Firm Performance Gains and Losses from Network Centrality in Cluster Located Firms: A Longitudinal Study*

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Abstract

This paper develops and tests theoretically derived arguments on the performance trade-offs that arise when firms located inside geographical clusters broaden their cluster networks and increase their centrality. Using three-year longitudinal data gathered on a sample of 89 small media firms located in a geographical cluster of Northern Italy we model growth in revenues and in employees as a function of their centrality in different types of networks. We find an inverted U-shaped effect of centrality across all types of networks. We also find strong evidence of negative interactivity between network types in predicting sales and employee growth. This result not only concurs with the view that centrality brings tangible and intangible benefits, but also provides empirical support for the contention that centrality fosters dispositions and disturbances that undermine performance.

Key words: geographical clusters, interorganizational networks, firm performance, growth, network centrality.

INTRODUCTION

Over the past two decades, network-oriented explanations of organizational outcomes have been center stage in the literature on geographical clusters and systematic empirical attention has been increasingly devoted to the social networks that underpin the performance and behavior of firms located within geographical clusters (Powell & Owen-Smith, 2004; Ter Wal and Boschma, 2011; Powell et al., 2012; Giuliani, 2013; Glückler and Doreian, 2016). Typically, scholarship in this area draws on knowledge transfer and structural embeddedness arguments to draw causal inferences on the relationship between network location and firm performance (Giuliani, 2007). Central to this logic is the idea that cluster networks provide the conduits through which information flows. Thus, to the extent that firms occupy heterogeneous network positions, they vary in their access to this information. And to the degree that firm performance hinges on access to idiosyncratic and private information, differences in network positions can help explain inter-firm variance in performance.

These types of arguments are abundant within the cluster literature, yet actual empirical findings on the effect of interfirm networks on the performance of firms located within geographical clusters remain rather mixed. On the one hand, one stream of scholarship supports the view that high cluster connectedness improves performance. This line of work dates back to classic arguments from the new economic sociology that views networks as an essential component of markets because they securely channel flows of information from position to position within an interorganizational structure (Podolny, 2001). In short, this literature "puts a strong premium on the geographical concentration of knowledge flows between firms within clusters" (Ter Wal and Boschma, 2011, p. 921). On the other hand, a second stream of work warns of the costs associated to high cluster connectedness. This work draws on bounded rationality and economic geography to expose the potential downsides of establishing and expanding connections in a context where spatial proximity and institutional communalities may exacerbate leakages of potentially relevant information to competitive rivals and accentuate isomorphic pressures (Owen-Smith & Powell, 2004). According to this second view, highly central firms do worse than their lower-centrality counterparts because of the distraction of focus and leakages that accrete around central positions in the cluster network.

These contradictory findings prompt two opposing interpretations of the relationship between centrality and performance within geographical clusters: one that sees cluster connectedness as beneficial, the other that cautions against its drawbacks. Which one of these two perspectives comes closer to reality? Are there cluster-specific theoretical reasons why we should expect these conflicting results? And are these views in any way reconcilable? In what follows, we summarize the two views and analyze multi-network data that we have collected on interorganizational networks within a geographical cluster as an empirical opportunity to test these conflicting perspectives. To this end, we propose a theoretically derived model according to which the performance of firms located within the cluster is a curvilinear function of network centrality as measured by the firms' location in two different types of interfirm networks. We summarize this idea through the notion of "liability of connectedness", i.e., the existence of marginally decreasing and ultimately negative returns to centrality.

We test and find support for our model using a multi method approach that combines interview information with unique longitudinal data from a geographical cluster of small multimedia firms located in Northern Italy, where we investigate the relationship between network centrality and performance using two different, types of interorganizational linkages: formal ties, represented by business alliances, and informal ties, represented by advice ties. Including both types of ties is a crucial element of our study because few scholars examine the separate performance effects of multiple types of ties within a single study (for recent exceptions see Bell, 2005; Giuliani, 2007; Lechner, Frankenberger and Floyd, 2010; Belso-Martínez et al., 2017), although a great deal of research exists about each. Examining two distinct types of networks also allows us to talk more persuasively about the impact of centrality on performance and alleviates the possibility that the idiosyncrasies of any one type of tie drive our results. The results prove robust to different specifications of firm performance, thus enhancing our confidence in the ability of the model to adequately address consistent calls by organizational as well as economic geography scholar to probe more deeply and systematically into the relationship between local network structure and performance within geographically bounded industries (Castilla, Hwang, Granovetter, and Granovetter, 2000; Molina Morales and Martinez-Fernandez, 2009; Ter Wal and Boschma, 2009). As pointed out by Ter Wal and Boschma (2009, p. 744): "large scale and convincing evidence on a positive or curvilinear relationship between network centrality and firm performance [within clusters] has not been shown yet. Only a longitudinal view on networks will reveal the stability or volatility of the positions firms take in these networks and whether a relationship with firm performance […] can be detected. To the best of our knowledge, such a hypothesis has not been tested yet".

In the following sections, we review the two contrasting lines of argument concerning the performance-related consequences of network centrality within geographical clusters. We begin with findings suggesting that cluster connectedness is beneficial to firm performance, and next turn to research highlighting the downsides of cluster networks. We then describe the data and the measurement strategy and present the results. We conclude by discussing the implications of the findings, their limitations and topics for future research.

CONTRASTING THEORETICAL ARGUMENTS

Geographical Clustering and Network Benefits

Several organization studies offer support to the contention that network ties, particularly their pattern or structure, affect firm performance because they channel and direct flows of information and resources from position to position within a social structure (Podolny, 2001). Scholars in this tradition emphasize the benefits that accrue to well-connected firms because of their position at the convergence of information and knowledge that percolates through their connections (Gulati, 1995; Powell, White, Koput, & Owen-Smith, 2005). For example, in a much cited study on the US biotech industry, Powell et al. (1996) found that the pathway to network centrality through interorganizational linkages was a crucial prerequisite for the success of biotech firms, due to better access to knowledge. They concluded the study by suggesting a liability of disconnectedness, in which less-linked organizations are the most likely to fail. In a follow-up study the same team of researchers also showed network centrality to be a good predictor of firms' financial performance and growth (Powell, Koput, Smith-Doerr & Owen-Smith, 1999). In another study on biotech firms, Baum and colleagues (2000) showed that the initial performance of startups increases with the size of their network of alliances (i.e., the degree centrality). Their main argument is that centrally located companies may benefit from better access to strategic and operational know how. In each of these pioneering studies, networks are important to markets in a particular way. They shape outcomes insofar as they are conduits for the flow of information or resources; metaphorically, they are "pipes" (Podolny, 2001) through which "stuff" flows (Borgatti & Foster, 2003).

Various researchers have advanced similar arguments to underscore the benefits accruing to firms located inside geographical clusters. In fact, this 'network-access' conceptualization seems particularly appropriate to characterize cluster settings where, as pointed out by Powell, Koput, Bowie, and Smith-Doerr (2002: 293) "The advantages of location […] are very much based on access and information." Similar findings are reported in a study on interfirm alliances within biotech clusters in which the authors come to the conclusion that "merely being part of a geographical cluster does not help firm performance […] Instead […] it is when firms establish formal alliances within the cluster that they benefit" (Zahara and George, 2004: 448). Supporters of this view emphasize that because cluster firms share a common institutional setting and are spatially proximate, they are more prone to circulate ideas, knowledge and fined-grained information that can be channeled and secured through the web of personal and professional ties that typically envelope their interactions (Lazerson and Lorenzoni, 1999). As noted by Breschi and Malerba (2005: 3): "The possibility for individual firms to tap into the body of localized knowledge and capabilities depends critically on the ability to establish and maintain effective linkages and connections with other members of the cluster environment." It follows from this line of arguments that those firms that are plugged into the network by maintaining more of these connections to other local actors are likely to perform better.

