Firm Performance Gains and Losses from Network Structuring in Cluster Located Firms:

A Media Cluster Study in Northern Italy*

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Abstract

Geographical clusters have long been at the center of the debate on the role of interfirm networks in regional success. While research in this field has contributed crucial insights to the understanding of interorganizational networks as determinants of local growth and systemic strength, there has been less focus on the role and performance of the specific cluster-located firm (CLF) as an essential and active constituent of this dense multirelational system. Furthermore, despite the great emphasis on relational processes that distinguish research on localized industries, only a few studies have endeavored to untangle such processes within a framework of formal network analytic measurement and operationalization. In addressing these shortcomings, the paper contributes three novel insights to the understanding of firm performance within geographical clusters: First, it postulates a stylized multirelational model of network ties as enablers of opportunity discovery and CLFs growth. Second, it emphasizes the role of CLFs’ absorptive capacity as a key moderator construct in the process of influence. Third, it provides an original operationalization approach to capture the multirelational nature of CLFs’ network connectedness. These ideas are presented and tested through the analysis of three-year longitudinal data gathered on a near-exhaustive sample of 89 small firms located in a geographical cluster of Northern Italy. Results from fixed-effect regressions provide mixed support for the role of interorganizational ties as enablers of growth, suggesting that the hypothesized process of influence is highly contingent on the richness of CLFs’ preexisting knowledge structure.
1. INTRODUCTION

The initial theoretical treatment of the phenomenon of geographical clustering is generally attributed to Alfred Marshall (1920). Marshall’s theorization of geographic clustering built on three key tenets: the benefit of labor pooling, specialized suppliers and rapid formal and informal communication due to a common base of knowledge across firms, employees, and the community. In particular, with his idea of an “industrial atmosphere” with “knowledge in the air,” Marshall initiated the concept of shared knowledge as a characteristic of localized economies.

Despite Marshall’s pioneering intuitions, for several decades research in this field has been focusing almost exclusively on efficiencies in supply chains, labor markets, and subcontracts, purported as the key drivers of the agglomerative advantage. However, as the theory of geographic clustering developed, economists also recognized the need to introduce wider institutional inputs, in part because cost based models alone fell short in addressing the condition of many smaller firms (Maskell, 2001; Tallman et al., 2004). More recently and consequently more socially and relationally oriented accounts have entered discourse on local agglomerations, and scholars became interested in the interaction effects among cluster located firms or CLFs (clusters of firms located together geographically). The general argument is that a local industrial structure with many small firms competing in the same industry, or collaborating across related industries, tends to initiate patterns of situation-specific knowledge transfer as well as exchange and circulation of ideas and information (Nohria, 1992; De Carolis and Deeds, 1999; Pinch et al., 2003; Inkpen and Tsang, 2005). As Tallman et al. (2004) note: “Knowledge creation and circulation of ideas under conditions of high social embeddedness allowing individual firms to tap the body of local knowledge are now seen as essential to explaining regional clusters.”

In this vein, more and more scholars have advocated the adoption of relational or network lenses to unfold and analyze the dense and overlapping social and professional interfirm relationships that shape geographical clusters. Despite this increasingly popular trend, relatively few attempts have been made to move beyond an empirically vague appreciation of the role and magnitude of the ‘network effect’ within geographical clusters (Sobrero, 2001). In particular, if we exclude a few isolated cases (McEvily and Zaheer,
1999; Owen-Smith and Powell, 2004), virtually no work has endeavored to introduce a network analytic approach within the boundaries of a geographical cluster or use such lenses to explain the performance of firms located in such contexts. This shortcoming is at least partially related to the prevailing tendency in the literature to consider geographical clusters as a whole, without focusing on what is happening at the micro level of individual firms within the cluster. In fact, while such a macro perspective has undoubtedly favored our understanding of the overall phenomena and their implications, it has also contributed to nurturing a somewhat latent assumption that all CLFs tend to be homogenous and thus do not merit special attention in their own right (Lazerson and Lorenzoni, 1999).

Indeed, some evidence suggests that while clusters are often populated by extremely dynamic and fast growing firms, some of these firms struggle to survive, grow a little or die during their first few years of operation, while only relatively few of them maintain the capability to successfully compete and grow (Saxenian, 1994). What is the source of such heterogeneity in the performance of CLFs? In order to address this question we build on McEvily and Zaheer’s (1999) finding that competitive capabilities of CLFs may radically differ depending on the differences in the way they are embedded in the dense system of interorganizational relations that shape the cluster. These two scholars focused on the heterogeneity of embeddedness in accounting for differences in CLFs capacity to compete. Their success provoked us to concentrate on the link between the structure of networks and growth as a tangible measure of CLF performance.

In line with the above more recent research we view CLF networks as devices for information gathering and knowledge transfer. As a result, depending on their network properties and attributes, CLFs are more or less likely to accrue valuable information flows that can be transformed into attractive growth opportunities. However, their growth performance is further examined in light of an important theoretical construct at the firm level: absorptive capacity, which we will argue exerts a moderating effect. Our longitudinal analysis of a sample of CLFs located in Northern Italy, which we track over a three year period, indicates that the growth performance benefits that these organizations accrue from multiple network structures in which they are embedded will be moderated by the richness of their preexisting knowledge structure. So, instead of
automatically benefiting from the information that stems from enriching the cluster networks, CLFs that extend their relational structure with disregard to the cognitive burden stemming from the growing inflow of information may suffer severe repercussions. We use this evidence to argue the benefits of bringing fresh cognitive perspectives to bear in the realm of interorganizational networks research.

2. THEORETICAL FRAMEWORK

Our theoretical framework draws on three interlinked arguments: (1) Relational ties within geographical clusters are imbued with value in the form of information and knowledge flows across the multiple ties in which firms are embedded, (2) the heterogeneous position of CLFs within this web of ties translates into diverse exposure to valuable opportunities and hence, into heterogeneous prospects for economic performance, and (3) CLFs that have the absorptive capacity to appreciate/understand the value of these opportunities are in a more advantageous position to translate this potential into real economic value than those who do not. We discuss each of these points in turn.

2.1. Interorganizational networks and information access within geographical clusters

While several mechanisms may affect firm behavior within interorganizational networks, the key argument behind a vast majority of influence models is that relational ties provide access to information and knowledge. The informational value of network ties is a well-established idea among network theorists (Freeman, 1979; Burt, 1992; Borgatti and Cross, 2003), and represents a core assumption in a variety of studies that have investigated the relational foundations of organizational level outcomes1 (Gulati, 1995, 1999; Beckman and Haunschild, 2002; Koka and Prescott, 2002).

This ‘network-access’ idea is particularly relevant in the context of tightly bounded (spatially and socially) geographical areas such are geographical clusters (Sorenson, 2005). As Powell et al. (2002) observe: “The advantages of location […] are very much based on access and information” (p. 293). In fact, as

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1 Gulati (1995) summarizes this point in stating “That social networks are conduits of valuable information has been observed in a variety of contexts, ranging from interpersonal ties…to interlocking directorates…The common theme throughout this body of research is that the social networks of ties in which actors are embedded shapes the flow of information between them. Differential access to information in turn, moderates the behavior of actors” (p. 624).
economic actors co-localize within spatially and socially bounded contexts, knowledge spillovers, buzz, and exchange of ideas are triggered while the local environment is gradually turned into a vibrant repository of information and opportunities (Grabher, 2002). This point is reaffirmed by DeCarolis and Deeds, who note: “The proximity of firms to competitors, suppliers, and a qualified labor pool increases the flow of knowledge across a firm’s boundary. Social interactions, both formally and informally, stimulate information exchange about such topics as competitor’s plans, developments in production technology, and recent developments within the local university’s labs” (1999, p. 956). Because CLFs share a common institutional environment, are spatially proximate and consequently interact more frequently, they are more prone to circulate ideas, knowledge and fined-grained information that can be channeled and secured through the thick web of overlapping personal and professional ties that typically emerge within these contexts (Lazerson and Lorenzoni, 1999; Maskell, 2001).

In such a tight-knit community, customers, suppliers, competitors, and allies, as well as institutions and informal relations, are all potential vehicles through which CLFs may tap into valuable information flows. As a result of this multirelational embeddedness phenomenon: “Increasing returns are present in the form of overlapping networks, recombinant projects, personal and professional relationships, and interpersonal trust and reputation, all of which are thickened over time. In such a milieu, access to reliable information ...occurs through personal as well as professional networks, and these ties are critical in reducing uncertainty about projects that are not well understood by non-experts, exceedingly risky in terms of their payoff and unclear in terms of their eventual market impact” (Powell et al., 2002, p293).

By tapping the multiple flows that circulate throughout the cluster, CLFs broaden their exposure to new opportunities and enhance their performance aspirations.

The Austrian Economics framework provides the theoretical grounding for linking this exposure of opportunities to performance, discussed next.
2.2. Information access and opportunity discovery as antecedents of growth

According to the Austrian Economics framework, accessing information is a crucial premise for discovering new opportunities. That is, finding potential economic profits that have not yet been grasped (Hayek, 1954; Kirzner, 1974). Opportunities exist because different people access and control different information. Yet, the discovery of these opportunities is rarely the result of a targeted search (because, as Kirzner (1997) posits, the searcher will be unaware of it until discovery); rather it depends on the recognition of the value of information that actors happen to receive through other means (Shane, 2000). Thus, while proactive searching may be an important enabling condition, results are often unintended and opportunities not necessarily consequential. This concept suggests two simple ideas: First, because interfirm networks may affect the firm’s exposure to the ‘information space’ that permeates the cluster environment, they may impact the likelihood of the CLFs discovering valuable opportunities. A stylized representation of this idea is provided in Figure 1.

