is specialized in of an amount equal to its AC in that knowledge. Consequently at time t+1 firms knowledge evolves in the following way:

Final firms (yellow)	→	c1(t + 1)= c1(t) + a-c1
		c2(t + 1)= c2(t)
		c3(t + 1)= c3(t)
Direct suppliers (green)	→	c1(t + 1)= c1(t)
		c2(t + 1)= c2(t) + a-c2
		c3(t + 1)= c3(t)
2nd level suppliers (blue)	→	c1(t + 1)= c1(t)
		c2(t + 1)= c2(t)
		c3(t + 1)= c3(t) + a-c3

Figure 2. Network Building Flow Chart



Source: Authors' illustration

2. **Check links:** each firm checks for the number N of active links. If N=0 the firm starts looking for a partner by picking another firm at random. If complementariness between knowledge assets exists, the two firms establish a link. If N>0 the firm checks for complementariness among the existing partners and will either confirm or break existing links. The process stops when the number of links achieves the maximum allowed value L. It is important to remark that L is a limitation only for the outgoing links, thus the overall number of links for a firm can be higher than L if there are enough incoming links from other partners.

3. **External learning.** External learning takes place through the same mechanism proposed by Cowan and Jonard, i.e. through knowledge reciprocal transfer from two firms having complementary knowledge assets, as in a bartering system. The knowledge gain is determined in the following way:

$$gain = a\text{-}ci^*(-0.04^*\Delta 2 + 0.4^*\Delta) \text{ if } \Delta < 100, 0 \text{ otherwise}$$

where Δ is the absolute value of the knowledge gap for ci. This quadratic function models the nonlinearity of the learning growth. It has a maximum when $\Delta = 50$ and drops to zero when

$\Delta = 100$, since no barter can happen if the knowledge gap is too high. Finally, the amount of bartered knowledge is limited by the absorptive capacity a-ci.

Let's consider the following example. Given two firms A and B such that A dominates over B with respect to c1 and B dominates over A with respect to c2. After the exchange firm A will increase c2 by an amount equal to:

(a-c2)*((-0.004*(c2-of B - c2-of A)2) + (0.4*(c2-of B - c2-of A)))

while firm B will increase c1 in the following way:

(a-c1)*((-0.004*(c1-of A - c1-of B)2) + (0.4 *(c1-of A - c1-of B)))

Obsolescence

In order to balance the learning effect that would imply a continuous growth of knowledge levels in each iteration, an "unlearning effect" has been introduced. Knowledge levels are decreased in each iteration of an amount equal to the obsolescence rate. This is modelled through a parameter obs ranging form 0 to 1 and assumed to be a constant. So knowledge levels will decrease with a constant pace after each cycle and firms who are not able to counterbalance this effect through learning will terminate.

4. Results

The model simulation was run with the initial conditions specified above. To measure the behaviour of the system the following variables have been observed:

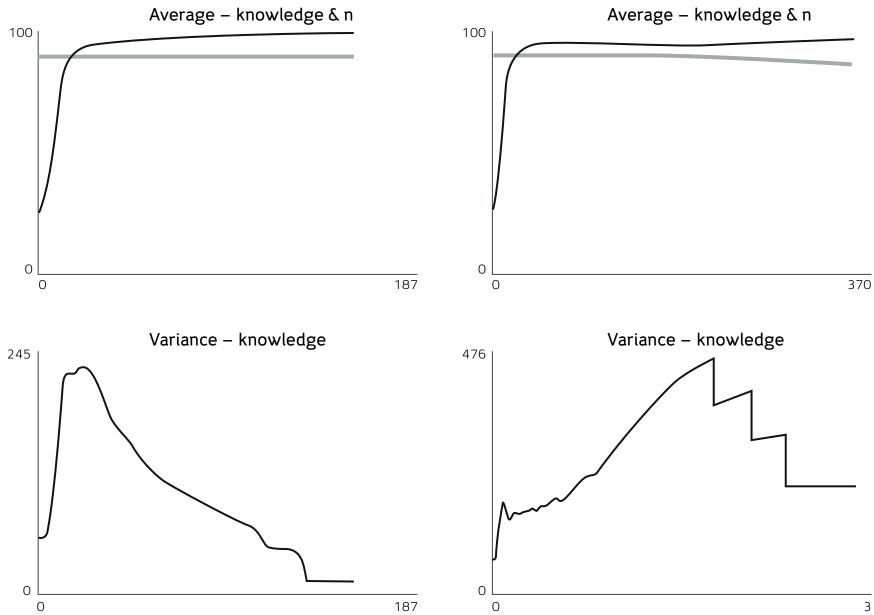
- N, number of surviving firms;
- Firm knowledge-level, level of knowledge achieved by a single firm computed as the arithmetic mean of the 3 knowledge levels K = (c1 + c2 + c3)/3;
- Network average-knowledge, computed as the mean value achieved by all firms in the cluster;
- Variance-knowledge: variance of the knowledge levels within the cluster;
- A-C, average value of the absorptive capacities of the firms in the cluster (the absorptive capacity of a firm is computed as the arithmetic mean of the a-ci).