Geographical clusters scholars who embrace this *connectionist* logic underscore the importance of network centrality as a critical path to firm performance (Molina-Morales & Martinez-Fernandez, 2004; Giuliani, 2007). 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). High centrality leads to higher volume of information (Koka and Prescott, 2002) and "the greater the information the higher the opportunity set" (Gulati, 1999, p. 399). Thus, by being at the point of convergence of multiple relationships central firms 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 made by one of the entrepreneurs we interviewed for this research:

> *"Partners, suppliers, contacts, 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 one of our collaborators"*

Furthermore, because centrality implies visibility, firms more centrally located enjoy status benefits such us a greater ability to undertake promising initiatives and/or attract further opportunities. They have higher reach and are also more accessible than others in the intra-cluster network. Another 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 make new business."*

Taken together, these lines of arguments suggest that higher centrality results in better performance and it is therefore plausible to expect highly central cluster firms to outperform their lower centrality counterparts.

Geographical Clustering and Network Downsides

Despite the preponderance of prior research underscoring the benefits of network centrality, a number of other studies point precisely in the opposite direction. For instance, consistent with this idea, Owen-Smith and Powell (2004) found that Boston biotech cluster firms that are centrally located in the web of cluster linkages are less likely to innovate. In the full model, the effect of betweenness centrality is indeed negative and highly significant, suggesting that an increase in centrality is conducive to performance losses for the biotech firms located in the Boston cluster. Wood, Watts, and Wardle (2005) analyze the relationship between various measures of local networking and growth orientation in the Sheffield Metal working cluster and, in line with Owen-Smith and Powell, find either a negative or non significant relationship. This contrasting view rests on multiple theoretical arguments tying together cluster connectedness and performance losses. First, because co-location makes knowledge "leakage" easier, cluster firms ability to benefit from their ties will depend on whether the competitive advantage gained from knowledge inflows outweighs the dilution of competitive advantage resulting from knowledge outflows (Shaver & Flyer, 2000). Maskell (2001), for instance, states that the agglomeration of similar activities in transparent clusters increase the odds that successful experiments by other local firms are quickly noticed, and taken up with limited costs. Thus, because increasing centrality implies not only greater access but also increasing accessibility with associated risks of spillovers and to the extent that other cluster members are effective in picking up these network leakages, broadening the network may become detrimental. A second argument tying together cluster connectivity and costs states that organizations that share the same bounded geographic area and therefore are embedded in a common milieu will tend to share the same slant on issues and attend to relatively similar information (see for example work by Glasmeier 1991 on Switzerland watch-making districts). Consequently, companies that tap knowledge extensively from other co-localized companies by broadening their centrality are more likely to come across information they already possess and that reflects a common understanding of the world (Bell & Zaheer, 2007) thus reducing the rent potential of this information. For instance, some related research suggests that common sources of information from, and extensive interaction with, like-minded actors may reinforce the cognitive models of competition shared by firms within the cluster (Pouder & St. John 1996), leading to forms of group-think. McEvily and Zaheer (1999) found that the interfirm information networks of enterprises in geographical clusters with greater redundancy tend to acquire fewer competitive capabilities and reduce their flexibility in creating new ties. These institutional pressures, in turn, might contribute to cluster-wide inertia, leading to additional costs in the form of foregone flexibility due to the persistence of established behaviors and taken-for-granted assumptions. This idea is captured by the observations of an owner-manager we interviewed who explained why he was relocating his company out of the cluster:

> *"here everybody knows what everybody else knows and the more you network the more you get bogged down the conventional wisdom of the industry"*

Third, ties may also generate cognitive costs in the form of attention diverted from other activities as well as coordination costs due to the complexity of monitoring multiple network contacts (Hansen, Podolny and Pfeffer, 2001). This idea has precursors in Gargiulo and Benassi's (1999) discussion of the downsides of social capital, in which social ties imprison actors in maladaptive situations or generate costs (Borgatti & Foster, 2003). As a result, managerial attention, frequently a constrained resource, may become overloaded. Cognitive research points to various disfunctionalities that may arise from 'information overload' (Simon, 1971) including a lack of perspective and an inability to select out irrelevant information, leading to cognitive strain that adversely affects the timeliness and quality of decisions (Eppler & Mengis, 2004; Ferriani et al., 2009). These cognitive costs, in turn, "should affect a range of performance-related goals. For example, decisions may be delayed or poorly made, production quality may suffer, and the degree of innovation may be lacking to the extent that individuals and groups do not fully commit time to conduct high-quality work because they spend time on networks" (Hansen et al., 2001: 50).

Summary

In short, alternative lines of research highlight the potential detrimental effects of investing time and energy in higher cluster centrality. This brings us back to the question of which of the two views of cluster networks and performance is more accurate. On the one hand, the dominant research stream and associated connectionist logic with which we began construes network centrality as an asset. The literature we just discussed, though, highlights a series of costs of connectedness. In what follows we seek to reconcile these views empirically by relaxing the prevailing assumption of linear-only relationship, testing for a curvilinear cluster network centrality-performance relationship. Underlying such test is the presumption that *as cluster centrality increases, the positive information access effects plateau at a certain point, and beyond that point the costs associated to the broadening of the network surpass the positive effects.*

The analysis of a geographical cluster situated in Northern Italy allows us to pit the two views against each other empirically by assessing how performance is affected by the firm's position in multiple cluster networks. The strength of our evidence will reside, in part, with the degree to which firm behavior generalizes across different types of network relationships.

METHODS AND MEASURES

Research Setting

The field setting of this research consists of a geographical cluster of micro and small multimedia enterprises located in the metropolitan area of Bologna, an area well known for the presence of important industrial districts (Lorenzoni & Lipparini, 1999). During the late 1980s and early 1990s this area was characterized by an entrepreneurial wave that led to a fertile and dense agglomeration of multimedia enterprises (Ferriani et al., 2013).

In the last two decades, a number of public authorities, 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. According to Braczyck, Fuchs, and Wolf, multimedia is "a paradigmatic example of industries of increasing importance to regional economic prosperity" (1999: 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). Furthermore, 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 firm clusters in the multimedia industry include the San Francisco Multimedia Gulch (Egan & Saxenian, 1999) and Silicon Alley in Manhattan (Neff, 2005). Analogous agglomerative dynamics have been shown to have occurred in the metropolitan area of Stockholm (Backlund & Sandberg, 2002), as well as in the German regions of Cologne-Düsseldorf and Berlin-Babelsberg (Sydow & Staber, 2002), Leipzig (Bathelt, 2005) and in the Netherlands (Gilsing & Nooteboom, 2005).

Data

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. 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[1]. 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 perceptions of the role cluster networks played in their business. These interviews reaffirmed the relevance of examining the link between networks and performance outcomes in this setting. The final questionnaire was then used during the personal interview phase with the participating companies.