Second, because the pattern of network linkages maintained by each of these firms is highly idiosyncratic (McEvily and Zaheer, 1999), the probability of discovering new opportunities via network ties may be unevenly distributed. Simply speaking, CLFs with a better network access will be more likely to come upon opportunities and improve their performance aspirations. In particular, because the discovery of opportunities has long been regarded as a crucial antecedent of growth (Penrose, 1959), we expect changes in CLFs’ network positions to translate into variations in growth probabilities\(^2\) and subsequent growth patterns.

It is now possible to tie our argument to the literature examining the role of network centrality. Network centrality refers to the extent to which the focal actor occupies a strategic position in the network by virtue of being involved in many ties simultaneously (Wasserman and Faust, 1994). As Owen-Smith and Powell (2004, p. 10) suggest: “Centrality makes organizations an obligatory passage point for the information

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\(^2\) The antecedents of firm growth are typically to be found in the discovery and recognition of one or more economic opportunities. Opportunities to expand the business, to enhance current activities, to enter new product domains, to learn new practices, improve the current skills or capitalize on existing resources. Many scholars support this idea by viewing the process of opportunity discovery and recognition as a crucial antecedent of firm growth (Timmons et al, 1987; Venkataraman 1997). In fact, not only the relationship between opportunity recognition and firm growth has been empirically proved (Corbett and Koberg, 2001), but it is also at the core of the Penrosian idea of growth as discovery of productive opportunities (Penrose, 1959). As Penrose stated: “A theory of the growth of the firm is essentially an examination of the changing productive opportunity of firms...It is clear that this opportunity will be restricted to the extent to which a firm does not see opportunities for expansion...” (1959, p. 31).
flowing through a network structure.” High centrality leads to higher volume of information\(^3\) (Koka and Prescott, 2002) and “the greater the information the higher the opportunity set” (Gulati, 1999, p. 399). Accordingly, we expect high centrality within the cluster’s relational environment to have a positive impact on the growth of the CLFs. In fact, by being at the point of convergence of multiple relationships, central CLFs may maximize their exposure to the developments, ideas and initiatives that resonate throughout the system and therefore, increase their likelihood of discovering valuable opportunities. This is vividly illustrated by the comments of one of the entrepreneurs we interviewed for this paper.

“Clients, suppliers and firms with which we collaborate, they all may be sources of valuable information; they all may open up valuable opportunities. One of the most important projects in the last few years popped up almost by chance … thanks to an information we got from a client.”

Furthermore, because centrality implies visibility and status, firms more centrally located enjoy power benefits such as a greater ability to undertake promising initiatives and/or attract further opportunities (Ibarra, 1993; Powell et al., 1996). A comment by an entrepreneur we interviewed exemplifies this point:

“Our growth proceeded hand in hand with our network … the more they knew us the easier it was to establish business relations.”

Clearly firms with high network centrality are in a better position than others to participate in the flows and thereby have higher exposure to opportunities. Because of the greater density of their linkages they are also more likely to recognize exposed opportunities. However, there is a gap between recognition and realization of opportunity. One must wonder what it takes to actualize such growth potential, or, stated differently, whether different firms are equally armed to recognize and exploit the potential for value creation inherent in their network-enabled opportunity space. This leads us to our second point.

2.3. The moderating role of absorptive capacity

A gap may exist between having the potential for growth and actually realizing it. In fact, an opportunity-rich position is likely to remain confined to the realm of perceptions and possibilities until active understanding of the opportunity’s value is reached. One way to discriminate among firms that may take this further step and those that do not is to focus on their knowledge base. This idea has been formalized by

\(^3\) i.e. The quantity of information that an actor may access via its relational ties (Koka and Prescott, 2002, p.798).
Cohen and Levinthal’s (1990) construct of *absorptive capacity*, that is: “the ability to recognize the value of new information, assimilate it, and apply it to commercial use” (p. 128). This suggests that in order to understand the CLFs’ network-enabled process of growth it may prove useful to take into account its absorptive capacity. The idea is consistent with Tsai’s (2001) finding that business units with high levels of absorptive capacity are more likely to benefit from their interorganizational network centrality in terms of innovation and performance. Similarly, research by Reagans and McEvily (2003) suggests that absorptive capacity plays an important role in sustaining the transfer of knowledge across network ties.

According to Cohen and Levinthal the absorptive capacity of an organization heavily depends on the “richness of its preexisting knowledge structure” (p.131). Whether developed from work experience, education, or other means, the preexisting knowledge structure influences the firm’s ability to comprehend, extrapolate, interpret, and apply new information in ways that those lacking it cannot replicate (Roberts, 1991). Consistent with this idea Shane (2000) for instance relates the level of prior knowledge to the entrepreneur’s ability to recognize new opportunities. As he notes: “Each person’s idiosyncratic prior knowledge creates a ‘knowledge corridor’ that allows him/her to recognize certain opportunities, but not others” (p. 452). This concept is well reflected in the following sample quote by one of the owner/managers we interviewed:

“... that project turned into nothing because we had no ideas about the opportunities it could pave the way to…probably it would have jumped us into the advertising segment and we would have been much farther by now… if we had recognized the importance of that contact we wouldn’t have let it go.”

Following this line of reasoning we contend that the network position’s effect on growth will be moderated by the CLFs’ level of preexisting knowledge structure.

In summary, we can envision the absorptive capacity construct as the point of junction between the information space and the opportunity space: the higher the firm’s exposure and access to external knowledge and information, the higher the need for absorptive capacity in order to benefit from such resources.

3. HYPOTHESES

The above argument leads to two straightforward hypotheses:
Hypothesis 1: Other things being equal, an increase in the overall network centrality of a CLF will be positively associated with its growth.

Hypothesis 2: Other things being equal, an increase in the overall network centrality of a CLF is more likely to be positively related to its growth when the CLF has a rich preexisting knowledge structure rather than when the firm has a poor preexisting knowledge structure.

4. METHODS

4.1. Research setting

The field setting of this research consists of a geographical cluster of micro and small multimedia enterprises located in the area of Bologna, a city in Northern Italy. During the late 1980s and early 1990s the metropolitan area of Bologna was engulfed by an entrepreneurial wave that led to a fertile and dense agglomeration of multimedia enterprises, which is sometimes referred to as the Bologna Multimedia Cluster (Lorenzoni and Ferriani, 2004).

There are several reasons for considering this setting. First, in the last decade, a number of governments, regional development associations, and trade organizations have sought to promote the development of multimedia clusters. These initiatives can be partly attributed to a global interest in the potential for multimedia to drive growth in regional economies (Lutz, Sydow and Staber, 2003). According to Braczyck, Fuchs and Wolf, multimedia is "a paradigmatic example of industries of increasing importance to regional economic prosperity" (1999, p. 301). This is not only because multimedia is a high-technology industry, but also because it is simultaneously a form of cultural production that is increasingly critical to strategies of economic growth (Scott, 1998). Second, despite the relatively young age of the industry, entrepreneurial processes in the multimedia field have consistently translated into agglomerations of small and micro firms all over the world (Braczyck et al., 1999), a circumstance that implies at least some prospect for theoretical inference beyond the local boundaries of the phenomena presented here. Well-documented cases of small firm clusters in the multimedia industry are, for example, the San Francisco Multimedia Gulch (Egan and Saxenian, 1999) or the New Media Cluster in Toronto (Mills and Brail, 2002), while analogous
phenomena have been investigated in the metropolitan area of Stockholm (Backlund and Sandberg, 2002), as well as in the German regions of Cologne-Düsseldorf and Berlin-Babelsberg (Sydow and Staber, 2002). Third, because multimedia is an emerging and relatively young industry the importance of networks and external ties is likely maximized. In fact, findings in institutional economics suggest that emerging economic settings are characterized as having significant voids in informational markets and social networks often substitute for such failures (Peng and Luo, 2000). According to this literature the informational benefits of external ties are then likely to be greater in such a setting, thus maximizing the chances of observing their performance consequences.

4.2. Data collection

Data collection began in 2001 and extended over a two-year period. As a first step we developed a list of all the multimedia firms located within the Bologna cluster. We accomplished this by using ‘InfoImprese’, which is a comprehensive database operated by the Italian Chambers of Commerce to provide basic demographic information and classification criteria on all of the companies operating on the Italian territory. According to such classification, six industry segments were identified as the constituents of the emerging multimedia complex: publishing, audiovisual, computer graphics, communication and advertising, film, and music.

Overall, the database returned a population of 205 multimedia firms concentrated within the area of Bologna. The distribution of these firms by industry segment is provided in Table 1.

All these companies were initially contacted by telephone, told the purpose of the study, and asked for their cooperation. As a result 102 companies agreed to participate. Seven of these companies were randomly selected to conduct a pilot study in order to test interview questions. During this phase interview questions were initially open-ended and grew in detail over time, with the goal of understanding how firms scanned the environment for information, and the function of their networks in decision-making processes. We also stimulated the informants to provide any kind of anecdotal evidence that might help flesh out their

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4 Companies that refused to be involved in the study appeared randomly mixed between those not interested in the research and those without time to devote to the interview.
perceptions of the role cluster networks played in their business. These interviews reaffirmed the relevance of examining the link between external networks and performance outcomes in this setting. The final questionnaire was then used during the personal interview phase with the 102 participating companies.

