Adaptive capacity of geographical clusters: Complexity science and network theory approach

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This paper deals with the adaptive capacity of geographical clusters (GCs), that is a relevant topic in the literature. To address this topic, GC is considered as a complex adaptive system (CAS). Three theoretical propositions concerning the GC adaptive capacity are formulated by using complexity theory. First, we identify three main properties of CASs that affect the adaptive capacity, namely the interconnectivity, the heterogeneity, and the level of control, and define how the value of these properties influence the adaptive capacity. Then, we associate these properties with specific GC characteristics so obtaining the key conditions of GCs that give them the adaptive capacity so assuring their competitive advantage. To test these theoretical propositions, a case study on two real GCs is carried out. The considered GCs are modeled as networks where firms are nodes and inter-firms relationships are links. Heterogeneity, interconnectivity, and level of control are considered as network properties and thus measured by using the methods of the network theory.

1 Introduction

Geographical clusters (GCs) are geographically defined production systems, characterized by a large number of small and medium sized firms that are involved at various phases in the production of a homogeneous product family. These firms are highly specialized in a few phases of the production process, and

integrated through a complex network of inter-organizational relationships [Porter 1998].
The literature on GCs is quite rich and involves different streams of research, such as social sciences, regional economics, economic geography, political economy, and industrial organization. Referring to this literature, studies have mainly provided key notions and models to explain the reasons of GC competitive success [Krugman 1991; Maillat et al. 1995; Marshall 1920; Sabel 1984]. However, in the recent competitive context the foregoing studies do not explain why some GCs fail and some other not and why some GCs evolve by assuming different structures to remain competitive and other not. They in fact adopt a static perspective to analyze GCs restricting the analysis to the definition of a set of conditions explaining GC competitive advantage in a particular context. In addition they focus on the system as a whole and not on the single components (firms), observe the phenomena when they are already happened at the system level, and describe them in terms of cause-effect relations by adopting a top-down approach.
Our intention is to overcome these limitations by adopting a different approach. We look at the GC competitive advantage as not the result of a set of pre-defined features characterizing GCs but as the result of two different capabilities, namely adaptability and co-evolution of GCs with the external environment. The high the GC adaptive and co-evolution capabilities, the high the GC competitive success. In fact, if GCs possess the conditions that allow them to adapt and co-evolve with the environment, they will modify themselves so as to be more successful in that environment. In this way, GCs have competitive advantage not because they are characterized by a set of features but because they are able to evolve exhibiting features that are the spontaneous result of the adaptation to the environment. This result is not known *a priori*, but emerges from the interactions among the system components and between them with the environment.
This approach is consistent with the perspective adopted in the paper to study GCs by using complexity science [Cowan et al. 1994], which studies the complex adaptive systems (CASs) and explains causes and processes underlying emergence in CASs. Once GCs have been recognized as CASs, CAS theory on co-evolution is used to look for GC features that allow the adaptability of GCs in "high velocity" environments [Eisenhardt 1989]. In particular, three theoretical propositions regarding GC structural conditions supporting GC adaptability are formulated.
To test these theoretical propositions, a case study on two real GCs is carried out. The considered GCs are modeled as networks where firms are nodes and inter-firms relationships are links. Heterogeneity, interconnectivity, and level of control are considered as network attributes and thus measured by using the methods of the network theory.
In the next we give a brief review of CASs, we show that GCs possess relevant properties of CASs, and based on CAS theory we derive the propositions on the GC co-evolution in "high velocity" environments. Then, we present the methodology applied to this research and the empirical evidence.