With this step (refining the questionnaire) completed, we 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[2]. The distribution of these firms by industry segment in the original population and in the sample is provided in Table 1.

Table I here

On average, firms in the sample were approximately 8 years old, with annual turnover lower than Euro 300,000 and less than 9 employees. 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 sociometric interviews[3], with an average duration of about 90 minutes 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 into 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 terms of education and previous professional experience. In the second, more time demanding part the informant was required to provide information on the company's network and to recollect their change over time (see below for details). Tracking the evolution of the network was an important requirement in addressing key issues of causality.

In reconstructing the cluster networks, we focused on two types ties: alliances and advice relationships. We focused on these networks for two reasons: First, their role in shaping performance is well established in the cluster literature. For instance, information transmission is a driving mechanisms of the performance-enhancing collaborative patterns widely investigated by Powell and colleagues (2002, 2005, 2009) in the biotech clusters of Northern U.S. Similarly, in their study of the metal-working cluster McEvily and Zaheer's (1999) emphasize the central role played by firms' advice networks in providing access to heterogeneous niches of information, which in turn sustain the development of competitive capabilities. Second, while there is obviously a plethora of formal and informal ties that contribute to the structure of the cluster interorganizational network, focusing on a critical subset of ties may help maintain clarity and provide momentum in the empirical development of the conceptual arguments.

Thus, each informant was presented with two network questionnaires, matching the types of network tie just described. For each sociometric question, respondents were provided with a list of all the other 204 firms included in our cluster population list. In response to the list (with the same list reported two 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[4]. In essence, the respondents had to indicate those companies that they identified either as their business partners or companies whose founders they recognized as individuals on whom they usually relied for advice and information. In line with previous research (Powell et al. 1996, 2005) a partnership tie was defined as any contractual asset pooling or resource exchange agreement. This procedure was repeated on two occasions, at the beginning of 2001, when the interviewees were required to provide sociometric data concerning 2000 and 1999, and at the beginning of 2002, when they were asked to complete the questionnaire with regard to their networking activity in 2001 (see section I of the methodological appendix for an overview of sociometric questions). The procedure resulted in a three-year bi-relational dataset for the 89 sampled firms. These data were then converted into 2 sociomatrices (2 adjacency matrices - representing the 2 types of relationships between the firms -

for each of the 3 years, totaling 6 sociomatrices over the full period), which were used for the computation of network measures. As a final step, between January and February 2003 all of the firmss were recontacted by telephone in order to obtain updated performance data as of 2002.

Dependent Variable

We employed two measures of growth as dependent variables. Although other indicators such us accounting profits are perhaps more commonly employed as measures of firm performance, the chosen indictors were the only one available for all the firms in the sample. This codification strategy was necessary because 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. Besides, managers commonly focus on growth as key performance metrics, both because growth may lead to higher profitability and because firms frequently value growth independent of profitability. In addition, firm growth tends to correlate to greater business survival chances, which managers and stakeholders value (Singh & Mitchell, 2005). Based on the above, we indexed growth in two ways: (1) we used the reported number of employees at time t ($Emplo_t$) to compute a measure of year by year absolute growth, and (2) we used the reported market sales at time t ($Sales_t$) to compute an ordered class dependent variable ranging from 1 to 8, based on an eight points scale of increasing market sales brackets defined during the pilot study. The respondents were asked to indicate their performance 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

Network centrality. Using the two aforementioned types of ties we calculated two distinct centrality measures: *Formal Network Centrality*, based on the alliance network and *Informal Network Centrality*, based on the advice network. While both types of ties capture the extent of cluster firms' involvement in the networking activity of the cluster they are also intrinsically different. The first type of tie is of a purely business nature and defines the position of the firm in the formal 'plumbing' of the market. Advice ties, on the other hand, signal the firm position in the informal texture of the cluster and even if they may be highly consequential in the attainment of business relevant information, they are more personal and have a fundamentally social nature. Besides, while partnership ties are inherently symmetric, advice ties are not (the fact that A turn to B for getting information does not mean that B turn to A for information). This was confirmed by the analysis of the reciprocation rate that was 73% in the collaboration network, and 49% in the advice network. This is not surprising given that high-status individuals are less likely to reciprocate their lower-status advice contacts than vice versa (Krackhardt 1987). Accordingly, while we symmetrized the alliance network we preserved the observed asymmetries in the advice network. More specifically, we transformed the alliance data in one non-directed symmetrical network, which records the existence of a formal business linkage whenever a business collaboration exists between any two cluster firms. This adjacency matrix represents the formal network. We then built a directed adjacency matrix that differentiates between advice ties that were originated by actor i versus those originated by actor j. This matrix represents the informal network. The network centralities were calculated based on these two matrices, which were created for each of the 3 years of the study.

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). Different approaches, however, make different assumptions about how traffic flows through the network, which means that different measures are more or less appropriate depending on how closely the flow of interest matches those assumptions (Borgatti, 2005). Since we were primarily interested in the movement of information across the network and the risk of exposure of each node (firm) to such flows, we opted for the eigenvector centrality measure (Bonacich, 1972). According to the eigenvector approach, central nodes are those connected to other nodes that are themselves well-connected[5]. We therefore calculated the variable *Formal Network Centrality* (FNC) by applying the eigenvector procedure to each of the three adjacency matrices representing the Formal Networks in 1999, 2000 and 2001. These networks are almost fully connected; with only 4 firms being isolated in 1999 and 3 in 2000 and 2001 (these firms were assigned a centrality score of 0). We could not apply the eigenvector approach to the Informal Network, being this network asymmetric and substantially more fragmented. In its place, we computed outdegree centrality. In our context, the outdegree corresponds to the number of firms that the focal firm actively reaches out to and gets information from. Although degree centrality is somewhat inferior to eigenvector in that it only counts the direct ties that emanate form a node, it embodies the same flow assumptions as the eigenvector measure, thus making it an appropriate indicator for the causal mechanisms of interest in this study. We therefore created the variable *Informal Network Centrality* as the firms' outdegree in the three adjacency matrices representing the advice networks in 1999, 2000 and 2001. The centrality indices were calculated using UCINET 6 (Borgatti, Everett and Freeman 2002) and their 1-year lagged versions were included in the estimation model.

Control Variables

To rule out possible competing explanations, we included the following control variables in the final model specification.

Company age. Age is related with performance in many entrepreneurship studies (Low & MacMillan, 1988). It appears as a predictor in ecological and life-cycle theories of firm survival, and it also serves as a proxy for experience or advantages due to the establishment of internal routines. We computed the variable firm age for each firm in each year as the number of years a firm has been in business (date of founding subtracted from the current date).

Industry segment. Firms in different industry segments may experience different market conditions or competitive intensity. Besides, there may be systematic differences among firms of different segments in their networking proclivity. We therefore use dummies to control for possible performance differences between firms across sub-sectors (sector 6 was used as the holdout comparison category).

Team size. Because measures of team heterogeneity are size-dependent (i.e., larger teams may be more diverse), team size was controlled as the total number of individuals on the founding team.