With this step completed, we then started gathering data on each of the remaining 95 firms who had expressed their willingness to be part of the research. However, because 6 of them turned out to be ineligible to participate in our study, the final sample reduced to 89 firms. On average, firms in the sample were approximately 8 years old, with annual turnover lower than Euro 300,000 and less than 9 employees. These demographics, which show the predominance of small and micro enterprises, are consistent with other surveys that were carried out in the area (Lorenzoni and Ferriani, 2004). The topographic localization of these firms within the Bologna cluster is provided in the appendix (Figure 5 of Section 5).

An outline of questions, statement of research purpose, and assurance of confidentiality, together with a copy of a research report on the local industry previously written by one of the authors, were mailed prior to every personal interview. These measures helped guarantee the entrepreneurs’ long-term commitment to the study.

Two structured face to face interviews on two separate occasions were conducted for each company, one in 2001 the other in 2002, for a total of 174 interviews, with an average duration of about 2 hours per interview. In all of the cases the respondent was the founder (or one of the co-founders) of the firm. Each interview was divided in two parts. The first part included structured and semi-structured questions about the firm history, products, and performance as well as the background of the entrepreneurs in term of education and previous professional experience. In the second part the informant was required to provide relational information. Specifically, they were asked to map the multirelational web of interorganizational ties contributing to the CLF’s inflow of information and to track the evolution of these networks over time. Tracking the network evolution was an important requirement in addressing key issues of causality.

5 The six excluded firms had been founded later than 1999. They were considered ineligible since they couldn’t provide retrospective network data for 1999, our starting data point.
6 Four companies contributed only one interview having ceased their activity after 2001.
A wide array of economic actors can contribute to the CLFs’ inflow of information. Actors as diverse as customers, suppliers, allies, and so on all represent potential sources from which CLFs may tap the flow of information and knowledge that circulate throughout the cluster environment (Porter, 1998). In order to approximate this vibrant relational space without losing analytical focus, we decided to concentrate on four kinds of actors: customers, suppliers, collaborators and advisors. Correspondingly, we identified three network types, which we labeled as follow: Transaction network (which captures the CLFs’ buyer-supplier relationships), Collaboration network (which represents interfirm collaboration linkages), and Advice network (which encompasses the informal ties established by the informant with members of other CLFs). We focused on these networks for two reasons: First, their importance in enabling information and knowledge access is well established in the literature. Second, while there is obviously a plethora of formal and informal ties that contribute to the structure of the CLFs’ interorganizational field, focusing on a critical subset of these ties may help maintain clarity and provide momentum in the empirical development of the conceptual arguments.

Thus, each informant was presented with three relational questionnaires, matching the network types described above. For each relational question respondents were provided with a list of all the other 204 CLFs included in our cluster population list. In response to the list (with the same list reported three times, one for each sociometric question), we asked them to put a check by all the actors whom they recognized as their network contacts in the specified kind of relation. In essence, the respondents had to indicate those companies that they identified either as their transaction network partners (buyers – suppliers), as their collaborators, or, finally, companies whose members they recognized as individuals on whom they usually relied for valuable advice and information. This procedure was repeated on two occasions, at the beginning of

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7 Buyer-supplier networks in industrial districts in the “Third Italy” (Piore and Sabel 1984) and in the Manhattan garment industry (Uzzi 1996) have been shown to offer benefits to connected partners by channeling valuable information and knowledge (Inkpen and Tsang, 2005). The transmission of information is portrayed as a driving force of the collaborative patterns widely investigated by Powell and colleagues (1996, 2002) in the biotech clusters of Northern U.S. In a similar vein, McEvily and Zaheer’s (1999) research highlights the role of a cluster of small firms’ advice networks in providing access to heterogeneous niches of information, which in turn may help sustain the development of competitive capabilities.

8 Each of the questionnaires were also integrated by a free recall area (Wasserman and Faust, 1994), in which respondents could add other company names that had not been included in the list. These data, which we did not include in the analysis, allowed us to assess the degree of CLFs’ internal vs. external relationality. External relationality accounted for about 30% of the total relationality of the sampled firms, suggesting that most of the CLFs’ network activity was taking place within the boundaries defined by our population
of 2001, when the interviewees were required to provide relational data concerning 2000 and 1999, and in the
beginning of 2002, when they were asked to complete the questionnaire with regard to their relational activity
in 2001 (see section I of the methodological appendix for an overview of sociometric questions). The process
resulted in a three-year multirelational dataset for the 89 sampled firms. These data were then converted into
3 sociomatrices (3 adjacency matrices - representing the three types of relationships between the firms - for
each of the 3 years, totaling 9 sociomatrices over the full period), which were used for the computation of
network and non-network measures (see section II of the methodological appendix for details on the creation
and manipulation of sociomatrices). The 3 matrices can be viewed as layers in a three dimensional space
matrix 89x204x3 “big,” or, in Wasserman and Faust’s (1994) terminology, as constituents of a super-
sociomatrix.

As a final step, between January and February 2003 all of the CLFs were recontacted by telephone in
order to obtain updated growth data as of 2002.

4.3. Operationalization and Measures

Dependent Variables

Growth: Many different variables have been proposed to capture firm growth. Delmar (1997), based on an
extensive review of the literature, provides a list of suitable measures of firm growth: assets, employment,
market share, physical output, profit and sales. For a number of reasons we chose to focus on two of the
above variables: sales growth and employment growth. First, these variables represent the most widely used
measures in empirical research on growth (Delmar, 1997). Second, these indicators are the only ones available
in the present study for all of the firms of interest. Third, other indicators have limits that constrain their
suitability beyond certain specific contexts (see Delmar et al., 2003, for an extensive discussion). Based on the
above we indexed growth in two ways: (1) We used the reported number of employees at time t +1
(EMPLOY_{t+1}) to compute a measure of year by year absolute growth, and (2) we used the reported market

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list. This is not surprising given that the cluster is still in an early stage of development (on the localized nature of cluster networks see
sales at time $t+1$ ($\text{SALES}_{t+1}$) to compute an ordered class dependent variable ranging from 1 to 8, based on an eight point scale of increasing market sales brackets defined during the pilot study.

This codification strategy was necessary due to the fact that most of the companies in this study were privately held, and did not disclose financial information to the public; thus only self-reported data were available\(^9\). The respondents were asked to indicate their growth values with respect to each of the two items for each of the years of observation. Brackets were used because of a possible reluctance to reveal precise financial data. The convenience of categorical options may also have increased the questionnaire completion rate (Lee and Tsang, 2001).

**Independent Variables**

**Overall Network Centrality:** Our approach to operationalize the network construct was driven by two basic concerns: First, with information as the key element of our relational conceptualization of CLFs performance, we were interested in developing a network measure capable of capturing the extent of information accessible by firms via their position in the cluster network. Second, we wanted these measures to reflect the multirelational nature of CLFs connectedness, that is to account for the fact that CLFs are embedded in a number of different relationships that may all simultaneously contribute to the informational inflow and knowledge exposure of these organizations. Operationally speaking this required identifying an adequate measure for gauging the overall network centrality of the CLFs.

In a way akin to Koka and Prescott’s (2002) strategy for operationalizing social capital, we addressed these issues by developing and testing a multi-measure model. Besides reducing the overall effect of measurement error of any individual observed variable on the accuracy of results, this method allowed us to approach the variable of theoretical interest as a latent construct with simultaneous manifestations on multiple networks. We developed this operationalization strategy in two steps. As a first step we identified a series of indicators to operationalize CLFs’ network centrality as a first order latent construct in each of the three networks of interest. As a second step, we postulated the resulting three constructs (one centrality factor for each of the three networks) to be indicators of a higher order factor, representing the overall network

\(^9\) For those firms providing publicly disclosed financial data a cross check was assured to grant measure reliability (9 firms out of 89). For a discussion on the caveats of relying on self reporting data see also the ‘Limitations’ section (p. 26).
centrality of the CLFs. We tested the empirical saliency of the resulting measurement model, which is graphically illustrated in Figure 2 as a hierarchical confirmatory factor analysis (CFA) using structural equation modeling. As the graph shows, there are three first order latent constructs encapsulated within one second order factor. This model includes as first order factors: Transaction Network Centrality, Collaborative Network Centrality, and Advice Network Centrality. The intercorrelations among these factors are accounted for by the second order construct Overall Network Centrality.

Multiple indicators, calculated across each of the three network types, were used in order to operationalize the model. In particular, to operationalize the three first order centrality factors we used two measures: the Freeman’s degree centrality (DEGREE$_{1,3}$) and the Bonacich’s (1972) eigenvector centrality (EIGEN$_{1,3}$). Section II of the methodological appendix provides a detailed description of all such indicators, which were selected based on the operationalization approach already introduced by Koka and Prescott (2002). Using these indicators we estimated the measurement model year-wise for the three-year period 1999-2001. We started the model assessment by checking the convergent and discriminant validity of the first order structural model, then we moved to the hierarchical specification. Satisfactory and consistent factor loadings and fit indices over time enhanced our confidence in measurement reliability of the higher order network construct. Finally, using factor scores, we translated this construct in a single composite measure: OVERCEN. This measure represents our main explanatory network variable in the regression analysis.

Figure 2 incorporates key statistics of the measurement models for year 2001, including path coefficients and fit indices. Full specifications and year-wise model estimates, including path coefficients, convergent and discriminant validity tests and fit statistics are provided in Section 3 of the methodological appendix.

