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GROWING BY BEING (MINDFULLY) EMBEDDED: A LONGITUDINAL STUDY OF A SMALL FIRM GEOGRAPHICAL CLUSTER

Simone FERRIANI[a], Ian MACMILLAN[b]

[a]Dipartimento di Discipline Economico Aziendali, Università di Bologna - Piazza Scaravilli, 2 - 40126 Bologna Tel: +39051 258073 - Fax: +39051 2098074 - rashomon@economia.unibo.it

[b] Sol C. Snider Entrepreneurial Research Center, The Wharton School - University of Pennsylvania -429 Vance Hall - 3733 Spruce Street Philadelphia, PA 19104-6374 Tel.: (1) 215.898.9472 Fax: Fax: (1) 215.898.1299 E-mail: macmillan@wharton.upenn.edu

SUMMARY

Geographical clusters have long been at the center stage of the debate on interfirm networks and regional success. While research in this field has contributed crucial insights to the understanding of interorganizational networks and embedded ties as determinants of local growth and systemic strength, much weaker focus has been placed on the role and performance of the cluster-located firm (CLF), as an active constituent of this dense multirelational local system. Furthermore, despite the great emphasis on relational processes that distinguish research on localized industries by and large, only 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, building on the notion of embedded networks as carriers of information and knowledge, 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 embeddedness. These ideas are presented and tested based on the analysis of three-year longitudinal data gathered on a sample of 89 small firms located in a geographical cluster of Northern Italy. Results from fixed-effect regressions provide mixed support to the role of embedded 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, Marshall initiated the concept of shared knowledge as a characteristic of localized economies with his idea of an "industrial atmosphere" with "knowledge in the air."

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. As the theory developed, though, economists also recognized the need to introduce wider institutional inputs within their frames of reference, one reason being the fact that cost based models alone fell short in addressing the condition of many smaller firms rather than a single large firm (Maskell, 2001; Tallman et al., 2004). Consequently, towards the recent turn of the century, a far more socially and relational oriented account has come to occupy centre stage in the discourse on local agglomerations. 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 trigger a higher degree of situation-specific knowledge transfer as well as exchange and circulation of new ideas and information (Nohria, 1992; Saxenian, 1994; De Carolis and Deeds, 1999). This process is indeed bolstered by the sharing of norms, values and institutions that shape the local culture and allow for the access to otherwise less valuable (as well as transferable) pieces of information (Storper, 1995; Porter, 1998).

Along this vein, more and more scholars have advocated the adoption of relational or network lenses to unfold and analyze the dense and overlapping social, professional and exchange interfirm relationships that shape geographical clusters.

Despite this increasingly popular trend however, only very 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 few isolated cases (McEvily and Zaheer, 1999; Castilla et al., 2000), virtually no work has endeavored to introduce a network analytic approach within the boundaries of a locally concentrated industry and use such lenses to explain the performance of the firms located within the cluster (herein referred to as CLFs). This is all the more surprising given the characteristic of tight spatial and socio relational boundedness that distinguishes these organizational realities, a unique feature that facilitates the often troublesome problem of specifying the boundaries on the set of units to be included in the network (Marsden, 1990). This shortcoming, we believe, 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 the single firm. In fact, while this macro perspective' has undoubtedly favored our understanding of the overall phenomena and its 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).

Some evidence, however, also suggests that whereas 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 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 take a rather different angle from the more established 'aggregate way' of looking at the phenomenon of localized industries. Instead of centering our perspective on the system and its aggregate properties, we focus on the actors and their performance, as a function of the actors' participation to the system. In adopting this perspective we build on McEvily and Zaheer's (1999) finding that competitive capabilities of CLFs may radically differ depending on their heterogeneous embeddedness within the dense system of interorganizational relations that shape the cluster. But whilst the two scholars elaborate on the embeddedness notion to account for differences in CLFs *capacity to compete*, we concentrate on the link between *networks and growth*, as a tangible measure of CLF performance. In line with previous research we see these 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 and incur into attractive business opportunities. This process is examined in the light of the possible moderating effect of an important theoretical construct at the firm level: *absorptive capacity*.

The structure of the work is as follow: I start by providing a short illustration of the phenomenon of small firm clusters, the reasons why interfirm networks represent a particularly apposite concept to understand the functioning of these organizational entities, together with the gaps that appear to affect this research domain. In the second part I elaborate on the strong tight-knit, socially embedded nature of networks within geographical clusters to sketch the basics for a multirelational influence model of network ties on CLFs performance. I do so by moving away from a purely structural conception of firm networking and focusing instead on the underlying informational and knowledge benefits that CLF firms derive from their participation in such multiple networks of relations. After describing the structure of the data, I proceed by adopting a multi-indicator approach for measuring the network constructs of interest. This approach allows me to distinguish among different informational dimensions of firm networks and come up with measures that summarize the rich relational texture of the CLF. These measures are then

incorporated as covariates into a longitudinal hybrid model where the effect of network variables on CLF performance is estimated together with a variety of control variables. I conclude the work by discussing the results and their theoretical and practical implications.

2. THEORETICAL FRAMEWORK

My theoretical framework rests on three interlinked arguments:

1. Relational ties within geographical clusters are imbued with value in the form of information and knowledge that 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 potentials for economic performance.
3. CLFs that are better armed to appreciate/understand the value of these opportunities are in an advantageous position to translate this potential into economic vale.