Commitment. Entrepreneurs may differ in terms of their commitment towards growth and risk-taking propensity towards emerging opportunities. Entrepreneurs with different commitment may therefore act differently on the information they come across through their networks or through their participation to the cluster life. We controlled for this effect with a variable that measures the amount of private equity invested by the entrepreneur (or entrepreneurial team) at founding. A higher equity commitment is consonant with the definition of risk-taking propensity and may signal a higher proactiveness towards promising opportunities (Miller, 1983).

Structural cohesion. Cohesion refers to the extent to which a relationship is surrounded by third-party connections. Cohesion affects the way that actors are socialized into a social circle and the internalization of group norms, including cooperation. The cooperative norms promoted by cohesion, in turn, can act to mitigate potential conflict and promote performance by facilitating knowledge transfer (Coleman, 1990). To account for this effect, for each firm in the alliance network we estimated Burt's (1992) classic network constraint index, which is the inverse of structural holes.

Lagged performance. Inclusion of the previous year measure of performance helps account for the possibility of any specification bias due to unobserved heterogeneity. In particular, controlling for lagged performance should mitigate spurious effects due to endogeneity

Year dummies. 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 munificence of the cluster environment or the extent of competitiveness.

Estimation Models

In order to test our theory longitudinally while accounting for the different nature of the dependent variables, we estimated two different longitudinal models: a GEE negative binomial to treat the discrete, count nature of the employees-based dependent variable, and a GEE 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. We thus included the stochastic component ε_{it} that allows for the effect of omitted explanatory variables to correct for this problem as follows

$$E[Y_{it}] = \lambda_{it} = \exp\,(y_{it} = \mu_t + \beta x_{it} + \gamma z_i + a_i + \varepsilon_{it})$$

where $\exp(\varepsilon_{it}) \sim \Gamma\,[1, \alpha]$ – i.e., it is assumed to have a gamma distribution. The subscripts i and t indicate that the parameter λ is allowed to vary across individuals (i = 1, …, n) and time (t = 1, …, *m*). In this formulation of the negative binomial model, the parameter α is estimated directly from the data and captures over-dispersion. Since λ cannot be less than 0, it is generally expressed as a log-linear function of the covariates as follows

$$\text{Log}\,\lambda_{it} = \alpha_i + \beta_1\,(\textit{Age}_{it}) + \beta_2\,(\textit{Industry segment}_{it}) + \beta_3\,(\textit{Team heterogeneity}_{it}) + \beta_4\,(\textit{Team Size}_{it}) + \beta_5\,(\textit{Commitment}_{it}) + \beta_6\,(\textit{Structural cohesion}_{it-1}) + \beta_6\,(\textit{Performance}_{it-1}) + \beta_7\,(\textit{Network centrality}_{it-1}) + \textit{Year Dummies}$$

Cumulative logit models are a generalization of logit models specifically suited to handle ordered categories (Allison, 2005). We estimated this model in order to predict the variation in market sales to be expected over of time. The variation can then be modeled as follows:

$$\log\left(\frac{F_{ijt}}{1-F_{ijt}}\right) = \mu_{t-1j} + \beta x_{it-1} + \gamma z_i + \alpha_i \qquad j = 1,\ldots, J-1$$

where $F_{ijt} = \sum_{m=j}^{J} p_{imt}$ is the "cumulative" probability of being in category *j* or higher; μ_{t-1} is an intercept which is allowed to vary with time, z_i is a column vector of variables that describe the persons but do not vary over time; x_{it-1} is a column vector of lagged variables that vary both over individuals and over time for each individual and α_i represents all differences between persons that are stable over time and not otherwise accounted for by γz_i.

Both models were estimated by using the Generalized Estimating Equations (GEE) with standard errors and associated statistics calculated using the robust method of White (1980) to control for firm heterogeneity and the existence of any systematic difference across firms due to unobserved effects. This method allows for correlation in the dependent variable across observations over time – due to repeated yearly measurements – by estimating the correlation structure of the error terms (Liang & Zeger, 1986). By using an autoregressive structure, we assumed the correlations between repeated measurements of the dependent variable to decline from period to period (Allison, 2005). We also ran the model by imposing an exchangeable correlation structure, which assumes the correlations between repeated measurements of the dependent variable are equal across time. We finally tried a less restrictive specification in which the correlation matrix for values of the dependent variable across the observation years has a "banded" structure. There is, in other words, one correlation for values that are one year apart, another correlation for values that are two years apart, and so on (for a more comprehensive analysis, see Allison, 2005: 97). Results turned out to be consistent across all such specifications.

RESULTS

Table 2 shows the descriptive statistics and multicollinearity checks for the variables included in the analysis. We assessed multicollinearity by regressing each of the variables against all other explanatory variables and then calculating a variance inflation factor (VIF), measured as one over the difference between one and R2. While there is no formal cutoff value for determining presence of multicollinearity, statisticians sometimes suggest 2 as a threshold level above which one should be concerned. As displayed in the last column of Table 2, we found Formal Network Centrality and Informal Network Centrality to be moderately inflated, their VIF being 2.1 and 2.2 respectively. Accordingly, the effects of these two variables were estimated separately.

Table II here

In Tables 3 and 4 we reported the results of the regression analysis. Table 3 reports the model estimated by using the number of employees as the dependent variable (($EMPLO_t$). There are three versions of this model. Model 1a is the baseline model. In model 2a and 3a we provide tests for the existence of a curvilinear effect of centrality on performance by introducing the two versions of our variables of theoretical interest together with their squared versions, one at a time. Table 4 shows the cumulative logit estimates. The same variables were entered to estimate their effect on the alternative sales-based measure of performance. Again, we provided two subsets of explanatory variables in order to separate the two correlated centralities and display their incremental contribution. The last row of the tables highlights the change in fit using deviance and the likelihood ratio chi-square test for adding new variables to the model respectively.

Table III here

Model 1a in Table 3 includes only the control variables. Among the controls, it is notable the significant and negative effect of segments 2 and 5 (as contrasted to the reference segment) as well as a negative trend in year 1. The effect of the commitment variable is negative and significant. Although we used the founders' equity as a proxy for commitment, this variable might also suggest a process of self-selection whereby entrepreneurs who put a lot of personal equity in the venture are those who have not received a favorable assessment by professional investors, due to weak growth prospects. Lagged performance is positive and highly significant as expected. Team size, age, and structural cohesion have no significant effect on growth. Model 2a presents the results after the inclusion of the first version of the variable of theoretical interest (*Formal Network Centrality*), which gauges the extent to which firms occupy a central position in the cluster alliance network. Both the linear and the quadratic terms are statistically significant. Firms that increase their centrality in the formal 'plumbing' of the cluster are more likely to experience performance benefits, but beyond a given threshold the effect turns negative. Model 3a corroborates these findings when using the alternative advice ties-based measure of centrality (*Informal Network Centrality*) thereby confirming that, regardless of the type of tie, network centrality has a non-monotonic effect on performance.