Absorptive capacity: A common approach in the literature for measuring absorptive capacity is to use the firm’s research and development (R&D) intensity. Such a strategy, however, was not possible in our context

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10 The choice of this approach rests on the conjecture that network properties of small and micro companies like the ones that are the object of this research, may be conceived as manifestations of an inherent ‘relational propensity’ of the organization. Thus, whilst firms establish and discard linkages across different network types, they make choices that are not perfectly independent. Instead they tend to be driven by an underlying relational behavior that is organization-specific and that generates commonalities across network fields. We believe that this specificity stems from the high degree of overlap that exists in small organizations between firm and owner behavior, where the art of interweaving ties and linkages is profoundly shaped by the owner-manager’s relational skills and attitude.
of study. In fact, only a minor proportion of companies had reported investments in R&D, and even in these cases the level was generally trivial. This was not surprising, though. Previous research in the field (Grimaldi and Munari, 2001) indicates that the innovation activity of these companies is based more on the identification and exploitation of new market opportunities (demand pull) rather than on the development of new technology by means of investment in R&D (technology push). Research on small multimedia firms in the San Francisco Gulch also suggests that the drivers of competitive advantage of these types of companies are typically found in their ability to create and assemble content in innovative ways rather than developing technology (Egan and Saxenian, 1999)\textsuperscript{11}.

Given such specificities we had to choose a different route to operationalize the construct. We decided to focus on the characteristics of the owner-managers, following Cohen and Levinthal’s idea that the absorptive capacity of an organization will depend on the absorptive capacity of its members. In fact, we believe that the plausibility of this assumption is enhanced in a context of micro and small organizations, where the behavior of the firm is widely reflected in the choices and decisions of its owner-manager. Cohen and Levinthal suggest two ideas to assess the richness of the pre-existing knowledge structure of the organization. One is the idea of having prior related knowledge (because learning is cumulative, absorption performance is greatest when the object of learning is related to what is already known). Second is the idea of knowledge diversity (in uncertain environments new useful information may stem from various different sources, thus a heterogeneous knowledge base provides a more robust basis for absorption “because it increase the prospects that incoming information will relate to what is already known” (p. 131)).

In order to capture these two complementary sources of absorptive capacity we introduced two measures: PRIOR is a dummy variable indicating whether or not at least one of the owner-managers (in case of different founding members) had already developed prior professional experience in the current field of specialization of the company. In order to extrapolate this information we used the respondents’ answers to the following question: “Would you consider the field of specialization of your company consistent with the

\textsuperscript{11} “In a production system increasingly composed of standard hardware and software elements, the distinguishing characteristic of multimedia products becomes their content: the degree to which they harness the power of interactive multimedia in creative and appealing ways” (Egan and Saxenian, 1999 p.18).
professional experience you have been acquiring during your career?” KNOWHET is a measure of internal knowledge diversity based on both the educational background of the founding members and their professional experience. We created this variable by computing two Blau’s indices of heterogeneity, one for each of the two knowledge domains and by taking their arithmetic average12.

Control variables

Powerful classes of multivariate analysis techniques for longitudinal data that help reconcile the complexity of accounting for a large number of controls, with the goal of minimizing the possibility of confounding effects, are the so called fixed-effects estimation methods. Indeed, the major attraction of fixed-effects methods in nonexperimental research is the ability to control for all unobserved and unknown stable characteristics in the study, thereby eliminating large sources of bias. Although fixed-effects methods cannot provide coefficient estimates of time-invariant factors, they do consent to control for them, in fact the control is likely to be much more effective than in conventional regression (Allison, 1999). Furthermore, while stable covariates cannot be estimated their interaction with variables that do change over time can. Based on these considerations, only a limited set of time-variant controls were included in the analysis: Lagged growth 1 (EMPLOt) - Inclusion of the previous year measure of growth helps account for the possibility of any specification bias due to unobserved heterogeneity. In particular, controlling for lagged growth should mitigate spurious effects due to endogeneity. Lagged growth 2 (SALES) - Current growth rate on one of the two dependent constructs may also depend on lagged value of the other dimension. Consequently, in addition to the lagged value of the dependent variable we introduced a lagged control for the other dependent variable in each of the equations. Time (YEAR) – We included a dummy variable for each year in order to capture any effects of temporal trends related to contemporaneous economic and environmental conditions that may have influenced the availability of growth opportunities within the cluster. Age (AGE) – We also controlled for firms’ age (measured as the number of years since founding) in order to avoid the possibility that any significant effects of the theorized variables were simply a spurious outcome of aging related differences.

12 Founders’ educational background was classified within four types, based on the orientation of their formal training: art, science, business or humanities. Similarly, founders were grouped according to their previous field of specialization. We used Blau’s formula with these two sets of categories for computing KNOWHET.
4.4. Model Estimation

In order to test our hypotheses longitudinally while accounting for the different nature of the dependent variables, we estimated two different longitudinal models: a fixed-effect negative binomial to treat the discrete, count nature of the employees-based dependent variable, and a fixed-effect cumulative logit model, to estimate variations in the ordered categorical dependent variable. The negative binomial is a generalization of the Poisson model that is specially suited to cope with the overdispersion problem. While the estimation of a Poisson model requires an ad hoc correction of the standard errors and chi-squares based on the goodness-of-fit ratios, the negative binomial directly builds in the overdispersion term, allowing a more appropriate treatment of the problem. Cumulative logit models are a generalization of logit models specifically suited to handle ordered categories (Allison, 1999).

The selection of the estimation techniques reflects two prominent statistical issues, namely unobserved heterogeneity and autocorrelation. Unobserved heterogeneity arises from the possibility that observationally equivalent firms may differ due to unmeasured characteristics that may affect both independent and dependent variables. To eliminate any spurious effect due to unobserved differences among firms we included in the model a fixed effect term; estimated coefficients are then interpretable as the amount by which the within-firm deviation on the dependent variable shifts in response to a preceding change in the deviations of the covariates. Furthermore, by introducing firm-specific effect we correct for autocorrelation by permitting observations of the same firm to be correlated across periods and thus by building serial correlation directly into the model (for further detail on the selected models and related econometric issues see section 4 of methodological appendix).

5. RESULTS

Tables 2 and 3 present basic descriptive statistics, bivariate correlations and multicollinearity check for the variables included in the analysis. We assessed multicollinearity by regressing each of the variables against all other explanatory variables and then by calculating a tolerance factor, measured as the difference between $R^2$ and one. While there is no formal cutoff value for determining presence of multicollinearity, statisticians
sometimes suggest 0.4 as a threshold level below which one should be concerned. As displayed in the last column of Table 2, no variable violates such level.

In Tables 4 and 5 we reported the results of regression analysis. Hypotheses were assessed sequentially, for each of the two models. Model 1 (Table 4) was estimated by using the number of employees as the dependent variable (EMPLOY_{t+1}). There are three versions of this model. Model 1a is the baseline model. In model 1b and 1c we provide tests for Hypotheses 1 and 2 by introducing the two variables of theoretical interests, one at a time. The second model (Table 5) provides the cumulative logit estimates. The same set of hypothesis was tested based on the alternative measure of growth (SALES_{t+1}). Again we provided two subsets of explanatory variables, so as to display the incremental contribution of the variables of theoretical interest. The last row of the tables highlights the improvement in fit using the likelihood ratio chi-square test for adding new variables to the model.

The results provide mixed support to our predictions. Starting from model 1b, which presents tests of Hypothesis 1, it is notable that the coefficient estimate of OVERCEN, is negative and significant, suggesting an effect opposite to what we had expected. This is an important result – in the absence of the variance contributed by absorptive capacity effects there is no apparent positive benefit from network centrality. In other words, once one begins to delve into the network structures of individual firms, in the absence of absorptive capacity data the rules from the macro studies do not appear to apply. Both the direction and the significance of this effect, however, change dramatically when the level of prior related knowledge and knowledge heterogeneity are taken into account (model 1d). In fact, the both of the two interaction terms (OVERCEN*PRIOR and OVERCEN*KNOWHET) coefficients are positive and significant, supporting Hypothesis 2. For those firms with prior related experience the net effect of centrality is positive, and it increases as the level of knowledge heterogeneity increases. Consistency of results across the two models provides further support to the robustness of the analysis. As illustrated in Table 5, model 2b reaffirms the negative impact of OVERCEN, the corresponding coefficient being negative and statistically significant. Likewise, turning to model 2d, the effect of this variable on sales growth appears highly contingent on the level of prior related knowledge and knowledge heterogeneity, an indication of the mutual reinforcing nature of the constructs.
For purposes of illustration it may prove helpful to provide some quantitative and graphical interpretation of the coefficients. In particular, using partial differentiation we can examine the interaction coefficients for overall network centrality in both models.

**Interaction between overall centrality and absorptive capacity**

Starting from model one (1c), we have that the full effect of overall centrality on the employee-based growth measure (EGM) is given by:

\[
EGM = -0.33 \times (\text{OVERCEN}_t) + 0.41 \times (\text{OVERCEN}_t) \times (\text{PRIOR}) + 0.19 \times (\text{OVERCEN}_t) \times (\text{KNOWHET})
\]

Note that because PRIOR is a dummy variable we have two different equations, depending on whether the firm does or does not have prior experience in the field.

Thus, if PRIOR=1:

\[
EGM = 0.41 \times (\text{OVERCEN}_t) + 0.19 \times (\text{OVERCEN}_t) \times (\text{KNOWHET})
\]

\[
\frac{\Delta EGM}{\Delta \text{OVERCEN}_t} = 0.09 + 0.19 \times (\text{KNOWHET})
\]

As the range of KNOWHET goes from 0 to 1, this variation is always greater than 0.09 and tends to rise as the level of knowledge heterogeneity rises. In other words, if the firm has prior experience in the industry, no matter how undiversified the knowledge base of the firm, increases in centrality pay off in **INCREASING** growth performance.