Each of these points is discussed below:

2. 1 Interorganizational networks and information access within geographical cluster

While several mechanisms may be identified through which interorganizational networks may affect firm behavior, 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 prominent and well-established idea among social network theorists (Stephenson and Zelen, 1989; Burt, 1992; Wassermann and Faust, 1994), and represents a core assumption in a variety of studies that have investigated the relational foundations of organizational level outcomes[1] (Gulati, 1995, 1999; Hansen, 1999; Koka and Prescott, 2002). This 'network-access' idea is particularly relevant in the context of tightly spatially and socially bounded geographical areas such are geographical clusters. As Powell et al. (2002) observe: "The advantages of location… are very much based on access and information' (p. 293**)**. 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; Porter, 2000; Maskell, 2001)[2]. In such a tight-knit community, customers, suppliers, competitors, allies as well

[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).

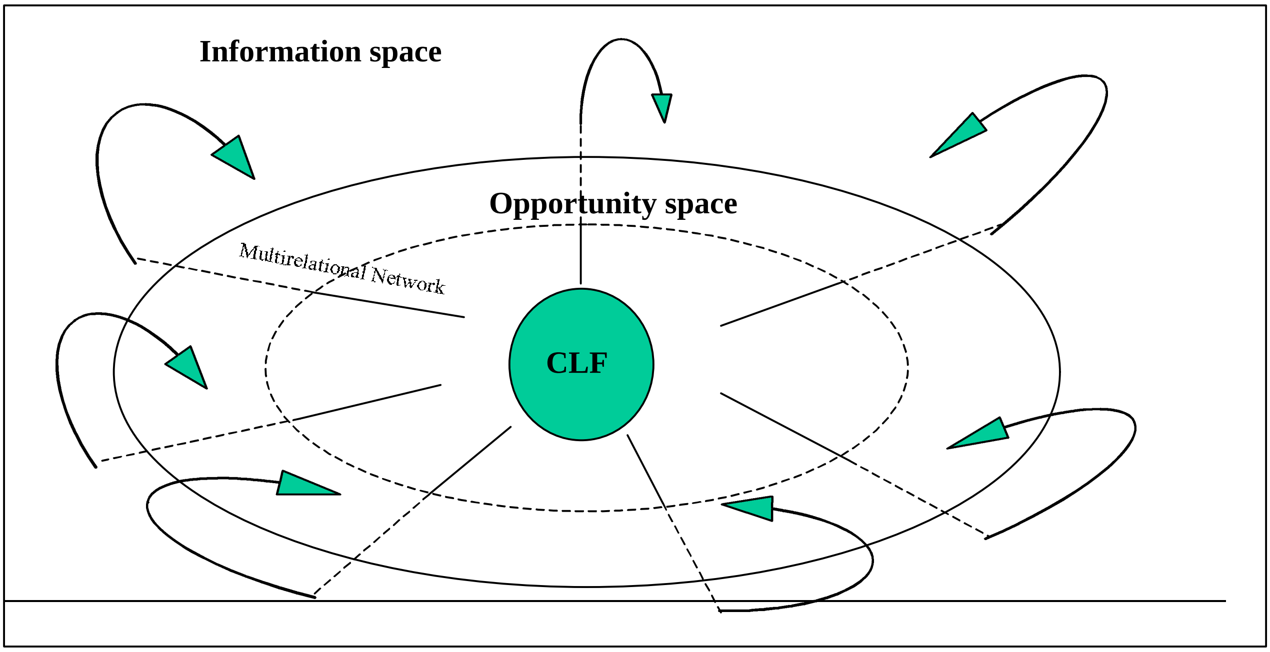
[2] Any infringement of trust by firms in such closely knitted business networks is so severely penalized that in effect malfeasance becomes a non-option. Cheaters are selected to make a convincing reparative gesture for any first-time misdeed however small. The collective awareness of this mechanism makes it possible to exchange knowledge even between competitors within a network, to an extent that no outsider can aspire to achieve (Maskell, 2001).

as institutions and informal relations are all potential vehicles through which CLFs may tap valuable information flows. As a result of this '*multirelational embeddedness*' phenomena: "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., 1996)

2.2 Information access and opportunity discovery as antecedents of growth

According to the Austrian Economics accessing information is a crucial premise for discovering new opportunities that is, finding potential economic profits that have not been grasped yet (Hayek, 1954; Kirzner, 1974). Opportunities exist because different people access and control different information. These concepts suggest two simple ideas: First, because interfirm networks may affect the firm's exposure to the 'information space' that permeates the local environment, they may impact the likelihood for the CLFs to discover valuable opportunities. A stylized representation of this idea is provided in figure 1.

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



Second, because the pattern of network linkages maintained by each of these firms is highly idiosyncratic, 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 enhance their performance.

2.3 The moderating role of absorptive capacity

An opportunity rich position is likely to remain confined in the realm of perceptions and possibilities until active understanding and appreciation of the opportunity value is reached. This idea has been convincingly formalized by Cohen and Levinthal's (1990) *absorptive capacity* construct, that is: "the ability to recognize the value of new information, assimilate it, and apply it to commercial use" (p. 128). In abstract, the absorptive capacity construct may be imagined as the point of junction between the information space and the opportunity space: the higher the exposition and accessibility of the firm to external knowledge and information, the higher the need for absorptive capacity in order to benefit from such knowledge.