Interestingly enough, across much of the centrality distribution of both types of network, performance rises before tipping at a significantly high level of centrality, after which firms do worse. More precisely the value of Informal Network Centrality such that performance reaches the maximum is given by:

$$\text{Informal Network Centrality Max} = -(0.242)/2^{*}(-0{,}011) = 11.$$

Thus, when Informal Network Centrality is lower than 11 the relative impact of its increase on the odds of experiencing an increase in the number of employees is positive. However, beyond this threshold level the average effect of any further increase in Informal Network Centrality becomes negative. Note that while this turning point falls within the actual range of variation of Informal Network Centrality (0 < Informal Network Centrality < 27) it exceeds its mean (6.3) appreciably. Similarly, the value of Formal Network Centrality so that firm performance gets to its maximum is

$$\text{Formal Network Centrality Max} = -(26.04)/2\ ^{*}(-102.29) = 0.13$$

Again, the turning point is within the variable range (0 < Formal Network Centrality < 0.55) and is greater than its mean (0.1).

Table IV here

As shown in Table 4, not only are these findings robust to the two alternative specifications of network centrality, but they are also fairly consistent across the two estimation models. With respect to the effect of Formal Network Centrality (model 2b) on sales-based performance, both the linear and the quadratic terms of the variable are in the expected direction; however, only the linear version is statistically significant ($p<0.05$), thus providing only partial support to the curvilinearity argument. Model 3b reaffirms the marginally decreasing and ultimately negative impact of Informal Network Centrality on cluster firms' sales growth. As informal centrality increases, so does the probability of being in a higher market sales category, but this effect becomes progressively smaller in magnitude and it finally becomes negative as centrality hits a threshold level of 14. This model fits the data significantly better than the baseline, as suggested by the difference in log-likelihoods. In all, three models out of four suggest the existence of a non-monotonic relationship between firm centrality and performance. Besides, the significant extent to which these turning points exceed the mean in each type of network is suggestive of differences in the relative weights on distinct effects that move with centrality. These results, in other words, indicate that benefits as well as downsides move at different rates with centrality. Indeed, for much of the centrality distributions the negative concomitants of centrality rise slowly and then turn sharply upwards for those firms that are positioned close to the extreme of the centrality distribution. Although further work in other settings is clearly necessary to better appreciate the typical location of tipping points (i.e., when centrality exerts negative effects), these initial findings provide important guidance for examining the distributional locations of centrality-related downturns in firm performance.

Next, to further analyze the downsides of networking, in Table 5 (model 1c and 2c) we explore the possibility of an interaction effect between the two types of centrality. Model 1c shows the effect of being central in both types of network on employee-based performance. Model 2 presents the same effect for sales-based performance. In both models, the interaction effect between Formal and Informal Network Centrality is negative and highly significant. So, for instance, as the level of centrality in the informal network increases, the positive effect of centrality in the formal network declines and eventually becomes negative. For example, to interpret this effect we can look at the implications of differentiating our employee-based performance measure (EM) with respect to our two key centrality variables: formal and informal centrality.

Table V here

EM = 21.31*Formal Network Centrality + 0.29*Informal Network Centrality – 2.66* Formal Network centrality *Informal Network centrality

Or: EM = 21.31*FC +0.29*IC - 2.66*FC*IC

Differentiating: $\delta EM/\delta FC = 21.31 - 2.66*IC$, which $=0$ when $IC = 8.01$

So $\delta EM/\delta FC < 0$ when $IC > 8.01$

Thus, performance declines as formal network centrality increases, when centrality in the informal network is higher than 8.01. In other words, the benefits that can be accrued from expanding one type of network marginally decrease as the actor broadens the other one. This effect eventually turns negative. The interpretation is similar for model 2c.

Sensitivity Analysis

At the beginning of 2001 we gathered network data for both 1999 and 2000. This raises two potential issues. First, the recollection of relationships that are two years old may be inaccurate due to memory biases and cognitive limits, thus resulting in more severe measurement errors (Calloway et al., 1993). Second, because the two networks were collected in the same occasion it was probably difficult for respondents to correctly differentiate between them, again leading to measurement biases. We took two steps to alleviate these concerns. We rerun the regressions using only 2000 and 2001 network data (recollected in 2001 and 2002 respectively) while removing 1999. We also rerun the analysis using a measure of centrality in the network computed by using only reciprocated relationships. In both cases, the results turned out to be consistent with those presented here.

As we discussed earlier the eigenvector centrality measure embodies nice theoretical assumptions that make it suitable for this study and has the attraction of measuring centrality relative to the whole network. Yet, just because this measure relies not only on ego's centrality but also on the centrality of alters it may experience substantial fluctuations when nodes are sampled like in our case. So, for instance, nodes that show up as marginal in the network might actually turn out to be more central due to high connectivity of alters to whom they are tied but that are not included in the sample. To account for this potential source of bias we re-estimated the models by substituting the eigenvector measure of formal network centrality with a measure of degree centrality. Because degree centrality is a local property and the degree centrality of ego is the same as the degree of the actor in the whole network, the sampling concern is not as strong as in the case of the eigenvector (Everett & Borgatti, 2005). This check did not result in appreciably different results from those presented in the paper (this is not surprising given the strong correlation between the two measures).

Finally, while our models and robustness checks provide evidence that changes in network centrality are associated with changes in firm performance (as gauged by growth measures), they do not demonstrate the direction of causality. A plausible alternative is that firms expand their network because they grow. Although the adoption of a longitudinal estimation procedure with lagged network effects lead us to believe that the causal relationship we specify is consistent with the results of the analysis, it would be imprudent to deny that firm network centrality and growth may have some reciprocal relationship. If that were the case, the consistency of our coefficient estimate for the network variables would be compromised. Estimating the determinants of network change over time, however, is fairly problematic. Not only the pooling of repeated observations on the same firms may violate the assumption of observation independence, resulting in diachronic (or temporal) autocorrelation of the model's residuals, but due to the dyadic nature of the dependent variable, the actions of one firm may be influenced by the contemporaneous network decisions of other firms in the network, a form of synchronic non-independence of observations that makes ordinary regression approaches inefficient. To get around these problems we resorted to the stochastic actor-driven modeling approach developed by Snijders (Snijders, 1996) and implemented in the SIENA software (Snijders et al., 2005). Without entering into the details of the estimation procedure, which is obviously beyond the scope of this study, the key idea of this approach is that network change is modeled based on a continuous Markov-Process, which does not need assume independence of observations[6]. Using Siena, we thus estimated a simple model of network evolution with the lagged number of employees as the monadic covariate (as well as controls for basic network-endogenous mechanisms) and the formal and informal networks as dependent variables. In this model the monadic effects did not show up as being significant in predicting the formation of a tie, suggesting that changes in firms network are not driven by their performance. Consistent with the observation by Powell et al. that "a firm grows by being a player; it does not become a player by growing" (1996: 122) we therefore conclude that endogeneity is unlikely to undermine the validity of our arguments.

DISCUSSION AND CONCLUSIONS

To summarize: At the beginning of this paper we raised the question about the contribution of interfirm networks to the performance of firms located within geographical clusters. Prior research has widely emphasized the role of localized networks in shaping the success of locally concentrated industries, but this "network effect," albeit widely recognized, has received only limited empirical attention with contradictory findings. In particular, while a few of these studies point to the performance benefits that accrue to well-positioned firms within the fabric of cluster networks, others have either pointed to performance losses or failed to show a significant relationship.