If PRIOR=0:

\[
EGM = -0.33 \times (\text{OVERCEN}_t) + 0.19 \times (\text{OVERCEN}_t) \times (\text{KNOWHET})
\]

\[
\frac{\Delta EGM}{\Delta \text{OVERCEN}_t} = -0.33 + 0.19 \times (\text{KNOWHET})
\]

When the company has no prior related knowledge, an increase in overall centrality is associated with a decrease in the expected number of employees. While the negative effect diminishes as the firm knowledge heterogeneity moves from 0 to 1, it only becomes \(\geq 0\) when knowledge heterogeneity is \(\geq 1.74\). This value, however, falls beyond the allowed variable boundary. In other words, if the firm has no prior knowledge to draw on, then no matter what level of diversity its experience, increasing overall network centrality becomes a burden. Figure 3 displays these interaction effects by plotting the two equations in 3-dimensional space.
These findings become even more interesting if we now look at the interaction among types of absorptive capacity, as shown in table 6. This shows the impact of growth rates of increasing network centrality when looking at the joint effects of the two types of absorptive capacity. When the firm has both prior knowledge and knowledge diversity, increasing network centrality is maximally beneficial to growth. When the firm has no prior knowledge and no knowledge diversity increasing centrality is maximally damaging to growth. Furthermore prior knowledge on its own benefits growth, but knowledge diversity does not.

All these tendencies persist when we used growth in sales instead of employees. Turning to model 2 (2d), where the effect of the interaction on the sales-based growth measure (SGM) is given by:

\[ SGM = -0.42 \times (OVERCEN_0) + 0.51 \times (OVERCEN_t) \times (KNOWHET) + 0.28 \times (OVERCEN_t) \times (KNOWHET) \]

If PRIOR=1:

\[ \Delta SGM / \Delta OVERCEN_t = 0.09 + 0.28 \times (KNOWHET) \]

This is always positive, being \(0 < KNOWHET < 1\).

If PRIOR=0:

\[ \Delta SGM / \Delta OVERCEN_t = -0.042 + 0.28 \times (KNOWHET) \]

Like in the previous model, knowledge heterogeneity alone is not sufficient to change the sign of the slope. The slope gets positive only when knowledge heterogeneity is \( \geq 1.5\), which is not in the acceptable range. Stated differently, while knowledge heterogeneity plays a positive reinforcing effect on centrality, the magnitude of such interaction is not so strong that it can substitute for the absence of prior knowledge. Figure 5 displays the two cases graphically.

6. DISCUSSION

Results provide mixed support for our predictions, indicating that an increase in overall network centrality over time is not unconditionally beneficial to CLFs’ growth. In fact, unless CLFs are endowed with a threshold level of absorptive capacity, the effect of centrality appears significantly negative. In contrast, the
presence of a strong preexisting knowledge structure radically inverts these effects, turning rich relational structures into effective growth enablers.

These findings are somewhat surprising. The assumption that CLFs may grow by being richly connected requires review and should be approached with caution. Our research suggests that by simply enriching their relational spectrum without the appropriate knowledge endowment, CLFs may incur unwanted negative effects. Why are these negative effects and what causes them? We submit three potential explanations. First, it is possible that CLFs may suffer an information overload or ‘cognitive tilt’ (Baron, 2004) due to over-connectedness. In fact, because extending the firm’s relational horizon poses extra information-processing requirements, it might be that CLFs without enough processing power experience a saturation problem (Koka and Prescott, 2002), resulting in lack of strategic focus, decisional impasse or inertia in the face of emerging opportunities. A second and worse possibility is that in the absence of a robust preexisting knowledge structure, an increase in connectedness would provoke decisional confusion. As a result, CLFs might be more prone to misjudgment errors, faulty decisions, erroneous inferences and costly dead-end searches, leading to resource dissipation (time, money, energy) and/or decline (Hodgkinson et al., 2002). Our third explanation has to do with the specificity of the research setting. As already pointed out, geographical clusters have often been depicted as contexts impregnated with information and knowledge. In this context - according to Grabher (2002, p. 209) – “actors are not deliberately ‘scanning’ their environment in search of a specific piece of information but rather are surrounded by a concoction of rumors, impressions, recommendations, trade folklore and strategic information.” Following this line of argument, it could be that within geographical clusters the informational advantage typically associated with network ties gets somewhat ‘diluted’ or even distorted. Recent research on interorganizational networks and information transfer among co-located biotech firms in the Boston Metropolitan Area seem to support this interpretation by suggesting that the information benefits associated with network centrality may become trivial when firms’ geographical proximity yields ongoing exposure to localized information spillovers (Owen-Smith and Powell, 2004).

Building ties is a demanding task whose benefits are not automatic. It is one thing to be exposed to multiple avenues for information and opportunities, but quite another to be able to evaluate, assess and
reflectively appreciate the value that is embodied in these flows. Consistent with this argument, our results suggest that the characteristics of the CLFs internal knowledge structure may impose radical limitations on the degree of connectedness that each CLF should strive for.

Thus, for example, it will be safer to invest in network building for those CLFs exhibiting at least some degree of knowledge heterogeneity and prior related knowledge in their internal knowledge structure. Given the dramatic positive impact of CLFs’ absorptive capacity on the network effect, it appears crucial for the CLFs to define a coherent strategy of connectedness, whereby the relational search for information and opportunities is consistently appraised against the cognitive limitations of the organization.

On the other hand, organizations that do not possess at least some degree of prior experience and knowledge breadth should be particularly prudent in aggressively pursuing linkages, since their benefits may not be appreciated or understood.

All in all, it is our conviction that this research cues a number of points for reflection on to the understanding of firm performance and interorganizational networking within geographical clusters, both on conceptual and empirical grounds. We discuss them separately.

6.1. Conceptual contributions

First, we contribute a novel, theoretically grounded conceptualization of relational ties as enablers of CLF growth. In fact, despite the size of the body of work on networks in localized industries, the driving forces of this process of relational influence often appear vague or loosely defined; either because the ‘networking metaphor’ is endorsed with a taken-for-granted facilitative role, or because it is credited with a multiplicity of overlapping benefits (resource, power, status, information, legitimacy, etc.), but with no clear explanation as to the basic underlying mechanism linking these elements to the process of firm growth.

We took two steps in order to address this issue: (1) Drawing on well-established ideas among network and organizational theorists, we provided an information-based conceptualization of network ties. We did so by moving away from a purely structural conception of firm networking and focusing instead on the underlying informational and knowledge benefits that CLFs may derive from their participation in such
multiple webs of relations; (2) Building on some key ideas dating back to the work of Penrose but mainly established within the Austrian Economics framework, we elaborated on the concept of firm growth as a process of discovery and recognition of economic opportunities. Opportunities exist because different firms have access to and control different information. By way of this heterogeneous exposition to information, firms wind up occupying diverse positions within the space of economic opportunities. As recently suggested by Dernell, Fang and Winter (2003, p. 18): “Firms can be expected to differ considerably in the information they possess… Such differences in information… typically imply differences in positioning relative to new opportunities.”

These two arguments allowed us to stretch out a more transparent line of causal reasoning between firm networks and firm growth. Because the discovery of economic opportunities is profoundly shaped by the availability and distribution of information in society, and since “information can be acquired by use of social relations maintained for various purposes” (Coleman, 1988, p. 104), CLFs networks represent a crucial interface between the information space and the opportunity space, and thus may play a critical role in the CLF growth process.

Second, we highlighted the benefits of integrating the analysis of network properties with the concept of absorptive capacity (Cohen and Levinthal, 1990) as a filter between the firm and its network environment. Absorptive capacity represents a powerful conceptual tool to improve our understanding of network based influences on firm behavior, yet there have been only sporadic attempts to incorporate this construct into organizational network research designs (Tsai, 2001; Reagans and McEvily, 2003). In this respect, and in line with recent theorizations on the contingent value of interfirm networks, we believe our findings contribute new perspectives from which we might start looking at the implications of network embeddedness on firm performance. In fact, not only should organizational networks be assessed in light of the characteristics of the environment in which they operate (Rowley et al., 2000; Beckman, Haunschild and Phillips, 2004), the existing socio-organizational structure of work (Burt, 1997), or the type of network under investigation (Ahuja, 2000), but also with an eye on the knowledge environment that internally characterizes the organization. Incorporating cognitive considerations into our account of the performance implications of
CLFs’ interfirm ties not only provides us with a more accurate representation of mechanisms at work but is consistent with the general observation that an actor’s network position and attributes offer complementary insights that, taken together, offer a fuller explanation of the actor’s action (Kilduff and Krachardt, 1994).