3. HYPOTHESES

Drawing on existing research I suggest two primary ways in which an actor's network position may impact his information access conditions: First, the structure of the social network may affect the *volume of information* accessed, which can be expressed as a function of the actor's *centrality* within the system; Second it can affect the *variety of information* accessed, which is interpretable as a function of the *range* (or diversity) of actor's ties (Koka and Prescott, 2002). Further, in order to account for the multirelational nature of CLFs embeddedness, I introduce the notion of '*overall network position'*, that is, the focal CLF's network position as resulting from the observation of its overall set of network ties with the key constituents of its multirelational cluster environment.

3.1 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). High centrality leads to higher *volume of information*[3] Koka and Prescott, 2002) and, as Gulati notes: "The greater the information the higher the opportunity set" (1999, p. 399). This is vividly illustrated by the comments of one of the entrepreneurs I interviewed.

[3] i.e. The quantity of information that an actor may access via its relational ties (Koka and Prescott, 2002, p.798)

"Clients, suppliers 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 sprang up almost by chance … thanks to an information we got from a client" (SonicRocket)

Consolidating the above reasoning I propose the following:

Hypothesis 1: *Other things being equal, an increase in the overall network centrality of a CLF will positively affect its growth probability.*

3.2 Network range

Because CLFs embedded in the network may operate in different segments, utilize different technologies and belong to different (but related) industries, they are also likely to be source of heterogeneous information. The sociologist Roland Burt (1983) defines the concept of network range as the extent to which an actor's network links it to diverse other units. Thus, while centrality emphasizes the volume dimension of information access, range has mainly to do with the variety of the information. Another entrepreneur I interviewed said:

"When you stick to the same circles for too long you loose the pioneer instinct, you have fewer incentives to explore new things and end up being unable to stay tuned with your times… when your network parties know each other it is unlikely that you get involved in challenging and stimulating undertakings …in a business reality like this one things change too quickly, and unless there is bum like in the '99, if you cannot find new stimuli you wind up getting bogged". (Officine Digitali)

Based on the above I suggest the following:

Hypothesis 2: *Other things being equal, an increase in the overall network range of a CLF will positively affect its growth probability.*

3.3 Preexisting knowledge structure

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 that prior information cannot replicate (Roberts, 1991). This concept is well reflected in the following sample quote, by one of the owner/managers I 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"   (Achtoons)

Following this line of reasoning I contend that the effect of network position on growth will be moderated by the CLFs' level of prior related knowledge. Hence, I posit:

Hypothesis 3: *Other things being equal, an increase in the overall network centrality of a CLF is more likely to be positively related to the firm's growth when the firm has a rich preexisting knowledge structure rather then when the firm has a poor preexisting knowledge structure.*

Hypothesis 3b: *Other things being equal, an increase in the overall network range of a CLF is more likely to be positively related to the firm's growth when the firm has a rich preexisting knowledge structure rather then when the firm has a poor preexisting knowledge structure.*

4. METHODS

4.1 Research setting

The field setting of this research consists on a geographical cluster of micro and small multimedia enterprises located in the area of Bologna, a city of Northern Italy. There are several reasons for considering this setting worth studying: 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 economic growth in urban centers. According to Fuchs and Wolf, multimedia is "a paradigmatic example of industries of increasing importance to regional economic prosperity" (1999, p. 301). Second, because multimedia is an emerging and relatively young industry the importance of social 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).

4.2 Data collection

Data collection started in 2001 and extended over a three-year period, from 2001 till 2003. As a first step I had to come up with a reliable list of all the multimedia firms located within the Bologna cluster. This list was built by using 'InfoImprese', which is a comprehensive database operated by the Italian Chambers of Commerce to provide basic demographic information on all of the companies operating on the Italian territory. The distribution of these firms by industry segment is provided in table 1.

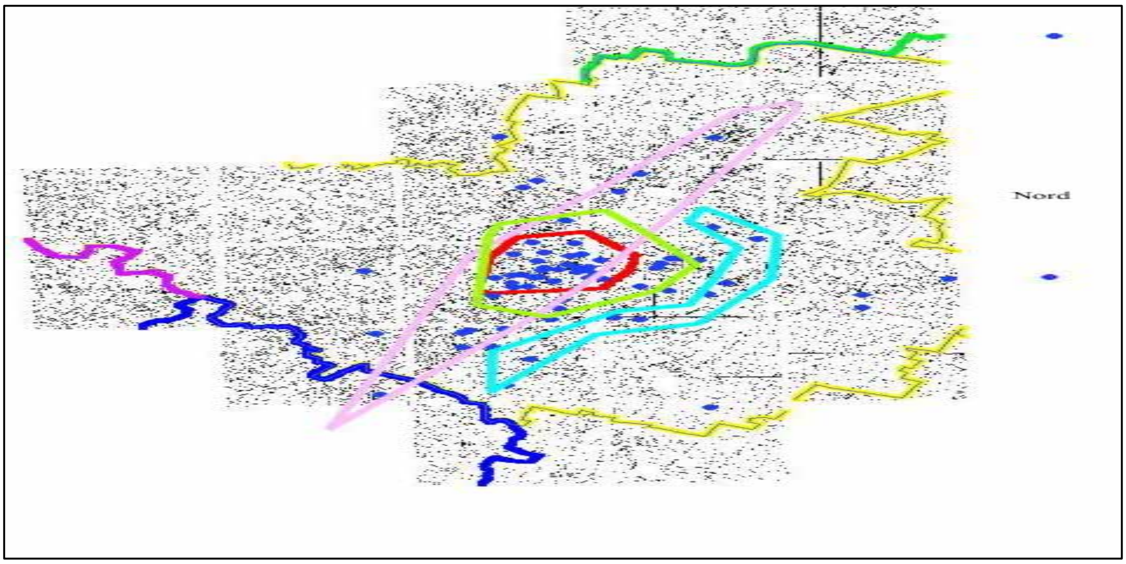
Table 1 Frequency distribution of CLFs by industry segment