To account for this empirical inconsistency we theorized about the existence of two diverging effects. The first, rooted in the new sociological rethinking of markets, emphasizes the informational benefits of network ties based on a connectionist logic of relational flow and access. According to this perspective, performance gains are to be expected for those firms that occupy a central position in the cluster networks. The second, grounded in literature on bounded rationality and economic geography, highlights the potential downsides of establishing and maintaining broad connections in a context where spatial and institutional proximity may exacerbate leakages of potentially relevant information and accentuate isomorphic pressures (Owen-Smith & Powell, 2004). Under such circumstances, the drawbacks of establishing local connections may more than compensate for their benefits resulting in performance losses. We summarized and tested these two competing predictions concerning the performance-related consequences of network centrality within geographical clusters.

Our context of study was a cluster of small multimedia firms located in Northern Italy. Building on qualitative evidence and social network data, we untangled the structure and change of the formal and informal networks established by these companies over a three-year period. These data also included information on firm-level characteristics and two measures of organizational performance – sales and employees growth, which we regressed against our two measures of centrality. We found that net of other variables centrality has an inverted U-shaped effect on performance across almost all model specifications. Firm performance increases with centrality, until a very high level of centrality is reached, after which performance wanes. The findings are important because they extend and clarify past research.

Implications for Theory and Practice

Our results show that high network centrality may be detrimental to firm performance, thereby suggesting a more nuanced view than extant prevailing perspectives on geographical clusters that emphasize networks as key drivers of the success of co-localized firms. In a context where spatial concentration creates a rich and diffuse information ecology where "it is almost unavoidable to receive information, rumors and news about other cluster firms and their actions" (Bathlet et al., 2004: 38), the extent to which firms may access strategic pieces of information by broadening their formal and/or informal linkages is somewhat constrained, leaving them with progressively smaller and ultimately negative returns on the time and costs necessary to establish and maintain such ties.

This result is particularly noteworthy in light of the vast research that has long espoused the benefits of cluster networks, not only for the collective economic development of the region but also for the single firms within them (Pouder & St. John, 1996).

More generally, by providing evidence for decreasing marginal, and ultimately negative, returns to centrality this study advances knowledge on the "dark side" of networks (Gargiulo & Benassi, 2000), suggesting that there are limits to the number of connections that are viable to sustain growth. Thus, the challenge for the cluster firms is to mine their network position for information without becoming "overconnected" (Ferriani et al., 2009). This is a provocative finding whose implications have been brought to the attention of cluster scholars only recently (Molina Morales and Martinez-Fernandez, 2009). First, in the network literature, there is ample discussion of the benefits of centrality, but few scholars have considered the liabilities of overconnectedness. For instance, Owen-Smith and Powell (2003) showed the existence of an inverted U-shaped relationship between the centrality of US universities in the biotechnology industry network and their patenting output, thus implying "the possibility that university patenting efforts may be harmed by a very high volume of firm connections" (p. 1707). An analogous pattern was found by McFadyen and Cannella (2004) in their individual-level study on the effect of scientists' co-authorship networks on scientific productivity. By expanding their network of co-authors scientists have the opportunity to add new information and know-how to their knowledge stocks. Yet, as further co-authoring relationships are added, the cost of developing the relationships eventually begins to outweigh the benefits. More recently, in a study looking at the patenting effects of inventors' networks in an R&D lab, Parachuri (2009) similarly found empirical support for the existence of marginally decreasing and ultimately negative returns to centrality, suggesting that "when this information flow increases beyond a certain amount, inventors cannot process all information properly because of their bounded rationality" (p. 2). In this respect, the evidence of diminishing returns to overly connected cluster firms is especially important, because it provides with a more accurate representation of the mechanisms at work alerting us on the potentially non-monotonic effect of centrality when modelling performance-related outcomes at different levels of analysis (for a comprehensive discussion see also Lechner, Frankenberger and Floyd, 2010). Second, our study is one of the very few (for a similar approach see Bell, 2005; Giulinai, 2007), to simultaneously analyse the performance effects of two different types of networks (formal, alliance-based ties as well as informal, advice-based ties). It provides suggestive evidence on the existence of similar mechanisms operating across network types as well as an interactive effect of types of network on performance. The significant robustness of our findings across formal and informal linkages as well as different performance measures gives us a validation for our arguments that is rare in the empirical study of interorganizational networks. One of our primary contributions is therefore to offer material for rethinking the manner in which the nature and consequences of centrality are understood. It is our hope that this study encourages other scholars to consider and test theoretical understandings using further types of interorganizational ties within and outside cluster settings. Doing this would help move toward a general theory of network influence that is independent of the specific type of network being studied. Similarly, the fact that the few prior studies highlighting the curvilinear effect of centrality on performance reach remarkably similar conclusions, despite focusing on different levels of analysis, is supportive of the idea that "inter-organizational networks are created by some of the same mechanisms that create interpersonal networks" (Brass et al., 2004: 807). Researchers could use this as a starting point to explore more fundamental questions about the stability of network effects across levels of analysis and types of ties (Rivera et al., 2010; Lechner, Frankenberger and Floyd, 2010).

As to overall conclusions, starting with the findings on curvilinearity, the results suggested that as centrality of either type increases there is at first an increasing positive impact on performance, but this declines, and at high levels of centrality becomes negative. This turning point occurs just after the mean levels for formal centrality and within one SD of the mean for informal centrality, so high networking centrality becomes disadvantageous for much of the upper ranges for both types of centrality. We take this as evidence from the results that both theoretical arguments regarding the role of centrality are supported, but each under appropriate boundary conditions. With both types of centrality, when network centrality is low, as centrality increases access and information advantages obtain. However as centrality of both types increases even further the downside thereof begins to manifest, first in the form of decreasing marginal performance benefit, then at even higher levels the overload costs of centrality kick in and actually inhibit performance. This occurs for much of the upper ranges of centrality, not just the extreme upper ranges.

Let us turn now to the findings on interaction, which have been plotted in Figure 1 below.

Figure 1 here

Figure 1 shows that at very low levels of both types of centrality, improvements in either type of centrality correlate with improvements in performance. Increasing either on their own has the steepest positive effects (Lines AB,AC), but if you increase both informal and formal centrality together there is an initial improvement which decelerates (line AD) and eventually leads to declines in performance (line DE) as levels of centrality jointly increase. Our conjecture is that the initial access and information benefits from increased centrality, espoused by the positive literature do apply for low centralities. However these benefits, start to get outweighed by the effort and costs that it takes to process and sustain the highly different networks, and furthermore that this effect is amplified by the compounding complexity as centrality of both types is increased. This leads to the overloaded cognitive and information processing capacity espoused by the negative literature. Once again, the results suggest that both literatures are supported but under appropriate boundary conditions. The implications of these two sets of results for network research are significant. There has been a propensity for researchers to enter into debates favouring one or another set of findings rather than probe for the boundary conditions under which their results pertain. In fact, any time there appears to be conflicting evidence from the literature could be a signal that we may be facing boundary conditions, which should then be explored (Meuleman, Lockett, Manigart and Wright, 2010).

We would like to emphasize that due to the challenges of gathering primary network data over multiple points in time, there are relatively few studies that employ longitudinal data to analyse networks, as already noted elsewhere (Ter Wal and Boschma, 2009). 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 network ties over a three-year period. While we are aware that this is a relatively short timeframe to infer decisive causal evidence, we also emphasize that the collection of field network-data over time and on a large sample still poses considerable organizational challenges as well as significant cost and time constraints. These obstacles notwithstanding, we believe that the research design and operationalization strategy advanced here can be flexibly adapted to other geographical clusters. Clearly, the replication of our findings in new settings would provide the strongest test for the validity of our causal assertions.