To evaluate the structural properties of the emerging networks we used the following variables:

- Degree-distribution: statistical distribution of the number of links per agent.
- Network-density: relational density of the network represented as cliquishness (ratio between existing relationships and the number of all possible elationships D = 2l/(n*(n - 1)), where l is the number of existing links and n is the number of nodes in the network.
- Network Clustering-coefficient: average value of the clustering coefficients of each node. For the node Cj the clustering coefficient is given by Cj=2Ej/(kj (kj- 1)) where kj is the number of possible edges connecting Cj with its neighbours and Ej is the number of existing edges with the neighbours.

In each simulation and for different values of the obsolescence rate the model achieved a stable performance in terms of Network average knowledge, though with a slower pace in the high obsolescence situation (Figure 3, top).

Figure 3. Average knowledge level and knowledge variance achieved by the system with low and high obsolescence rate (respectively obs=0.1 left and obs=0.9 right)



Source: Authors' illustration

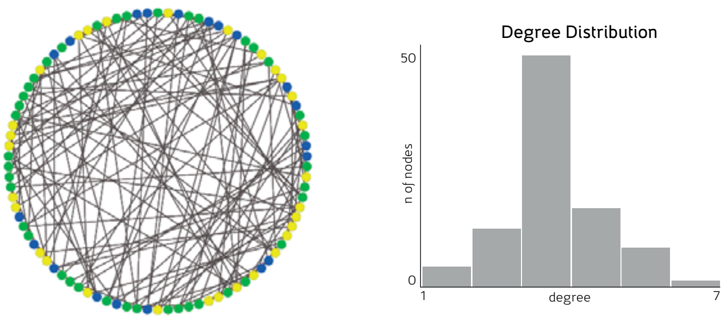
This result can be interpreted in terms of the cluster ability to effectively react to changes and achieve satisfying performances. While in the high obsolescence case a significant drop in performance was expected, the system was actually able to recover the same knowledge level, though it needed a longer recovery time and with less survived firms. This flexibility is a typical characteristic of IDs, especially when firms experience difficulties to innovate or rethink their market position; many IDs success stories show that in these situations IDs go through a selection process arter which a few firms survive and remain competitive.

The bottom of Figure 3 shows another interesting result: the variance of firms knowledge levels drops to very low values when obsolescence is low while it is higher when the obsolescence is moderate or high. In the low-obsolescence case knowledge becomes a commodity and all firms achieve the same level of knowledge like in perfect competition markets. In the moderate/high obsolescence case, instead, the system is able to preserve a certain level of internal diversity like in monopolistic competition markets. Finally, when the obsolescence rate is near to 1, only few similar firms are able to survive and the knowledge variance is again low, lie in an oligopoly.

The simulation produced interesting results with respect to the structural properties of the networks emerging from knowledge exchange between firms. With reference to our first research question (Is knowledge complementariness a sufficient reason to explain the emerging of a stable network?) the answer is affirmative. In all simulations we observed the emergence of a stable network of exchange (fig. 4, left). The final network configuration was achieved by the system in a two stage process: in the first stage, roughly corresponding to the ascending part of the network knowledge curve in fig.3 the firms in the cluster were busy in rewiring their connections in the attempt to find the best partners among the available ones. In the second stage, instead, firms consolidated and stabilized their links and as the whole Network evolved toward the equilibrium.

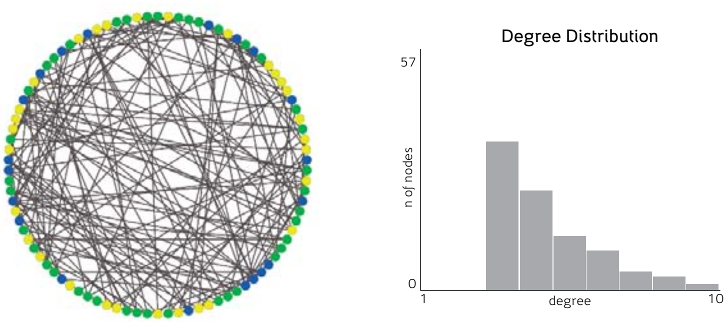
To answer to our second research question (Which are the structural properties of knowledge networks generated by complementary knowledge assets?), we plotted the statistical distribution of the number of links per agent, like in Figure 4 and 5.