Industry segment	Nr of firms	%
Publishing	31	0.15
Music	24	0.12
Film	11	0.05
Audiovisual	56	0.27
Computer Graphics & Multimedia Software	57	0.28
Advertising and Communication	26	0.13
TOTAL	**205**	**100%**

All these companies were initially contacted by telephone when the purpose of the study was explained and they were asked for cooperation. As a result 102 personal interviews with the company owners were secured[4]. Seven of these companies were randomly picked to conduct a pilot study. These interviews reaffirmed the relevance of examining the link between social networks and performance outcomes in this setting. The final questionnaire was defined using the feedback from the pilot study. Based on this protocol I then started gathering data on each of the remaining 95 firms who had expressed their willingness in being part of the research. The topographic localization of these firms within the Bologna cluster is provided in figure 2.

[4] Companies that refused to be involved in the study seemed randomly mixed between those not interested in the research and those without time to devote to the interview.

Figure 2 The Bologna Multimedia Cluster: a topographic illustration*



*GIS based elaboration. CLFs are represented as blue dots in the map. Map scale 1:

On average, firms in the sample were 8 years old, with annual turnover lower than Euro 300.000 and less than 10 employees.

Two structured face to face interviews in two different time points were conducted for each company, one in 2001 the other in 2002, for a total of 174 interviews[5], 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 the relational data to be used for creating network measures and matrixes. A wide array of economic actors may 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 circulates throughout the cluster environment (Porter, 1998, 2000). In order to approximate this vibrant relational space without loosing in analytical focus I decided to concentrate on four kinds of actors: Customers, suppliers, collaborators and social contacts. Correspondingly, I identified three network types, which I labeled as follow: Transaction network, Collaboration network, and Advice network. Each informant was thus presented with four relational questionnaires, matching the network types described above. For each sociometric question respondents were provided

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

with a list of all the other 204 CLFs included in our cluster population list. In response to the list (we asked them to put a check by all the alters whom they recognized as their contacts in the specified kind of relation. In essence, the respondents had to indicate those companies that they identified either as their transaction partners (buyers – suppliers), or as their collaborators, or, finally, companies whose members they recognized as individuals on whom they usually relied for valuable advice and information[6]. This procedure was repeated in two occasions, at the beginning of 2001, when the interviewees were required to provide relational data concerning 2000 and 1999, and in the same period of 2002, when they were asked to fill the questionnaire with regard to their relational activity in 2001. The process resulted in a 3-years multirelational dataset for the 89 sampled firms. These data were then converted into 3 sociomatrices which were used for the computation of network and non-network measures (see the operationalization section for details

4.3 Operationalization and Measures

Dependent Variables

Growth: Following well established arguments in the literature on firm growth (see in particular Delmar, 1997 and Delmar et al., 2003) I used two measures to operationalize growth: sales growth and employment growth. In particular:

1) I used the reported number of employees at time t +1 (EMPLOt+1) to compute a measure of year by year absolute growth.
2) I used the reported market sales at time t +1 ($SALES_{t+1}$) to compute an ordered class dependent variable ranging from 1 to 8, based on a eight point scale of increasing market sales brackets defined during the pilot study.