6.2. Empirical contributions

From an empirical standpoint, there are two contributions that are worth stressing. First, this research represents an original attempt to introduce network analytic tools within the boundaries of a geographical cluster. In fact, while networks are consistently portrayed as one of the most distinctive traits of localized industries (Nohria, 1992), few scholars, and mostly in recent years (McEvily and Zaheer, 1999; Owen-Smith and Powell, 2004), have endeavored to untangle such processes within a framework of formal network measurement and operationalization. In order to pursue this goal we took several measures. As a first step, we gathered network data based on multiple ego-centered relational questionnaires that allowed us to assess the CLFs’ degree of collaborative, transactional and advice-based participation to the interorganizational field shaping the cluster environment. Based on these multi-network data, we then elaborated a series of sociomatrices that we used to analyze the structural properties of the sample firms and compute measures of theoretical interest. Lastly, these measures were integrated, as manifest indicators, into an original confirmatory factor analysis model, which we developed in order to operationalize the multirelational nature of CLFs’ connectedness. To the best of our knowledge, this model represents the first attempt ever to operationally account for the fact that CLFs are embedded in a number of different relationships that may all simultaneously contribute to the informational inflow and knowledge exposure of these organizations. In pursuing this goal we tried to address the concerns of many scholars who lament too strong a tendency, among organizational network theorists, to concentrate on a single type of network, despite the multiplicity of relationships in which organizations are typically embedded. Barley et al. (1992), for instance, emphasize the fact that studies of network structure among profit-making firms have often focused on one or few interfirm relationships rather than capturing multiple ties among organizations. Similarly, Hedstrom (1994, p. 1177) noted that “much more analytical work is needed on the role of multiplex networks, particularly on how
multiple, overlapping networks of varying density and reach are likely to influence the diffusion of information.” By simultaneously accounting for the CLFs participation in three kinds of interorganizational networks (transactional, collaborative and advice-based networks), our composite measures represent an initial attempt to move towards the direction set forth by these and other scholars (see for example Gulati and Gargiulo, 1998; Gulati, 1999).

Second, due to the challenges of gathering network data over multiple points in time, there are relatively few studies that employ longitudinal data to analyze networks. Burt (2000) has voiced a similar concern that most studies of network structure are cross-sectional. In general, while some progress has been made analyzing the dynamics of dyads (Gulati and Gargiulo, 1999), little attention has been given to dynamics of networks over time (Powell et al., 2004). One crucial problem is that the use of cross-sectional network data precludes a robust understanding of the causal mechanisms at work. This study is distinctive in that it tackles the above concern by assessing the performance implication of CLFs’ interorganizational ties over a three year period. As far as we know, no prior study on geographical clusters has ever approached this topic within a framework of longitudinal network measurement and estimation.

6.3. Limitations and avenues for future research

In order to better appreciate the findings discussed so far, we recognize that the study is subject to a number of potential limitations. Noting them may provide ideas for extension and improvement.

First of all, clusters of firms (or CLFs) – spatially concentrated groups of firms competing in the same or related industries - are often the expression of a complex mixture of local socio-economic conditions and institutional forces that combine to create a unique environment for the development and growth of economic activities. We should be careful with generalizations. It is nonetheless notable that the empirical setting object of this research does not represent an isolated occurrence. In fact, it is fairly intriguing to observe the maps in appendix (Section 5 of the appendix), and realize that the clustering of small firms in the multimedia field is far from unique. Although the degree of generalizability across institutional environments
is challengeable, that fact that we have found a connection between benefits of network centrality and absorptive capacity in this setting may be cause for revisiting the research in argument in other settings.

Second, because all the CLFs share the same social, spatial and institutional environment, it might well be the case that the observed effects are the spurious manifestations of common forces operating at the cluster level. On the other hand, by using fixed-effect estimations we were able to control for all unobserved and unknown time invariant variables that may affect the dependent variable. In that sense, we believe we provided an extremely conservative and scrupulous test for our predictions.

Third, in building the conceptual framework, we made a strong ‘homogeneity assumption’ with regard to the informational value of ties across network types. For example, we did not elaborate on the possibility that different kinds of relations may lead to information of different value. The rationale for this choice is consistent with our adherence to the Austrian approach, that is, to the idea that valuable information emerges more often as the byproduct of relational ties with a different purpose rather than the expected outcome of deliberate ties. Accordingly opportunity discovery is more an unpredictable phenomena than a purposeful one. Based on such a premise, we implicitly assumed the diffusion of valuable information via cluster networks to be essentially a stochastic process; in other words, relevant information may spring up in every part of the cluster's relational system network. Nonetheless, while in principle it is impossible to anticipate what network conduits the relevant information will be channeled from, there may be rationales for modeling the informational value of different network ties according to some fine-grained probability distribution. Given the considerable efforts in joint problem solving that an alliance most commonly implies, one might for example consider these kinds of relations as ‘imbued’ with a higher amount of informational value than other sorts of linkages (Koka and Prescott, 2002). Such an approach could then be easily translated into a model that allows for a weighting scheme of ties, based for example on their content and/or origin.

Fourth, there are inevitably methodological caveats with respect to the measurement of CLFs networking activity and self-reporting data. It is important to note, for example, that the research design called for a single respondent per organization and a single sociometric question for each network type. As to the first point, because of the size of the organizations (micro and small) we decided to rely exclusively on network data
provided by our key informant, that is, the CLF’s owner manager. Although we believe this to be a reasonable way to proceed for collecting this kind of data (on this point see, for example, Cooper et al. 1993 and McEvily and Zaheer, 1999), we are aware that the use of only one respondent per firm might be a source of measurement error for the network constructs (Marsden, 1990). In fact, a majority of the firms do actually have more than one owner. In an attempt to alleviate the potential for distortion, each interviewee was explicitly required not only to check off those firms whose members he identified as constituents of his own advice network, but also those that he was able to recognize as actors in his partner/partners advice network. Obviously, with this as the only marginal measure, further investigation is needed.

As to the second point, our data collection design is limited in that network data were collected based on responses to a single question for each network. Although some scholars have criticized that asking a single sociometric question is equivalent to measuring an attitude with a single-item scale (Rogers & Kincaid, 1981), in an extensive review of the research evidence Marsden (1990) concluded that this approach is largely reliable when measures are taken to facilitate individuals’ capacity to recall and report their network links accurately (Marsden, 2002). Two features of this study served to mitigate the risks of informant recalling accuracy. First, respondents were given a list of all the potential network members and were asked to indicate the presence of a relationship; thus, we did not exclusively rely on respondents to accurately recall the names of those to whom they are tied. Second, because all the roster members were interviewed, it was possible to assess the rate of ties reciprocation, which is close to 76%. While there may be several reasons contributing to the absence of a perfect match (see footnote 15 in the appendix for further discussion), the degree of correspondence is still substantial, suggesting that accuracy fallacies, wherever present, should not subtract too much from the validity of the results (for a discussion on these aspects see also Ibarra, 1993, p. 481).

6.4. Summary and concluding remarks

As pointed out by Castilla, Hwang, Granovetter and Granovetter (2000, p. 246-247): “The important work in industrial organization that has pointed to the centrality of networks cannot progress further without an adequate toolkit of methods for clear and detailed analysis of the complex data presented by the actual
networks in particular regions.” Our study sought to address this crucial shortcoming by departing from a purely descriptive ground in favor of empirically based research that relies on network analysis and data on a panel of small firms situated in a Northern Italy geographical cluster. Drawing on previous findings on spatially and socially bounded industries that emphasize the high degree of embeddedness and connectedness that characterizes such firms, we advanced a stylized multirelational model of network ties as enablers of opportunity discovery and CLF growth. Further, based on the simple idea that distinct CLFs may vary in their ability to understand and assess the value of the information they accrue from their networks, we also postulated the existence of a moderating effect depending on the richness of CLFs’ preexisting knowledge structure.

Our findings demonstrate that even in a highly relational environment, such as is usually the case with local agglomerations of knowledge-intensive firms, being unconnected may not necessarily result in a liability.

On the other hand, CLFs that expanded their networks with no regard to the limits of their cognitive frames seem to suffer an overload shock, that is to say failure to process the burdening mass of information flowing from the cluster environment to the firm, via multiple relational conduits. Results indicate that the consequences may be detrimental for the firm route to growth. While this is probably the most intriguing finding of our study, we believe it is just an initial step towards many promising research opportunities.
References


Grimaldi, R., F. Munari. 2001. Entrepreneurs as gatekeepers in transferring technological knowledge from universities to companies. Working Paper, Management Department, University of Bologna.


Tables & Figures

Figure 1 CLFs' multirelational embedded ties as bridges between information space and opportunity space.

Table 1 Frequency distribution of CLFs by industry segment

<table>
<thead>
<tr>
<th>Industry segment</th>
<th>No. of firms</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publishing</td>
<td>31</td>
<td>0.15</td>
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<tr>
<td>Music</td>
<td>24</td>
<td>0.12</td>
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<td>Film</td>
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<td>Audiovisual</td>
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<td>Computer Graphics and Multimedia Software</td>
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<td>0.28</td>
</tr>
<tr>
<td>Advertising and Communication</td>
<td>26</td>
<td>0.13</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>205</strong></td>
<td><strong>100%</strong></td>
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</table>
Figure 2 Network Centrality as second order latent factor in a multirelational space

Table 2 Basic descriptive statistics and multicollinearity check

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Variance Inflation</th>
<th>Tolerance</th>
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</thead>
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<tr>
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<td>-</td>
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<td>-</td>
</tr>
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<td>1.4814</td>
<td>0.67504</td>
</tr>
<tr>
<td>EMPLOt</td>
<td>8.41</td>
<td>11.55</td>
<td>0</td>
<td>70</td>
<td>1.18884</td>
<td>0.84116</td>
</tr>
</tbody>
</table>