Figure 4. Statistical distribution oflinks per agent (random network, normal distribution)



Source: Authors' illustration, NetLog

Figure 5. Statistical distribution of links per agent (scale free network, power law distribution)



Source: Authors' illustration, NetLog

For any value of the obsolescence rate, in the first phase of the simulation the network assumed a random structure with a normal distribution of links, but eventually always evolved at the equilibrium into a hub and spoke network topology, characterized by a few agents (hubs) that are largely more connected than others (spokes). The link distribution in hub and spoke networks, also known as small world or scale free networks, follows a power law curve.

Which are the characteristics of the hub-firms? Interestingly enough, the hub firms achieved intermediate knowledge performances compared to the overall network when the obsolescence was moderate to high (high knowledge variance). In this case they acted as brokers connecting high and low performance firms. Instead, they achieved the top knowledge performances in the opposite cases of low or very high obsolescence.

How certain firms become hubs? By observing the evolution of the Network nodes that eventually became hubs, we noticed that the firms having the highest number of links at the beginning of the simulation had the highest chance to become hubs at the equilibrium. This behaviour is due to a typical mechanism of scale-free networks known as preferential attachment (Barabasi, 2002), according to which nodes that are more connected are more attractive than less connected ones. The implication for firms clusters is that those firms with higher relational capital have a greater chance to become leading firms in the cluster.

5. Conclusions

In this paper we use agent-based modelling to represent and analyze the behaviour of clusters of firms. Previous research works on firms' networks can be roughly classified in two major streams: studies in the first stream assume the network as a given and concerned with the measuring of network properties and performances; works in the second stream use traditional statistical methods to find out the determinants of the network. Our objective instead was to explore the process through which networks are built and emerge from interactions among heterogeneous and autonomous agents. In particular we focused our attention to knowledge exchange in the assumption of complementariness between firms' knowledge assets, as it happens in Industrial Districts whose coordinating mechanism is based on flexible specialization. Our next research step is to test, for the proposed model, the ability to predict network structure of real IDs.

The possibility to observe the processes through which social aggregates are formed, represents a major advantage of agent-based modelling over traditional methodologies in social sciences. Like narrative or qualitative methods, agent-based models can be used to provide causal accounts of collective phenomena, but additionally they offer the rigour and the objectivity of traditional quantitative methodologies. A second advantage of agent-based modelling is that it provides researchers with a virtual lab where generative experiments can be performed to test if specific assumptions about individual agents behaviour are sufficient conditions to generate the expected emergence of aggregate regularities.

The sufficiency of explanation is a major limitation of this methodological approach. A second major limitation of agent-based models is that they can implement extremely simplified representation of the reality they intend to model. However, it is important to stress that the use of agent-based models for predictions or simulation of a real systems' behaviour can hardly be successful when the complexity of the systems is too high to be captured by analytic yet tractable representations. Agent-based modelling is instead to be used for purposes that go beyond the "representational" trap, namely for theory testing and building purposes. Being extremely reductionist, this approach can help researchers to reflect on and find out the critical relevant variables in the elaboration of a theory. Computationally, agent-based modelling can be used to see theories in action, e.g. to observe incoherence or unexpected consequences of a theory. Finally, as with any theory, a computationally generated theory can be evaluated on the basis of traditional epistemic criteria such as its explanatory power.

In agent-based models there is considerable value added in the same process of model construction since computation enhances the traditional learning process through which researchers learn from their errors, through early, "quick and dirty" implementation and simulation of models.

There are several warnings. First there is a risk of developing tautological models, i.e. models containing argumentative loops in which at least some of the hypotheses to be tested may be actually hidden assumptions. Second, the representational trap can induce the building of very complex models characterized by too many parameters whose robustness and relevance is hard to assess.

The results produced by agent-based modelling can be used to construct hypothesis to be tested through traditional empirical investigation. In the ID's case, for instance, one can investigate in more depth the characteristics and properties of hub firms or about how absorptive capacity is influenced by structural properties of the network.

Agent-based models can have interesting implications for managers and policy making. Again, their power is not in simulating reality to make predictions, but to help managers and policy-makers to observe the coherence of certain choices, their potential unexpected consequences as well as to find creative ways to deal with specific problems thanks to a deeper understanding of them. For instance, the results produced by the model presented in this paper show that in scale free networks it makes much more sense to develop selective policies to support and develop hubs or favour the emergence of brokers rather than promote undifferentiated interventions on the whole cluster population.

References

Arthur, W.B., S.N. Durlauf, and D.A. Lane (eds). 1997. The Economy as an Evolving Complex System. Redwood (CA): Addison-Wesley Longman.