Independent Variables

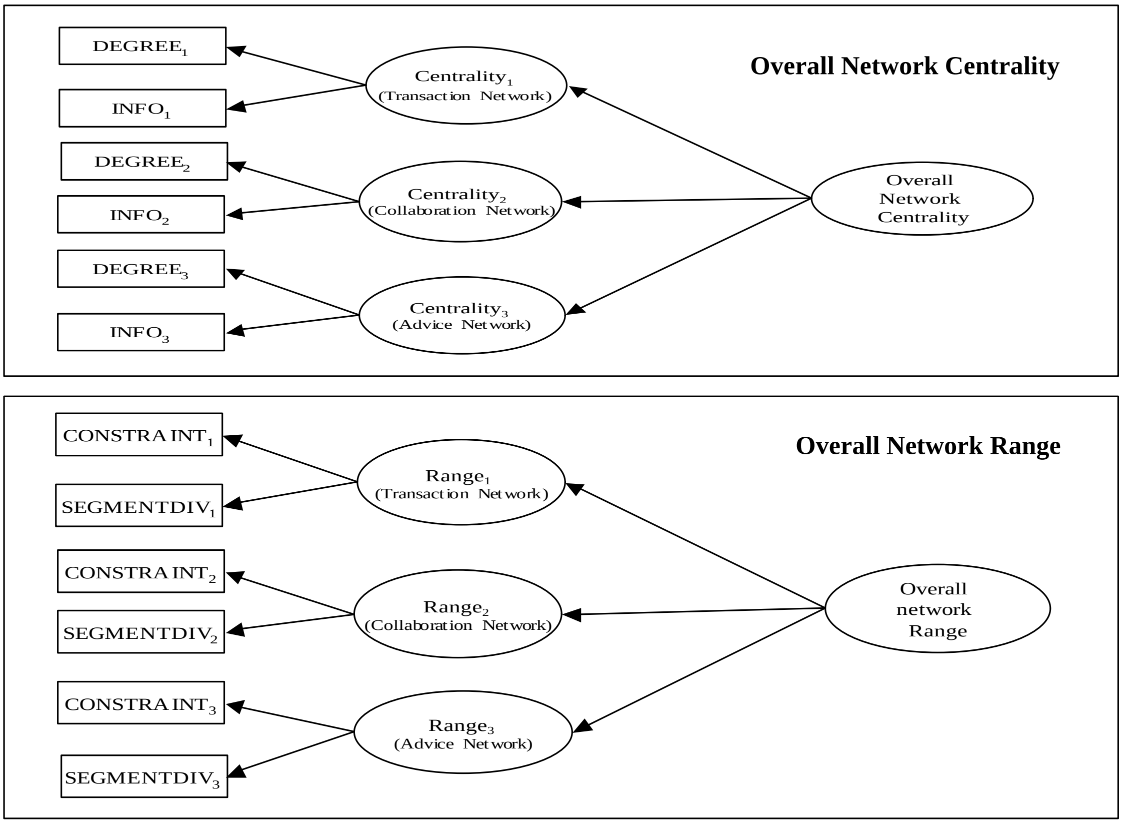
Network variables: My approach to operationalize the network variables was driven by two basic concerns: First, being information the key element of our relational conceptualization of CLFs performance, I was interested in developing network measures capable to capture the extent of information accessible by firms via their position in the cluster network; Second, I wanted these measures to reflect the multirelational nature of CLFs embeddedness, 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

[6] Each of the questionnaires were also integrated by a *free recall area* (Wasserman and Faust, 1994), in which respondents had the possibility to 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 list.

organizations. Operationally speaking this required identifying two adequate measures for the two original constructs introduced together with the hypotheses: overall network centrality and overall network range. In a way akin to Koka and Prescott's (2002) strategy for operationalizing social capital, I addressed these issues by developing and testing a multi-measure model for all the relational variables. I developed this operationalization strategy in two steps: As a first step I identified a series of indicators to operationalize CLFs' centrality and range as first order latent constructs in each of the three networks of interest; As a second step, I postulated the resulting six constructs (one centrality factor and one range factor for each of the three networks) to be indicators of two higher order factors, representing the overall centrality and range of the CLFs[7].

I tested the empirical saliency of the resulting measurement models, which are graphically illustrated in figure 3, as a hierarchical confirmatory factor analysis (CFA) using structural equation modeling.

Figure 3 Centrality and Range as second order latent factors in a multirelational space



[7] The choice of this approach rested 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.

As figure 3 shows, there are 6 first order latent constructs encapsulated within two different measurement models, representing the two distinct network-based informational features associated to CLFs multirelational networks. The upper measurement model includes as first order factors: *Transaction Network Centrality*, *Cooperation Network Centrality*, *and Advice Network Centrality*. The intercorrelations among these factors are accounted for by the second order construct: *Overall Network Centrality*. *Transaction Network Range, Cooperation Network Range and Advice Network Range* are part of the lower model; where *Overall Network Range* is the common, higher level cause. Multiple indicators, calculated across each of the three network types, were used in order to operationalize the model. In short:

- *Centrality* was measured by using Freeman's '*degree centrality'* ($\text{DEGREE}_{1\text{-}3}$) and Stephenson and Zelen's (1989) '*information centrality*' score ($\text{INFO}_{1\text{-}3}$), which uses all paths in the network, and weights them based on their length. I computed these two indices using the sociomatrices originated from the four relational questionnaires
- *Range* was measured using *Burt's constraint index* (Burt, 1992), which measures the degree to which a CLF's contacts are themselves connected to one another ($\text{CONSTRAINT}_{1\text{-}3}$)and *Blau's index of heterogeneity (1977)*, where diversity was considered in terms of the industry segments of CLFs' contacts ($\text{SEGMENT}_{1\text{-}3}$).

Using these indicators[8] I estimated the measurement model year-wise, for the three-year period 1999-2001. 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 two network constructs of theoretical interest: *Overall Network Centrality and Overall Network Range.* Using factor scores, I then obtained a single composite measure for each of these two constructs: OVERCEN_t and $\text{OVERRAN}_{t.}$ These two measures represent our variables of theoretical interest (refer to paragraph 3.3.2 of the dissertation for analytic details on the measurement model).

<u>Preexisting knowledge structure</u>: 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*; the other is the idea of *knowledge diversity*. In order to capture these two complementary sources of absorptive capacity I 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. KNOWHET is a measure of internal knowledge diversity based

[8] All the variables were log transformed in the analysis to alleviate skewness.

on both the educational background of the founding members and their professional experience. I created this variable by computing two Blau's indices of heterogeneity for each of the two knowledge domains and by taking their arithmetic average[9].