2 The complexity science approach to GC competitive advantage

Complexity science studies CAS and their dynamics. CASs consist in evolving network of heterogeneous, localized and functionally-integrated interacting agents. They interact in a non-linear fashion, can adapt and learn, thereby evolving and developing a form of self-organization that enables them to acquire collective properties that each of them does not have individually. CASs have adaptive capability and co-evolve with the external environment, modifying it and being modified [Axelrod and Cohen 1999; Gell-Mann 1994; Lane 2002].
During the 1990s, there was an explosion of interest in complexity science as it relates to organizations and strategy. The complexity science offers a number of new insights that can be used to seek new dynamic sources of competitive advantage. In fact, application of complexity science to organization and strategy identifies key conditions that determine the success of firms in changing environments associated with their capacity to self-organize and create a new order, learn and adapt [Levy 2000; Mckelvey and Maguire 1999].
Complexity science is used in this study to identify what conditions of GCs enabling them to adapt to external environment. Therefore, the basic assumption of this study is that GCs are CASs given that they exhibit different properties of CAS, such as the existence of different agents (e.g. firms and institutions), the non-linearity, different types of interactions among agents and between agents and the environment, distributed decision making, decentralized information flows, and adaptive capacity [Albino et al. 2005].
In the follow three theoretical propositions concerning the GC adaptive capacity are formulated by using CAS theory.

Interconnectivity. CAS theory identifies the number of interconnections within the system as a critical condition for self-organization and emergence. Kauffman [1995] points out that the number of interconnections among agents of an ecosystem influences the adaptive capacities of the ecosystem. He uses the NK model to investigate the rate of adaptation and level of success of a system in a particular scenario. The adaptation of the system is modeled as a walk on a landscape. During the walk, agents move by looking for positions that improve their fitness represented by the height of that position. A successful adaptation is achieved when the highest peak of the landscape is reached. The ruggedness of the landscape influences the rate of adaptation of the system. When the landscape has a very wide global optimum, the adaptive walk will lead toward the global optimum. In a rugged landscape, given that there are many peaks less differentiated, the adaptive walk will be trapped on the many suboptimal local peaks.
By using the concept of tunable landscape and the NK model, Kauffman [1995] demonstrates that the number of interconnections among agents (K) influences the ruggedness of the landscape. As K increases, the ruggedness raises and the rate of adaptation decreases. Therefore, in order to assure the adaptation of the system to the landscape, the value of K should not be high.
This result has been largely applied in organization studies to modeling organizational change and technological innovation [Levinthal 1997; Rivkin and Siggelkow 2002]. In organization studies the K parameter has an appealing interpretation, namely, the extent to which components of the organization affect each other.
Similarly, it can be used to study the adaptation of GCs, by considering that the level of interconnectivity of CGs is determined by the social and economic links among the CG firms. When the number of links among firms is high, the

behavior of a particular firm is strongly affected by the behavior of the other firms.
On the basis of the discussion above, we formulate the following proposition:
Proposition 1. A medium number of links among GC firms assures the highest GC adaptive capacity.

Heterogeneity. Different studies on complexity highlight that variety destroys variety. As an example, Ashby [1956] suggests that successful adaptation requires a system to have an internal variety that at least matches environmental variety. Systems having agents with appropriate requisite variety will evolve faster than those without. The same topic is studied by Allen [2001] and LeBaron [2001]. Their agent-based models show that novelty, innovation, and learning all collapse as the nature of agents collapses from heterogeneity to homogeneity. Dooley [2002] states that one of the main properties of a complex system that supports the evolution is diversity. Such a property is related to the fact that each agent is potentially unique not only in the resources that they hold, but also in terms of the behavioral rules that define how they see the world and how they react. In a complex system diversity is the key towards survival. Without diversity, a complex system converges to a single mode of behavior.
Referring to firms, the concept of agent heterogeneity can be associated to competitive strategy of firms. This in fact results from the resources that firm possesses and defines the behavior rules and the actions of firms in the competitive environment [Grant 1998].
Therefore, we assume that:
Proposition 2. The greater the differentiation of the competitive strategies adopted by GCs firms, the higher the GC adaptive capacity.

Level of control. The governance of a system is a further important characteristic influencing CAS self-organization and adaptive behaviors. Le Moigne [1990] observes that CASs are not controlled by a hierarchical command-and-control center and manifest a certain form of autonomy. The latter is necessary to allow evolution and adaptation of the system. A strong control orientation tends to produce tall hierarchies that are slow to respond [Carzo and Yanousas 1969] and invariably reduce heterogeneity [Jones 2000]. The presence of “nearly” autonomous subunits characterized by weak but not negligible interactions is essential for the long-term adaptation and survival of organizations [Simon 1996]. Furthermore, Granovetter’s [1973] research finding is that novelty and innovation happen more frequently in networks consisting mostly of “weak ties” as opposed to “strong ties”. The latter tend to produce group think.
The level of control in GCs is determined by the governance of the GC organizational structure. Higher the degree of governance, higher the level of control exerted by one or more firms on the other GC firms.
Therefore, we assume that:
Proposition 3. A medium degree of governance of the GC organizational structure improves the GC adaptive capacity.