What do these results imply for practice - more specifically for strategy practice?. First, the results caution against striving for ever increasing centrality – the practitioner should be alert to, and look for evidence of, the increases in effort and energy needed to sustain network activity. In particular where the firm has mid-range levels of both informal and formal centrality, it may pay substantially in terms of performance to reduce centrality of one centrality type. This could allow the capture of the steep increase in performance depicted by line DB or DC in Figure 1.

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, geographical clusters of firms 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 (Romanelli & Khessina, 2005). We should therefore be careful with generalizations. It is nonetheless notable that the empirical setting object of this research does not represent an isolated occurrence. In fact, the clustering of small firms in the multimedia field is far from unique (for a review of well-documented cases of geographical clustering in the multimedia industry see for instance Barczyk et al., 1999). Thus, although we certainly do not expect to observe non-monotonic effects of centrality on firm performance ubiquitously, we believe that our findings may be replicated and extended in a number of empirical settings. Second, there are inevitably methodological caveats with respect to the measurement of cluster firms' 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 two single sociometric questions. As to the first point, while we are conscious that the use of only one respondent per firm might be a source of measurement error for the network construct (Marsden, 1990), we believe that given the very small size of the companies relying on the owner-manager represents a reasonable way to proceed for collecting this kind of data (on this point see, for example, McEvily and Zaheer, 1999). As to the second point, 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 (2005) concluded that this approach is largely reliable when measures are taken to facilitate individuals' capacity to recall and report their network links accurately. Besides, since respondents were given a list of all the potential network members and were asked to indicate the presence of a relationship; we did not exclusively rely on respondents' memory to accurately recall the names of those to whom they are tied. This feature of the data collection design study may well have contributed to mitigate the memory bias as the list allows respondents to recognize rather than recall relationships, thus requiring a less demanding cognitive effort (Brewer, 2000).

In conclusion, we wish to underscore that our emphasis on networks within geographically bounded areas is not meant to downplay other classic mechanisms of endogenous regional growth based on agglomeration economies but, less ambitiously, to provide a more analytically grounded account of how networks shape firm-level performance in clusters. As pointed out by Castilla, Hwang, Granovetter, and Granovetter (2000: 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." We believe that the type of analysis and evidence reported here show the promise of such further development, and represent an important step in developing a more nuanced understanding of networks, clusters and organizational performance.

NOTES

[1] 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. Possible non response bias was analyzed by comparing respondents and non respondents in terms of industry segments, founding year, and employees. We collected data on industry segment and founding years for all non responding firms from the InfoImprese database and employee data for only a sub-sample of non respondents for which data were publicly available from the Chambers of Commerce. T-tests revealed no significant differences between respondents and non respondents across these variables, hence suggesting the representativeness of our sample.

[2] 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.

[3] Four companies contributed only one interview having ceased their activity after 2001.

[4] The questionnaires also included a free recall area (Wasserman & 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 firms' internal vs.

external connectedness. External connectedness accounted for about 30% of the total connectedness of the sampled firms, suggesting that most of the firms' network activity was taking place within the boundaries defined by our population 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 in particular Sorenson, 2005).

[5] This measure appears particularly well suited to our purposes as it does not embody so stringent assumptions as other equally popular measures. In particular, unlike centrality measures that only count geodesic paths like closeness and betweenness, the eigenvector measure does not imply that whatever moves through the network will only follow the shortest path, which is surely not the case with information (firms may share information along multiple paths, and not just the shortest path). Nor does it assume that the traffic moves from node to node (as it is implied by betweenness centrality) rather than being broadcast from a node, like the spread of information. Instead, the eigenvector measure assumes "that traffic is able to move via unrestricted walks rather than being constrained by trails, paths or geodesics. In addition, the measure […] is consistent with a mechanism in which each node affects all of its neighbors simultaneously" (Borgatti, 2005: 62). These properties make this measure well suited to the type of connectionist argument advanced in this study.

[6] For methodological details see Snijders (1996) and Snijders et al. (2005). For recent sociological applications of SIENA to the organizational study of network dynamics over time see Schulte, Cohen and Kleine (2012).

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TABLES AND FIGURES

Table I. Frequency Distribution of Cluster Firms by Industry Segment

	Industry segment	Total firms	Population %	Sampled firms	Sample %
1	Publishing	31	0.15	11	0.12
2	Music	24	0.12	12	0.13
3	Film	11	0.05	6	0.07
4	Audiovisual	56	0.27	25	0.28
5	Computer Graphics and Multimedia Software	57	0.28	20	0.23
6	Advertising and Communication	26	0.13	15	0.17
	TOTAL	**205**	**100%**	**89**	**100%**

Table II. Means, Standard Deviations and Correlations

	Variables	Mean	S.D.	V.I.F.	1	2	3	4	5	6	7	8	9	10
1	Employees	8.5	11.5	-	1.00									
2	Sales	5.8	2.13	-	0.35	1.00								
3	Lagged employees	8.4	11.6	1.19	0.90	0.27	1.00							
4	Lagged sales	5.6	2.15	1.48	0.37	0.90	0.35	1.00						
5	Age	3.8	1.6	1.16	0.21	0.32	0.21	0.32	1.00					
6	Team size	3.51	2.06	1.07	0.17	0.28	0.19	0.29	0.19	1.00				
7	Commitment	0.68	0.31	1.06	-0.04	0.04	-0.04	0.03	0.10	-0.07	1.00			
8	Structural cohesion	0.44	0.36	1.02	0.08	0.20	0.09	0.22	0.15	0.06	0.04	1.00		
9	Formal Network Centrality	0.1	0.07	2.11	0.06	0.16	0.08	0.14	0.23	-0.02	-0.05	0.02	1.00	
10	Informal Network Centrality	6.3	5.2	2.24	0.01	0.30	0.01	0.41	0.24	0.01	-0.11	0.05	0.60	1.00

Table III. GEE Estimates for a Negative Binomial Regression Model Predicting Cluster Firms Growth (employee-based)

	Model 1a		Model 2a		Model 3a	
Parameter	Estimate	Error	Estimate	Error	Estimate	Error
Intercept	0.438	0.471	-2.55	0.558	-5.028	0.558
Year1	-0.482***	0.131	-0.472***	0.135	-0.445***	0.129
Year2	-0.180†	0.072	-0.171†	0.069	-0.157†	0.088
Year3 (ref)	0	0	0	0	0	0
Age	0.009	0.015	0.004	0.015	0.022	0.015
Segment1	-0.054†	0.3	-0.587†	0.33	-0.388	0.343
Segment2	-1.120***	0.339	-1.47***	0.367	-1.565***	0.380
Segment3	0.578	0.485	-0.02	0.505	0.174	0.504
Segment4	-0. 271	0.296	-0.351	0.323	-0.396	0.319
Segment5	-0.932**	0.289	-1.296***	0.322	-1.132***	0.333
Segment6 (ref)	0	0	0	0	0	0
Commitment	-0.731**	0.268	-0.946**	0.298	-1.337***	0.304
Team size	0.015	0.031	0.03	0.035	0.017	0.036
Structural cohesion	0.123	0.176	-0.110	0.211	0.07	0.23
Lagged performance	0.188***	0.050	0.131*	0.052	0.101*	0.05
Formal network centrality			26.044***	6.399		
Formal network centrality sq			-102.29**	31.138		
Informal network centrality					0.242***	0.056
Informal network centrality sq					-0.011***	0.003
Deviance	225		224		224	
Firm-year observations	263		263		263	

† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$ - Standard errors are heteroskedastic-consistent (“robust”) - Two-tailed tests for all variable.