Control variables

Powerful classes of multivariate analysis techniques for longitudinal data that help reconciling the complexity of accounting for a large number of controls, with the necessity to minimize 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. Based on these considerations, only a limited set of time-variant controls were included in the analysis[10]:

Lagged growth 1 ($EMPLO_t$) - Inclusion of the previous year measure of growth helps account for the possibility of any specification bias due to unobserved heterogeneity.

Lagged growth 2 ($SALES_t$) - 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 I introduced a lagged control for the other dependent variable in each of the equations.

Time (YEAR) – I 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) – I 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.

4.4 Model Estimation

The data set consists of three year of cross sectional records. Given the different nature of the dependent variables, in order to test the proposed hypotheses I estimated two different longitudinal models: <u>a fixed effect cumulative logit model</u>, to estimate variations in the ordered categorical dependent variable, and a <u>fixed effect negative binomial</u> to treat the discrete, count nature of the employees-based dependent variable.

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[9] 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.

[10] Drawing on past research, I also run separate random-effects analyses with a wider set of individual and firm specific time-invariant variables. Findings were generally consistent with this literature. These results are available from the author upon request.

The selection of these techniques reflects two prominent statistical issues, namely unobserved heterogeneity and autocorrelation.

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

$$\Pr(y_{it} = r) = \frac{\Gamma(q + r)}{\Gamma(q)\Gamma(r+1)}\left(\frac{l_{it}}{l_{it} + q}\right)^{r}\left(\frac{q}{l_{it} + q}\right)^{q}$$

In this equation l_{it} is the expected value of y_{it}, q is the overdispersion parameter, and $\Gamma(.)$ is the gamma function. As $q \rightarrow \infty$, 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,

$$\log l_{it} = a y_{it-1} + m_{t-1} + b x_{it-1} + g z_i + a_i$$

where a is a parameter that indicates how current growth depend on prior growth, x_{it-1} represents the time-varying vector of predictor variables at time t-1, z_i denotes the time-invariant predictors, and a_i denotes the un observed “fixed effects”. 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.

Cumulative logit models are a generalization of logit models specifically suited to handle ordered categories (Allison, 1999). The growth can then be modeled as follow:

$$\log\left(\frac{F_{ijt}}{1 - F_{ijt}}\right) = a y_{it-1} + m_{t-1j} + b x_{it-1} + g z_i + a_i \qquad j = 1, \ldots, J-1$$

where $F_{ijt} = \sum_{m=j}^{J} p_{imt}$ is the “cumulative” probability of being in category j or higher; m_{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 a_i represents all differences between persons that are stable over time and not otherwise accounted for by gz_i. Finally, a is the parameter for the lagged dependent variable.

5. DISCUSSION OF RESULTS

In table 2 and 3 I reported the results of regression analysis. Hypotheses were assessed sequentially, for each of the two models.

Table 2 – Model 1: Fixed-effect negative binomial estimate of (employees-based) CLFs growth

	1a		1b		1c	
	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
Intercept	1.295*	0.5218	1.4815*	0.6083	0.8655**	0.1678
$YEAR_1$	0.0800	0.051	0.08	0.0571	-0.0642	0.049
$YEAR_2$	-0.0276	0.0677	-0.026	0.06	0.025	0.06
$YEAR_3$ (reference cat.)	0	0	0	0	0	0
AGE	0.42828*	0.1836	0.2696	0.1722	0.258	0.163
$SALES_t$	0.1444**	0.044	0.1222**	0.04	0.1233**	0.038
$EMPLO_t$	0.2613**	0.0864	0.25**	0.0879	0.2449**	0.079
$OVERCEN_t$			-0.33*	0.17		
$OVERANGE_t$					-0.15701	0.131
$OVERCEN_t$*PRIOR			0.41*	0.2		
$OVERCEN_t$*KNOWHET			0.1949*	0.0909		
$OVERANGE_t$*PRIOR					0.1818*	0.088
$OVERANGE_t$*KNOWHET					0.1014*	0.05
Likel. Ratio vs Baseline (4 d.f.)	-		15.18**		12.678*	

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

Model 1 (table 2) was estimated by using the number of employees as the dependent variable ($EMPLO_{t+1}$). The second model (table 3) provides cumulative logit estimates ($SALES_{t+1}$). Positive coefficients of variables indicate a positive influence of those variables on growth likelihood. Negative coefficients, conversely, show a lower probability of firm's growth when those independent variables increase.

Table 3 – Model 2: Fixed-effect cumulative logit estimate of (sales-based) CLFs growth.

	2a		2b		2c	
	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
$YEAR_1$	0.5329	0.3961	0.534	0.4361	0.52	0.4422
$YEAR_2$	-0.3377	0.3875	-0.3288	0.37	-0.31	0.37
$YEAR_3$	0	0	0	0	0	0
AGE	0.0254	0.0213	0.023	0.0217	0.0252	0.0231
$SALES_t$	0.9453**	0.2436	0.89***	0.247	0.85***	0.2401
$EMPLO_t$	0.09*	0.0453	0.083^	0.046	0.08*	0.04
$OVERCEN_t$			-0.42*	0.1494		
$OVERANGE_t$					-0.1064	0.17
$OVERCEN_t$*PRIOR			0.51*	0.1951		
$OVERCEN_t$*KNOWHET			0.28*	0.085		
$OVERANGE_t$*PRIOR					0.25	0.164
$OVERANGE_t$*KNOWHET					0.05165*	0.0256
Likel. Ratio vs Baseline (4 d.f.)	-		9.01*		8.4†	