3 Research methodology

The proposed theoretical propositions have been supported by the results of an empirical investigation. The empirical investigation, adopting a multiple-case study approach [Yin 1989], involves three in-depth case studies on real GCs. To address the purpose of our research we selected the GCs on the basis of their competitive advantage and we modeled each GCs as a network where firms are nodes and inter-firms relationships are links. In particular, we chosen three cases characterized by a different degree of success in the competitive scenario and by using the methods of the network theory we measured the GC structural characteristics identified in the three theoretical propositions as network attributes.

We considered two Italian Industrial districts[1]: the leather sofa district of Bari-Matera and the agro-industrial district of Foggia, both localized in Southern Italy. The leather sofa district of Bari-Matera has been analyzed in two different years, 1990 and 2000, which correspond to different stages of its life-cycle, Development and Maturity respectively [Carbonara et al. 2002].

The case studies have been preceded from an explorative phase addressed to delineate the characteristics of the considered GCs. Such phase involved two stages: 1) the collection of data and qualitative information from the firm annual reports and the relations of Trade Associations and Chambers of Commerce; 2) the survey of the firms operating in the two GCs, based on the Cerved database (the electronic database of all the Italian Chambers of Commerce).

The analysis of data collected during stage one has been addressed to evaluate the competitive performance of the three cases. In particular, for each case we measured the percentage ratio between export and turnover (Table 1).

Through the survey it has been possible to define the dimension of the considered GCs in terms of number of firms.

Successively, a sample of firms has been selected within each GCs. A reputational sampling technique [Scott 1991] has been used rather than a random one. To do this, we asked a key GC informant to select a sample of firms based on their reputations as both main players of the GC and active players in the network. This sampling technique ensures to identify a sample of firms that better represents the population.

The three networks that model each considered GCs are: 1) the network of the agro-industrial district of Foggia; 2) the network of the leather sofa district of Bari-Matera in the Development stage; 3) the network of the leather sofa district of Bari-Matera in the Maturity stage. We labeled these three networks “alfa-net”, “beta-net”, and “gamma-net”, respectively.

Table. 1: Geographical clusters’ dimension and competitive performance.

	Agro-industrial district of Foggia	Leather sofa district of Bari-Matera Development Stage (1990)	Leather sofa district of Bari-Matera Maturity Stage (2000)
Number of firms	140	101	293
Export/turnover (%)	33%	60%	77%

In particular, we selected 66 firms active in the alfa-net, 43 in the beta-net, and 58 in the gamma-net.

These samples represent the 47 percent, the 43 percent, and the 20 percent of the GC’s total firm population, respectively.

[1] Industrial districts are a specific production model characterized by the agglomeration of small- and medium-sized firms integrated through a complex network of buyer-supplier relationships and managed by both cooperative and competitive policies.

The data on each firm of the three networks have been collected through interviews with the managers of the firms and questionnaires.
In particular, we collected network structure data by asking respondents to indicate with which other sample firms they have business exchanges. We then used these data to build the network of business inter-firm relationships characterizing each considered GCs.

4 The network analysis

To test the three theoretical propositions by the empirical study the measurement of the three features of the GC organizational structure, namely heterogeneity, interconnectivity, and level of control, is required. To this aim we have first operationalized the three GC structural features in terms of network attributes and then we have measured the identified network attributes by using the methods of the network theory.
In particular, we have used the following set of measures:

- network density;
- network heterogeneity;
- network centrality.