Table IV. GEE Estimates for a Cumulative Logit Regression Model Predicting Cluster Firms Growth (sales-based)

	Model 1b		Model 2b		Model 3b	
Parameter	Estimate	Error	Estimate	Error	Estimate	Error
Intercept	Yes		Yes		Yes	
Year1	-0.331*	0.169	-0.441**	0.171	0.4175*	0.185
Year2	0.095	0.112	0.085	0.119	0.1681	0.135
Year3 (ref)	0	0	0	0	0	0
Age	0.045	0.033	0.035	0.034	0.044	0.034
Segment1	0.288	0.734	0.297	0.766	0.845	0.752
Segment2	-0.951	0.854	-1.190	0.857	-1.330	0.876
Segment3	-2.386*	0.953	-3.454***	0.929	-3.789***	1.027
Segment4	-0.064	0.668	-0.698	0.754	-0.746	0.765
Segment5	-0.976	0.668	-1.164†	0.697	-0.820	0.674
Segment6 (ref)	0	0	0	0	0	0
Commitment	-0.033	0.70	-0.342	0.660	-0.415	0.653
Team size	0.131†	0.079	0.135†	0.078	0.153†	0.082
Structural cohesion	0.700	0.536	0.480	0.559	0.469	0.547
Lagged performance	0.061**	0.022	0.055*	0.022	0.066**	0.024
Formal network centrality			30.494*	13.835		
Formal network centrality sq			-80.135	66.114		
Informal network centrality					0.426**	0.134
Informal network centrality sq					-0.015*	0.006
Likel. Ratio vs Baseline			10**		8**	
Firm-year observations	263		263		263	

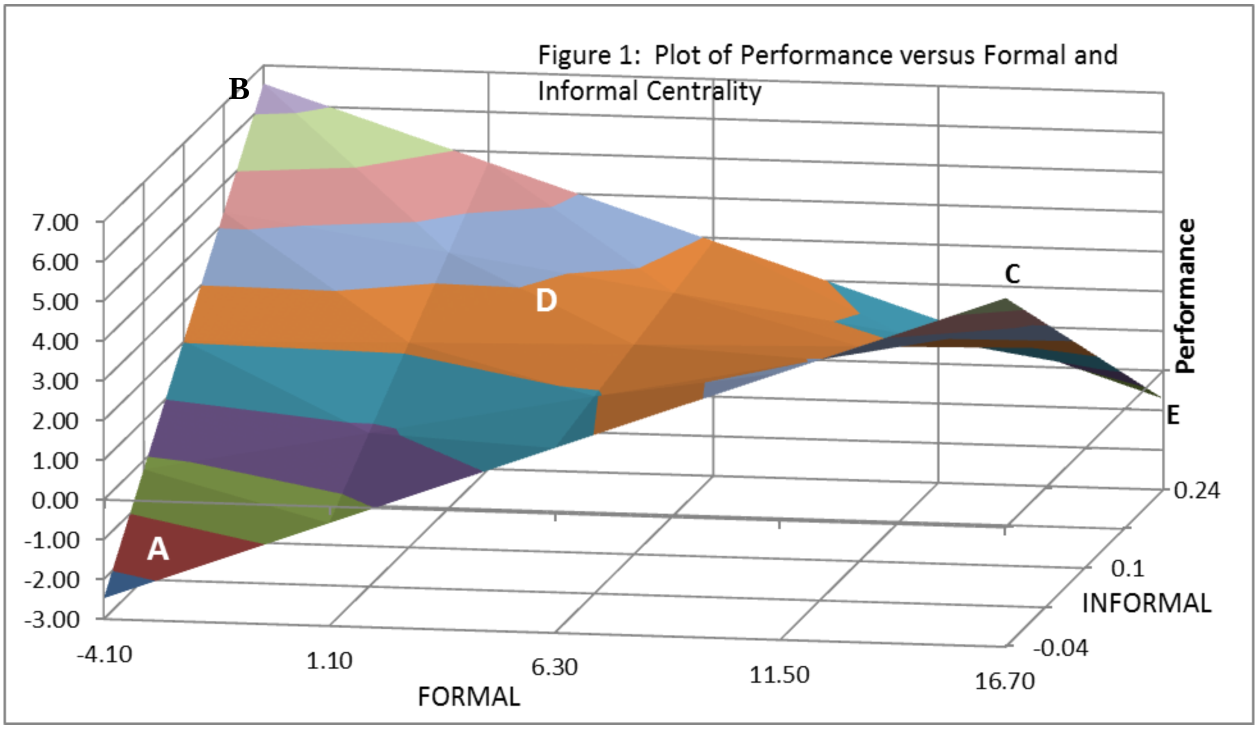
† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. Notes: Standard errors (in parentheses) are heteroskedastic consistent (“robust”).

Table V. GEE Estimates for a Negative Binomial Regression Model Predicting Cluster Firms Growth and a Cumulative Logit Regression Model Predicting Cluster Firms Growth (sales-based)

	Model 1c Negative Binomial		**Model 2c Cumulative Logit**	
Parameter	Estimate	Error	Estimate	Error
Year1	-0.436***	0.130	-0,471**	0,179
Year2	-0.137†	0.078	0,150	0,140
Year3 (ref)	0	0	0	0
Age	0.019	0.015	0,031	0,034
Segment1	-0.343	0.343	0,593	0,713
Segment2	-1.604***	0.378	-1,354	0,864
Segment3	0.226	0.506	-3,951***	1,014
Segment4	-0.252	0.327	-0,757	0,8001
Segment5	-1.179***	0.330	-0,919	0,693
Segment6 (ref)	0	0	0	0
Commitment	-1.090***	0.299	-0,421	0,625
Team size	0.015	0.036	0,141†	0,080
Structural cohesion	0.003	0.233	0,307	0,571
Lagged performance	0.064*	0.031	0,063**	0,023
Formal network centrality	21.331***	4.117	24,342**	8,495
Informal network centrality	0.295***	0.048	0,362***	0,096
Formal*Informal	-2.660***	0.433	-2,409**	0,839
Likel. Ratio vs Baseline			10**	
Firm-year observations	263		263	
Deviance	23			

† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. Notes: Standard errors (in parentheses) are heteroskedastic consistent ("robust").

Figure 1. Plot of Performance versus Formal and Informal Network Centrality



METHODOLOGICAL APPENDIX

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.

	1999	2000	2001
Firm 1			
Firm 2			
Firm 3			
.			
.			
.			
.			
.			
Firm 204			
(Others)			
“			
“			

Question 2

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.

	1999	2000	2001
Firm 1			
Firm 2			
Firm 3			
.			
.			
.			
.			
Firm 204			
(Others)			
“			
“			

Question 2b

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?

	1999	2000	2001
Firm 1			
Firm 2			
Firm 3			
.			
.			
.			
.			
.			
Firm 204			
(Others)			
"			
"			