Table 3 Bivariate correlations

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>5</th>
<th>6</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. SALESt+1</td>
<td>0.36***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. EMPLOt+1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. OVERCENt</td>
<td>-0.30***</td>
<td>-0.19**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. PRIOR</td>
<td>0.28**</td>
<td>0.15*</td>
<td>0.16*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. KNOWHET</td>
<td>0.07</td>
<td>0.14*</td>
<td>0.10</td>
<td>-0.19**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. YEAR</td>
<td>0.03</td>
<td>0.04</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. AGE</td>
<td>0.21**</td>
<td>0.27***</td>
<td>0.18**</td>
<td>-0.12</td>
<td>-0.02</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. SALESt</td>
<td>0.90***</td>
<td>0.37***</td>
<td>0.25**</td>
<td>0.27***</td>
<td>0.06</td>
<td>0.08</td>
<td>0.32***</td>
<td></td>
</tr>
<tr>
<td>9. EMPLOt</td>
<td>0.27***</td>
<td>0.90***</td>
<td>0.08</td>
<td>0.16*</td>
<td>0.13</td>
<td>0.14*</td>
<td>0.21**</td>
<td>0.35***</td>
</tr>
</tbody>
</table>

***p<0.001, **p<0.01, *p<0.05
Table 4 Model 1: Fixed-effect negative binomial estimate of (employees-based) CLFs growth

<table>
<thead>
<tr>
<th></th>
<th>1a</th>
<th>1b</th>
<th>1c</th>
</tr>
</thead>
<tbody>
<tr>
<td>YEAR₁</td>
<td>-0.080</td>
<td>0.051</td>
<td>-0.078</td>
</tr>
<tr>
<td>YEAR₂</td>
<td>0.027</td>
<td>0.067</td>
<td>0.027</td>
</tr>
<tr>
<td>YEAR₃ (reference cat.)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AGE</td>
<td>0.428*</td>
<td>0.183</td>
<td>0.27*</td>
</tr>
<tr>
<td>SALEₜ</td>
<td>0.144*</td>
<td>0.094</td>
<td>0.137†</td>
</tr>
<tr>
<td>EMPLOₜ</td>
<td>0.261**</td>
<td>0.086</td>
<td>0.23**</td>
</tr>
<tr>
<td>OVERCENₜ</td>
<td>-0.316*</td>
<td>0.16</td>
<td>-0.336*</td>
</tr>
<tr>
<td>OVERCENₜ*PRIOR</td>
<td>0.410*</td>
<td>0.201</td>
<td></td>
</tr>
<tr>
<td>OVERCENₜ*KNOWHET</td>
<td>0.195*</td>
<td>0.091</td>
<td></td>
</tr>
</tbody>
</table>

Likel. Ratio vs Baseline - 6.59* 15.18**

***p<0.001, **p<0.01, *p<0.05

Table 5 Model 2: Fixed-effect cumulative logit estimate of (sales-based) CLFs growth

<table>
<thead>
<tr>
<th></th>
<th>2a</th>
<th>2b</th>
<th>2c</th>
</tr>
</thead>
<tbody>
<tr>
<td>YEAR₁</td>
<td>0.533</td>
<td>0.356</td>
<td>0.483</td>
</tr>
<tr>
<td>YEAR₂</td>
<td>-0.337</td>
<td>0.387</td>
<td>-0.533</td>
</tr>
<tr>
<td>YEAR₃</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AGE</td>
<td>0.025</td>
<td>0.021</td>
<td>0.017</td>
</tr>
<tr>
<td>SALEₜ</td>
<td>2.21***</td>
<td>0.291</td>
<td>2.12***</td>
</tr>
<tr>
<td>EMPLOₜ</td>
<td>0.084†</td>
<td>0.038</td>
<td>0.079†</td>
</tr>
<tr>
<td>OVERCENₜ</td>
<td>-0.312*</td>
<td>0.152</td>
<td>-0.420*</td>
</tr>
<tr>
<td>OVERCENₜ*PRIOR</td>
<td>0.510*</td>
<td>0.195</td>
<td></td>
</tr>
<tr>
<td>OVERCENₜ*KNOWHET</td>
<td>0.280*</td>
<td>0.085</td>
<td></td>
</tr>
</tbody>
</table>

Likel. Ratio vs Baseline - 5.01* 9.01*

***p<0.001, **p<0.01, *p<0.05, † p<0.1
Table 6: Interactions among types of absorptive capacity: Rates of growth change associated with increasing network centrality

<table>
<thead>
<tr>
<th></th>
<th>KNOWHET = 0</th>
<th>KNOWHET = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRIOR = 0</td>
<td>-0.33</td>
<td>-0.24</td>
</tr>
<tr>
<td>PRIOR = 1</td>
<td>0.19</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Figure 3 Interaction between Overall Centrality and Absorptive Capacity for Employee-based growth (EGM)
Figure 4 Interaction between Overall Centrality and Absorptive Capacity for Sales-based growth (SGM)

Without prior knowledge (PRIOR=0)

With prior knowledge (PRIOR=1)
Methodological appendix

1. Relational questionnaires: Sociometric questions

Question 1

Check off the cells in correspondence of the firms with whom, over the indicated years, you have established collaborative linkages. Check off the cell if there was a linkage in the specified year. If there are further companies with which you have collaborated than those herein provided, indicate them at the end of the document.

<table>
<thead>
<tr>
<th>Firm</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 204</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Others)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot;&quot;</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Question 2

Check off the cells in correspondence of the firms that you recognize as parties of your supply-network. Like in the previous case, check off a cell if there was a supply relationship in the indicated year. If there are additional companies to those provided here, name them at the end of the document.

<table>
<thead>
<tr>
<th>Firm</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 3</td>
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<td></td>
</tr>
<tr>
<td>Firm 204</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Others)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot;&quot;</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

""
Question 3

Check off the cells in correspondence of the firms that you recognize as parties of your customer-network. Like in the previous case, check off the cell if there was a relationship with the corresponding firm in the indicated year. If there are additional companies to those provided here, that you would like to include, please name them at the end of the document.

<table>
<thead>
<tr>
<th></th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 2</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Firm 3</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>(Others)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Question 4

Thinking of the informal ties that you have established with other members of your cluster community over the past year, could you indicate what are the firms, among those provided in the list, whose members (one or more) you know personally and turn to for valuable advice, guidance or information relevant to the company? Are there other companies that you would include to the list? Use the same criteria as in the above cases.

<table>
<thead>
<tr>
<th></th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 3</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
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<td></td>
<td></td>
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<tr>
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<tr>
<td>(Others)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Question 4b

By the same token, are you knowledgeable of similar connections maintained by any of your partners with companies other than those you have just provided? Could you please check them off?

<table>
<thead>
<tr>
<th>Firm</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>.</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>.</td>
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<td></td>
</tr>
<tr>
<td>.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm 204</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Others)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot;</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2. Measurement model indicators

Network Centrality

There are several approaches to scrutinizing the centrality of firms in networks that are used to examine the extent of information available to actors (Freeman, 1979). The most intuitive and popular measure is probably the Freeman’s ‘degree centrality’ (DEGREE1-3): The actor with the most ties is the most central. As Freeman (1979) argued, degree centrality is the most suitable centrality measure for capturing an individual actor’s information or knowledge access. Degree centrality alone, however, may be deceiving. For instance, it is quite likely that information can flow through paths other than the geodesic. The Eigenvector Centrality (EIGEN1-3) approach is an effort to find the most central actors (i.e. those with the smallest farness from others) in terms of the “global” or “overall” structure of the network, and to pay less attention to patterns that are more “local” (Bonacich, 1972) The centrality of each vertex is therefore determined by the centrality of the vertices to which it is connected13.

13 Eigenvector centrality is defined as the principal eigenvector of the adjacency matrix defining the network. The defining equation of an eigenvector is $\lambda v = Av$ where A is the adjacency matrix of the graph, $\lambda$ is a constant (the eigenvalue), and v is the eigenvector. The equation suggests that a node that has a high eigenvector score is one that is adjacent to nodes that are themselves high scorers (for details see Borgatti, 2005). The parameter $\alpha$ is required to give the equations a non-trivial solution and is therefore the reciprocal of an eigenvalue. It follows that the centralities will be the elements of the corresponding eigenvector. The normalized eigenvector centrality
We computed these two indices using the sociomatrices originated from the four relational questionnaires, following the convention that if firm \( i \) reported \( j \) as a contact (customer, supplier, collaborator or social contact) then element in row \( i \) and column \( j \) was set to 1 (and to 0 otherwise). If the answers of all firms had been consistent the supply matrix would equal the transpose of the purchase matrix, and both the collaborative and the advice ties matrices should be symmetrical\(^{14}\). This however was not always the case, possibly a consequence of the fact that firms did not recall and report all their ties properly\(^{15}\). For all networks, we considered a tie to be present if it was reported by at least one of the connected firms. We also joined supply and purchase ties in one non-directed transaction network, which disregards the distinction between buyer and seller and records only the existence of a generic transaction tie between two firms. This resulted in the three (non-directed) networks introduced above: Transaction network, Collaboration network and Advice network. The adjacency matrix for the Transaction network was built by setting both elements \( ij \) and \( ji \), to 1 if either \( i \) or \( j \) reported the other as a customer or supplier. The adjacency matrices for the Collaboration and Advice networks were obtained by symmetrizing the corresponding raw matrices; both elements \( ij \) and \( ji \) were set to 1 if one of them equaled 1 in the raw non symmetrized matrix that is, if the cooperation or advice tie was reported by at least one of the two firms involved. For each of the three matrices the two indices were assessed using UCINET 6 (Borgatti, Everett and Freeman, 2002).

3. Reliability and validity of the measurement model

We estimated the measurement model year-wise, for the three-year period 1999-2001. We started the model assessment by checking the validity of the first order structural model. *Convergent validity* - whether a set of indicators is representative of the domain they’re supposed to measure - was assessed by examining whether each indicator’s estimated loading on its posited underlying factor was large. Kline (1998) suggests that factor loading should be statistically significant and shared variance should be not trivial. Values reported on tables 6-7 indicate that these criteria were met.