The test of *Proposition 1* has been based on a simple measure of the network structure, network density (*ND*), defined as the proportion of possible linkages that are actually present in a graph. The network density is calculated as the ratio of the number of linkages present, *L*, to its theoretical maximum in the network, *n(n-1)*[2], with *n* being the number of nodes in the network [Borgatti and Everett 1997]:

$$ND \equiv \frac{L}{n \bullet (n-1)}$$

To test *Proposition 2* we performed an analysis of the heterogeneity of the coreness of each actor in the network. By coreness we refer to the degree of closeness of each node to a core of densely connected nodes observable in the network [Borgatti and Everett 1999]. Using actor-level coreness data, we calculated the Gini coefficient, that is an index of network heterogeneity.
Finally, to test *Proposition 3* we used an index of network centrality: the average normalized degree centrality (*Average NDC*). The degree centrality of a node is defined as the number of edges incident upon that node. Thus, degree centrality refers to the extent to which an actor is central in a network on the basis of the ties that it has directly established with other actors of the network. This is measured as the sum of linkages of node *i* with other *j* nodes of the network.

$$DC(n_i) \equiv \sum x_{ij}$$

Due to the different sizes of the three networks, a normalized degree centrality *NDC* has been used [Giuliani 2005]. This is measured as the sum of linkages of node *i* with other *j* nodes of the network $DC(n_i)$ and standardized by $(n-1)$.

$$NDC(n_i) \equiv \frac{DC(n_i)}{(n-1)}$$

Once we have operationalized the GC structural features in terms of network properties, we applied network analysis techniques using UCINET (Borgatti *et*

[2] A directed graph without self-loops has at most n(n-1) possible edges and an undirected graph has half this value.

al., 2002) software to represent the three networks and to compute the identified network attributes (Table 2).

Table. 2: Measures of the three network attributes.

	Network density	Gini coefficient	Average Normalized degree centrality
Alfa-net	0,0138	0,041	2.751
Beta-net	0,0321	0.22	5.648
Gamma-net	0,0236	0.24	4.295

Each network attribute represents a structural GC characteristics. In particular, we used: 1) the network density to measure the GC interconnectivity, 2) the Gini coefficient to measure the GC heterogeneity, and 3) the average normalized degree centrality to measure the level of control inside the GC.
As regards the competitive performance of each GC, we used the percentage ratio between export and turnover. Export measures are usually adopted to evaluate the competitiveness at different levels, namely country, industry, firms and product [Buckley et al. 1998]. Increasing globalization has therefore made export activity more and more important for firms, regions, and countries [Leonidou and Katsikeas 1996]. Then, the percentage ratio between export and turnover can be considered as a good *proxi* to compare the competitive advantage of different firms and/or system of firms.
Results are summarized in Table 2 and confirm the three propositions.

5 Conclusion

This paper has used complexity science concepts to give new contributions to the theoretical understanding on Geographical Clusters (GCs) competitive advantage. In fact, the complexity science has been used as a conceptual framework to investigate the reasons for the success of GCs. This approach is particularly valuable given that allows the limits of traditional studies on GCs to be overcome. In particular, the GC competitive advantage is not the result of a set of pre-defined features characterizing GCs, but it is the result of dynamic processes of adaptability and evolution of GCs with the external environment. Therefore, the GC success is linked to the system adaptive capacity that is a key property of complex adaptive system (CAS).
Using the theory on CAS, the key conditions of GCs that give them the adaptive capacity have been identified, namely the number of links among GC firms, the level of differentiation of competitive strategies adopted by GCs firms, and the degree of governance of the GC organizational structure. The theory on CAS has been then used to identified the value that these variables should have to increase the system adaptive capacity. In this way, three theoretical propositions concerning GC adaptive capacitive have been formulated.
The proposed theoretical propositions have been supported by the results of an empirical investigation. In particular, the empirical investigation, adopting a multiple-case study approach, involves three in-depth case studies on real GCs.
The three cases were analyzed by using the methods of the network theory. We measured the GC structural characteristics identified in the three theoretical propositions as network attributes. Simulation results have confirmed the theoretical propositions showing that: (i) a medium network density assures the highest performance, measured in terms of percentage ratio between export and

turnover, (ii) the higher is the network heterogeneity, measured by the Gini coefficient, the higher the GC performance, and (iii) a medium value of the network centrality, measured by the average normalized degree centrality, determines the highest GC performance.

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