Aydalot, P. (ed). 1986. Milieux Innovateurs en Europe – Innovative Environments in Europe, Paris, Université de Paris I Sorbonne, GREMI - Groupement de Recherche sur les Milieux Innovateurs en Europe.

Barabasi, A.L. 2002. Linked: How Everything Is Connected to Everything Else and What It Means. Penguin Group.

Becattini, G. 1979. Dal settore industriale al distretto industriale. Alcune considerazioni sull'unità di indagine dell'economia industriale. L'Industria, No. 1.

Becattini, G. 1989. Riflessioni sul distretto industriale marshalliano come concetto socio economico. Stato e Mercato, 25, 111–128.

Boero, R. and F. Squazzoni. 2001. A Computational Prototype of Industrial District. Workshop on Complexity and Industrial Districts, Università di Modena e Reggio Emilia.

Brusco, S. 1982. The Emilian Model: Productive Decentralisation and Social Integration. – *Cambridge Journal of Economics*, 6, 167–184.

Camagni, R. 1989. Cambiamento tecnologico, milieu locale e reti d'imprese: verso una teoria dinamica dello spazio economico. Economia e Politica Industriale, 64, 209-236.

Camagni, R. 1991. Local Milieu, Uncertainty and Innovation Networks: towards a New Dynamic Theory of Economic Space. In: Camagni, R. ed. Innovation Networks: Spatial Perspectives. London: Belhaven Press.

Coase, R. 1937. The Nature of the Firms. – *Economica*, 4(16), 386–405.

Cohen, W. and D. Levinthal. 1989. Innovation and Learning: The Two Faces of R&D. – *Economic Journal*, 99, 397, 569–596.

Cowan, R. and Jonard, ?. 2004. Network Structure and the Diffusion of Knowledge. – *Journal of*

Economic Dynamics & Control, 28, 1557–1575.
Dhanaraj, C. and Parkhe, ?. 2006. Orchestrating Innovation Networks. Academy of Management Review. 31, 3, 659-669.
Fioretti, G. 2001. Information Structure and Behaviour of a Textile Industrial District. – *Journal of Artificial Societies and Social Simulation*. 4 (4).
Granovetter, M. 1985. Economic Action and Social Structure: The Problem of Embeddedness. – *American Journal of Sociology*, 91, 3, 481–510.
Jones, C., W.S. Hesterly, S.P. Borgatti. 1997. A General Theory of Network Governance: Exchange Conditions and Social Mechanisms. – *The Academy of Management Review*, 22, 4, 911–945.
Inkpen, A. C. and E.W.K. Tsang. 2005. Social Capital, Networks, and Knowledge Transfer. – *Academy of Management Review*, 30, 1, 146–165.
Kogut, B. 2000. The Network as Knowledge: Generative Rules and the Emergence of Structure. – *Strategic Management Journal*, 21, 405–425.
Marshall, A. 1919. *Industry and Trade,* London, MacMillan.
Piore, M.J. and C.F. Sabel. 1984. *The Second Industrial Divide: Possibilities for Prosperity*, New York, Basic Books.
Péli, G. And B. Nooteboom. 1997. Simulation of Learning in Supply Partnership. *Computational and Mathematical Organization Theory*, 3(1), 43–66.
Podolny, J. M. and K.L. Page. 1998. Network Forms of Organization. – *Annual Review of Sociology*, 24, 57–76.
Powell, W.W. 1991. Expanding the Scope of Institutional Analysis. In: Powell, W.W. and Di Maggio, P.J. eds. *The New Institutionalism in Organisational Analysis*, Chicago: The University of Chicago Press, 183–203.
Rullani, E. 1992. Networks and Internationalization: Managing Complexity through Knowledge. In: L. Zen, S. Zambon e A.M. Pettigrew, eds. *Perspectives on Strategic Change*. Norwell (MA): Kluwer Academic Publishers.
Strader, T.J., F. Lin and M.J. Shaw. 1998. Simulation of Order Fulfillment in Divergent Assembly Supply Chain. – *Journal of Artificial Societies and Social Simulation*, 1(2).
Tsai, W. 2001. Knowledge Transfer in Intraorganizational Networks: Effects of Network Position and Absorptive Capacity on Business Unit Innovation and Performance. – *Academy of Management Journal*, 44, 5, 996–1004.
Uzzi, B. 1996. The Sources and Consequences of Embeddedness for the Economic Performance of Organizations. – *American Sociological Review*, 61, 674–698.
Watts, D.J. and S.H. Strogatz. 1998. Collective Dynamics of ‘Small-world’ Networks. Nature.
Williamson, O. E. 1975. Markets and Hierarchies: Analysis and Antitrust Implications, New York: The Free Press.