Table 6 Factor loadings and composite reliability of first order centrality factors

<table>
<thead>
<tr>
<th>First Order Factor</th>
<th>Measurement item</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>Average CRI †</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centrality(^3)</td>
<td>DEGREE(^3)</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.87</td>
</tr>
</tbody>
</table>

is the scaled eigenvector centrality divided by the maximum difference possible expressed as a percentage (Bonacich, 1972).

\(^{14}\) In the first case, if firm \( i \) reports \( j \) as a customer, then \( j \) should report \( i \) as a supplier (both the elements \( ij \) of the supply matrix and \( ji \) of the purchase matrix should equal 1). In the second case, if collaboration between \( i \) and \( j \) is reported by \( i \) then also \( j \) should report it (both elements \( ij \) and \( ji \) of the cooperation matrix should equal 1); the same holds for the adjacency matrix of social ties.

\(^{15}\) This could be a consequence of distance in time; ties that were in place only in the first observed year can be expected to be more difficult to recall for all firms. Besides this, the same tie can be more important for one firm than for the other, and by consequence the first firm is more likely to recall and report about the tie. Also, recalling any single tie is more difficult in a firm that is tied to many others than for a less connected firm. Whatever the case, it is however notable that the reciprocation rate was extremely high, being close to 76%.
### Table 7 Discriminant validity tests of first order centrality factors

<table>
<thead>
<tr>
<th>Year</th>
<th>First order latent variables</th>
<th>Degrees of freedom</th>
<th>$\chi^2$</th>
<th>$\Delta \chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>All $\phi$s left free</td>
<td>6</td>
<td>9.298</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>$\phi_{12}$ fixed to 1 (Centrality3 and Centrality1)</td>
<td>7</td>
<td>18.15</td>
<td>8.852**</td>
</tr>
<tr>
<td></td>
<td>$\phi_{13}$ fixed to 1 (Centrality3 and Centrality2)</td>
<td>7</td>
<td>14.46</td>
<td>5.162*</td>
</tr>
</tbody>
</table>

$***p<0.001, **p<0.01, *p<0.05$

† Composite reliability index calculated over the three-year period. This index is analogous to coefficient alpha and reflects the internal consistency of the indicators measuring a given factor.

**Discriminant validity** - whether a construct differs from others - was assessed by constraining the correlation parameter between the factors at 1.0 and employing a chi-square difference test on chi-square values from the constrained and unconstrained models. Because the constrained version of the model is nested within the unconstrained one, the discriminant validity is achieved when the $\chi^2$ difference statistic is significant (i.e. the unconstrained model has a significantly lower chi-square value), indicating that the multiple first order factors are not redundant (Kline, 1998). As reported on tables 4 discriminant validity was consistently achieved over the three-year period.

After assessing the validity of the first order measurement model we moved to the hierarchical specification. Results are reported in table 6. Parameter estimates and goodness of fit statistics were computed for each of the three years. Consistency of results over this time span provides strong evidence for reliability.

The fit of the model was assessed with multiple indicators: the $\chi^2$ statistic test provides a test of the null hypothesis that the model fits the data. If the model provides a good fit, the $\chi^2$ will be relatively small and the corresponding p value non significant (p>.05), indicating that the model does not differ significantly from the data. The Goodness of Fit Index (GFI) is more standardized and less sensitive to sample size (Joreskog and Sorbom, 1996). Its value ranges from 0 (poor fit) to 1 (perfect fit) and indicates the relative amount of variance and covariance jointly explained by the model.
A GFI greater than 0.9 is usually considered an indication of acceptable fit. Bentler and Bonnet’s (1980) Normed Fit Index (NFI) has been proposed as an alternative to the $\chi^2$ test. This index indicates the proportion in the improvement of the overall fit of the postulated model relative to a null model (that is one in which the observed variables are assumed to be uncorrelated. The values on this index may range from 0 to 1, with values over 0.9 indicating an adequate fit of the model to the data. The Comparative Fit Index (CFI) is interpreted in the same way as the NFI (i.e., it is an incremental fit index) but it provides an assessment of fit regardless of sample size (Bentler’s Comparative Fit Index, 1990). The Standardized Root Mean Squared Residual is a standardized summary of the average covariance residuals. A favorable value of the SRMR is less than 0.1 (Kline, 1998). As summarized in the last column of table 8 all the relevant statistics are in an acceptable range, indicating that the overall fit of the hierarchical CFA model is satisfactory (Kline, 1998).

### Table 8 Hierarchical model: Overall Network Centrality

<table>
<thead>
<tr>
<th>Year</th>
<th>Path</th>
<th>Parameter Estimate</th>
<th>t Value</th>
<th>Composite Reliability</th>
<th>Fit Indices</th>
</tr>
</thead>
</table>
| 1999 | Overall Network Centrality →       | 0.77***             | 7.71    | 0.85                   | $\chi^2 = 9.29$  
|      | Centrality1                        |                    |         |                        | ($p = 0.157$)  
|      | Overall Network Centrality →       | 0.68***             | 6.56    |                        | GFI = 0.97    
|      | Centrality2                        |                    |         |                        | CFI = 0.99    
|      | Overall Network Centrality →       | 0.83***             | 8.36    |                        | NFI = 0.98    
|      | Centrality2                        |                    |         |                        | SRMR = 0.013 |
Turning to the path coefficients, it is notable that the vast majority of second order paths are statistically significant at $p < 0.001$, an indication of convergent validity (Bollen, 1989). Finally, the proportion of variance in the first order factors that is accounted for by the higher order constructs can be used to assess the reliability of the latent factors. As illustrated in the penultimate column of each table, the composite reliability ranges consistently from 0.66 to 0.88 over the three-year period, suggesting adequate reliability. The satisfactory indications offered by factor loadings and fit indices, and the robustness of results over time increased our confidence that the model provided a suitable assessment of the network constructs of theoretical interest.

4. Fixed-effect estimation models

A fixed effect negative binomial was used to estimate the probability of firm growth when using the employees-based dependent variable.

Negative binomial regression models can be formulated in different ways, the model used here is what Cameron and Trivedi (1998) call an NB2 model, where the probability function for $y_{it}$ is given by

$$
\Pr(y_{it} = r) = \frac{\Gamma(\theta + r)}{\Gamma(\theta)\Gamma(r+1)} \left( \frac{\lambda_{it}}{\lambda_{it} + \theta} \right)^r \left( \frac{\theta}{\lambda_{it} + \theta} \right)^	heta
$$

In this equation $\lambda_{it}$ is the expected value of $y_{it}$, $\theta$ is the overdispersion parameter, and $\Gamma(.)$ is the gamma function. As $\theta \to \infty$, this distribution converges to the Poisson distribution. We then specify how the parameter depends on the explanatory variable by assuming a loglinear regression decomposition of the expected value,
\[ \log \lambda_{it} = \alpha y_{i,t-1} + \mu_{t-1} + \beta x_{i,t-1} + \gamma z_i + \alpha_i \]

where \( \alpha \) is a parameter that indicates how current growth depend on prior growth, \( x_{i,t-1} \) represents the time-varying vector of predictor variables at time \( t-1 \), \( \gamma \) denotes the time-invariant predictors, and \( \alpha_i \) denotes the unobserved “fixed effects”. Inclusion of the lagged dependent variable among the predictors helps account for the endogeneity problem already discussed.

The model was estimated on the pooled dataset with each firm contributing a time series panel. An observation for every firm was entered for every year for which data is available. For example if a firm has three years of data, then it would contribute 3 observations to the analysis. The estimation procedure was based on unconditional maximum likelihood. In fact, while Hausman, Hall and Griliches (1984) proposed a different fixed-effects negative binomial regression model deriving a conditional maximum likelihood estimator for that model, Allison and Waterman (2002) have shown that this is not a true fixed-effects regression model, and the method does not control for all stable covariates.

Because the second growth measure is an ordered categorical variable in order to predict the variation in market sales to be expected in an interval of time we estimated a fixed effect cumulative logit. The variation in class of market sales over time can then be modeled as follow:

\[ \log \left( \frac{F_{ij}}{1 - F_{ij}} \right) = \alpha y_{i,t-1} + \mu_{t-1} + \beta x_{i,t-1} + \gamma z_i + \alpha_i \quad j = 1, \ldots, J - 1 \]

where \( F_{ij} = \sum_{m=1}^{J} p_{im} \) is the “cumulative” probability of being in category \( j \) or higher; \( \mu_{t-1} \) is an intercept which is allowed to vary with time, \( \gamma \) is a column vector of variables that describe the persons but do not vary over time; \( x_{i,t} \) is a column vector of lagged variables that vary both over individuals and over time for each individual and \( \alpha_i \) represents all differences between persons that are stable over time and not otherwise accounted for by \( \gamma z_i \). Finally, \( \alpha \) is the parameter for the lagged dependent variable.

4. Geographical clusters topographies
Figure 5 The Bologna Multimedia Cluster: a topographic illustration*

*GIS based elaboration. CLFs are represented as blue dots in the map.

Figure 6
The Multimedia District of Toronto
(source: Brail e Gertler, 1999)

Figure 7
The Baden-Wurttemberg Multimedia Cluster
(source: Fuchs e Wolf, 1999)

Figure 8
The Multimedia Gulch
(source: Scott, 2000)

Figure 9
The Los Angeles Multimedia Cluster
(source: Scott, 2000)