***p<0.001, **p<0.01, *p<0.05, † p<0.1

The results provide mixed support to my predictions. Starting from model 1b, which presents tests of hypotheses 1 and 3a, we note that the coefficient estimate of OVERCEN is negative and significative, suggesting an effect opposite to what I had expected. Both the direction and the significativity of this effect, however, change dramatically when the level of prior related knowledge and knowledge heterogeneity are taken into account. In fact, the OVERCEN*PRIOR and OVERCEN*KNOWHET coefficients are positive and significant, supporting hypothesis 3a. For those firms with prior related experience the effect of network centrality is positive, and it grows bigger as the level of knowledge heterogeneity increases. Results are somewhat similar when focusing on the effect of overall network range on growth (as measured by the nr of employees). Turning to model 1c, while, contrary to my predictions, the coefficient of OVERANGE is not significant, the positive and significant coefficient of this variable's interaction with the two measures of absorptive capacity provides corroboration to hypothesis 3b. The positive effect of network range on CLF's growth is dependent on the richness of its pre-existing knowledge structure and it increases with the level of KNOWHET. This is reflected in the two positive and statistically significant coefficients for OVERANGE*PRIOR, and OVERANGE*KNOWHET. Consistency of results across the two models provides further support to the robustness of the analysis.

Model 2b reaffirms the negative impact of OVERCEN, likewise, 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 two constructs. Like in the previous case, however, the possession of a heterogeneous knowledge base enables the RANGE effect to be leveraged. When the heterogeneity-based measure of absorptive capacity increases, the effect of OVERANGE is enhanced significantly.

6. SUMMARY AND CONCLUSIONS

In the last decade the *structural embeddedness* theory (Granovetter, 1985) has inspired and stimulated a growing number of scholars in the organizational field who have convincingly demonstrated both on a theoretical (Baum and Dutton, 1996) and empirical level (Powell et al., 1996; Ahuja, 2000), the profound influences that socio-relational activities exert on organizational behavior and performance. Part of these studies have analyzed the role of inter-organizational networks on alliance formation (Gulati, 1995), their impact on the likelihood of firm survival (Baum and Oliver, 1992), on competitive dynamics and organizational performance (Uzzi, 1997; Lorenzoni and Lipparini, 1999; Baum et al., 2000), on the development of new competencies and the process of organizational learning (McEvily and Zaheer, 1999). Similarly,

the role of relational activities has widely emerged also in the context of innovation (Freeman, 1991).

Building on this tradition of studies, the embeddedness perspective was here applied to analyze the organizational performance of a sample of small firms located in a *geographical cluster*. Regional Clusters, 2000), also known as Industrial Districts (Becattini, 1979), Localized Productive Systems (Maillat, 1995), Neo-Marshallian Nodes (Amin and Thrift, 1992), or Hot Spots (Pouder and St. John, 1996), are a prominent feature of our modern economy. Hollywood (Scott, 1998), Silicon Valley (Saxenian, 1994), Mototorsport Valley in South England (Pinch and Henry, 1999), or Sassuolo in Italy (Lorenzoni, 1992) are just a few renowned cases among the many manifestations of the phenomena of firms concentration within clearly definable and relatively small geographic areas. Scholars in the organizational, sociological and strategic field have long recognized the crucial importance of interfirm networks and embedded ties in supporting the success of geographical clusters and localized industries more in general (Nohria, 1992). Despite this trend, however, only sporadic studies have attempted to untangle such processes within a framework of formal analytic measurement and operationalization, so as to assess the extent to which the participation of CLFs to these networks is related to their organizational performance (Molina-Morales and Martinez-Fernandez, 2003). This shortcoming is consistent with what appears an overwhelmingly dominant tendency to approach firm clusters based on description oriented research strategies, more interested in exploring the extent to which the region or local agglomeration meets the defining characteristics of a business cluster than in the analytic understanding of the underlying mechanism that shape its internal functioning (Malmberg and Maskell, 2002; Morrison and Staber, 2000).

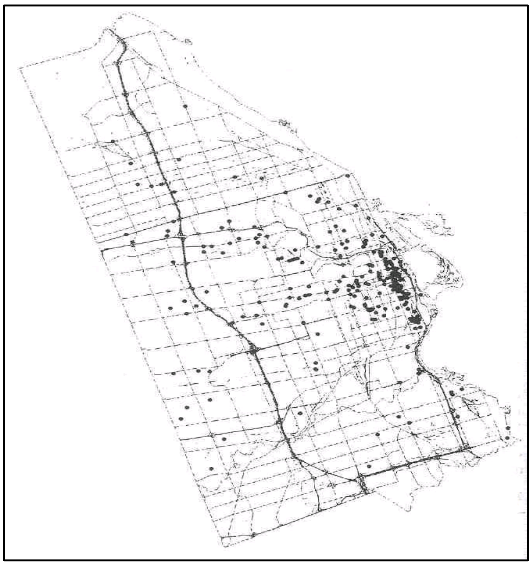
I addressed these issues by departing from a purely descriptive ground in favor of empirically based research that relies on network analysis and data on a panel of small firms situated in a Northern Italy cluster. Drawing and elaborating on previous findings on spatially and socially bounded industries that emphasize the high degree of embeddedness and connectedness characterizing firms herein located, I advanced a stylized multirelational model of network ties as enablers of opportunity discovery and CLFs growth. In essence, because embedded ties are imbued with value in the form of information and knowledge, they contribute to carve out and mold the space of opportunities to which CLFs may gain exposure. Accordingly, I predicted CLFs' performance asymmetries to stem from their structural differences, which I identified in terms of network centrality, as a proxy for information volume, and network range,

as a proxy for information diversity. Further, based on the simple idea that distinct CLFs may vary in their ability to understand and assess the importance of the information they accrue from their networks, I also postulated the existence of a moderating effect depending on the richness of CLFs' preexisting knowledge structure. I formalized and tested these ideas within a framework of longitudinal measurement and estimation. Results provided mixed support to our predictions indicating that an increase in centrality and range over time is not unconditionally beneficial to the firm performance. In fact, unless CLFs are endowed with a threshold level of absorptive capacity, the effect of centrality and range is either significantly negative or statistically insignificant. In contrast, the presence of a strong preexisting knowledge structure radically inverts these effects, turning rich and varied relational structures into effective enablers of growth.

To fully appreciate the substantive value of this research I believe it is very important to recognize the situated nature of this study. Cluster of firms, industrial districts and spatially concentrated industries more in general, are often the expression of a complex mixture of local socio-economic conditions and institutional forces that contribute to create a unique environment for the development and growth of economic activities. This simple consideration should come as a warning against any attempt to draw conclusion beyond the spatial and social boundaries of the phenomena herein investigated. Nonetheless, these are not isolated or uncommon phenomena. For instance, it is quite intriguing to observe the maps in figure 4-6 and realize that the clustering of small firms in the multimedia field is a widespread and growing phenomenon all over the world

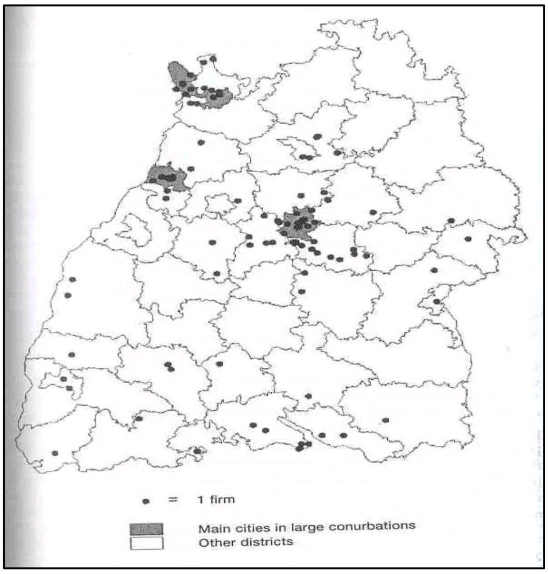
Such settings are ideal candidates for extending the avenues of investigation commenced here. While this study represents an initial attempt towards unlocking and measuring the network effect within the boundaries of a geographical cluster, I believe it is a first step towards a horizon fraught with promising research opportunities.

Fig. 4
Toronto multimedia agglomerate



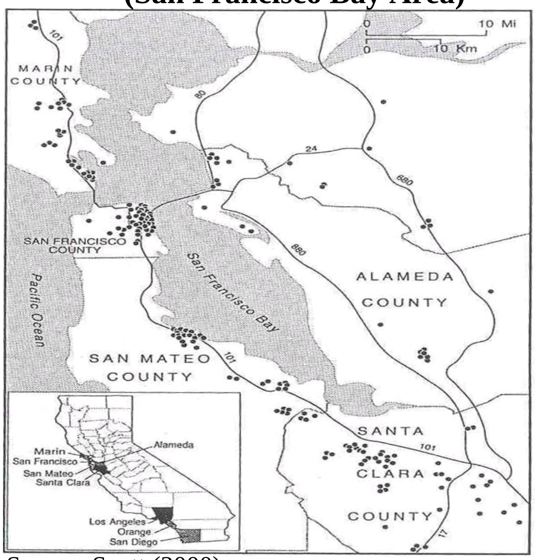
Fonte: Brail e Gertler (1999)

Fig. 5
Baden-Wurttemberg multimedia cluster



Source: Fuchs e Wolf (1999)

Fig. 6
The Multimedia Gulch
(San Francisco Bay Area)



Source: Scott (2000)

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ABSTRACT
Geographical clusters have long been at the center stage of the debate on interfirm networks and regional success. While research in this field has contributed crucial insights to the understanding of interorganizational networks and embedded ties as determinants of local growth and systemic strength, much weaker focus has been placed on the role and performance of the cluster-located firm (CLF), as an active constituent of this dense multirelational local system. Furthermore, despite the great emphasis on relational processes that distinguish research on localized industries by and large, only 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, building on the notion of embedded networks as carriers of information and knowledge, 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 embeddedness. These ideas are presented and tested based on the analysis of three-year longitudinal data gathered on a sample of 89 small firms located in a geographical cluster of Northern Italy. Results from fixed-effect regressions provide mixed support to the role of embedded ties as enablers of growth, suggesting that the hypothesized process of influence is highly contingent on the richness of CLFs' preexisting knowledge structure.