Paper presented at the 2008 Academy of Management Annual Meeting

August 8-13, 2008 - Anaheim, California

Theme: The Questions We Ask

Network Integration in Regional Clusters and Firm Innovation – A Comparison of Measures

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Abstract

This paper assesses the effects of network involvement on firm-level innovation. Results from a structural network analysis of firms in a regional photonics cluster in Germany indicate that clique overlap is a much better predictor of firm-level innovation in clusters than a firm's centrality, measured by the number of direct ties. The paper concludes with implications for network and cluster theory and for managing firms and networks in regional high-tech clusters.

There is growing consensus that networks, alliances, and clusters matter economically, especially in terms of innovation (e.g. Powell et al., 1996). Despite the rapid spread of these forms and the increasing prominence of a relational perspective on innovation (cf. Meeus & Faber, 2006), the specific effects of different elements of network structure on organizational performance remain unclear (Ahuja, 2000). This is particularly true for specific networked contexts such as regional clusters or industrial districts.

Clusters are most commonly defined as "geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (for example, universities, standards agencies, and trade associations) in particular fields that compete but also co-operate" (Porter, 1998: 197). Most research on clusters and other types of regional innovation systems (e.g. Cooke et al., 2004) points to the importance of a dense network of collaborative relationships for enhancing innovation outcomes such as new innovative products, publications, or patents. For this reason, the importance of *networks in clusters* has been emphasized (e.g. Staber, 1996; Sydow & Lerch, 2007). It is in these interconnected networks that operate within industry clusters where the "locus of innovation" (Powell et al., 1996) has been found, especially in knowledge-intensive industries such as biotechnology or photonics. Nevertheless, the processes of network-building in clusters and, in particular, their effects on firm innovation, are little understood, though the innovativeness of firms and their close collaboration with research organizations within dense regional networks of relationships are considered to be largely responsible for the innovativeness of a cluster.

Prior research has shown that firms often enter partnerships – inside or outside such geographical agglomerations – repeatedly with partners from previous interactions because of the knowledge gained about the partner and/or the reduced transaction costs resulting from trust-based relationships (Dyer & Chu, 2003; Gulati, 1995a, b; Podolny, 1994). Repeated partnerships, especially in extensive regionally embedded relational networks, can promote the development of shared norms and may foster interorganizational information transfer via the development of knowledge-sharing routines (Uzzi, 1997; Dyer & Nobeoka, 2000). On the negative side, opportunistic behavior is likely to be sanctioned by network and cluster participants in these dense networks (Coleman, 1988; Rowley et al., 2000), especially in regional clusters where shared norms and values are part of a common "industrial atmosphere" (Marshall, 1890). Even outside the regional innovation context, it has recently been demonstrated that the opportunistic behavior of involved partners and the exploitation of gaps in the network structure can have a negative effect on innovation (Ahuja, 2000). It has also been shown that the advantages of structural holes may be more applicable to networks of market-like transactions than to networks of cooperative relationships (Walker et al., 1997). Thus, in a collaborative innovation process situated in a regional cluster it is likely that networks of cooperative relationships will not only be present, but that they will be relevant for explaining the transfer of difficult-to-trade or even untradeable knowledge across organizational boundaries.

One leading school of thought in the social network literature proposes that densely connected networks are indeed beneficial for well-connected firms. Social structures that can be described as "closed" are predicted to be helpful for network participants (Coleman, 1988; Walker et al., 1997), though some empirical evidence suggests that too much closure and "overembeddedness" may well reduce their innovativeness (Uzzi, 1997).[1] In this study we will concentrate on the presumed value of dense, closed ties and analyze different network integration measures and their influence on firms' subsequent innovation output.

The aims of the research reported here are to disclose the actual networks of relationships in an industry cluster, to measure the integration of firms within the cluster, and to compare the extent to which two critical integration measures are able to predict firm-level innovation performance. For this purpose, network integration of cluster firms will be measured in two alternative ways: first with one type of centrality measure (Freeman, 1979), and second, by using the concept of cliques, and especially, clique overlap (Wasserman & Faust, 1994: 249-290). The different data were collected in a photonics cluster in Berlin-Brandenburg, Germany, during 2005 to 2007. Data were analyzed using four regression analyses in order to detect the influence of these two network integration measures upon firm-level innovation while controlling for firm level differences.

In the following section, we will elaborate the relationship between different elements of network structure and innovation outputs of firms in a regional agglomeration context. Then, based upon Coleman's (1988) position, a simple model will be presented that proposes that firms' innovation performance in regional clusters is explained to an important extent by network integration characteristics. Later sections describe the research setting and methodology and the analysis of the data. The paper concludes with a discussion of the findings, the limitations of the study, and implications for managers of firms and networks in regional high-tech clusters.

NETWORK STRUCTURE AND FIRM INNOVATION PERFORMANCE IN REGIONAL CLUSTERS

One line of thinking in the literature on industry clusters that takes the networked character of clusters into account focuses especially on the idea of knowledge transfer, and especially, local knowledge spillovers via dense relations as drivers of innovative activities (Malmberg & Maskell, 2002; Tallman & Jenkins, 2002). According to Pavitt (2002), it is tacit knowledge that constitutes the most important basis for innovation-based value creation. In a global economy with interconnected economic actors and the availability of information and communication technology and relatively easy access to codified knowledge and information, the creation of unique capabilities and innovative products depends on the utilization of tacit knowledge (Maskell & Malmberg, 1999: 172). This, however, is a truly regional argument because this line of thinking posits the exchange of tacit knowledge to be especially facilitated in regional agglomeration contexts via a dense network of relationships. It is also recursive, since the transfer of tacit knowledge is a key determinant in the regional agglomeration of innovative activities (Asheim & Gertler, 2005).

Two arguments are especially relevant for an explanation of why the maintenance of dense, interorganizational ties among firms in geographically proximate clusters matters in the innovation process. The first argument relates to the importance of the “stickiness” of context-laden tacit knowledge and the growing importance of social interaction. Polanyi (1958, 1966) was the first to argue that tacit knowledge is difficult to exchange over long distances because it defies easy articulation and codification. Additionally, it is most often infused with meaning resulting from the social and institutional regional context in which it is produced, making it even more spatially sticky (Gertler, 2003). The second argument is that the innovation process is based more and more on interactions and knowledge flows between economic agents such as firms (customers, suppliers, competitors), research organizations (universities, other public and private research institutions), and public agencies (technology transfer centers, development agencies). Not surprisingly, these organizations are often co-located in specific regions (Asheim & Gertler, 2005: 293).

Although the importance of the knowledge spillover debate may well have been overrated in the contemporary cluster discourse and that traditional Marshallian pecuniary advantages operating in regional industry clusters are still important (Breschi & Lissoni, 2001a, b), we will focus on localized knowledge spillovers via social interaction resulting from dense networks of relationships. These spillovers have the potential to provide a conceptual bridge between network structure and firms' innovation output in regional clusters. Researchers of regional innovation systems, for example, argue that innovation performance "depends to a large extent on how firms utilize the experience and knowledge of other firms, research organizations, government sector agencies, etc., in innovation processes, and how they blend this with the firm's internal capabilities" (Isaksen, 2001: 108; cf. Cooke et al., 2004). Others note that firms have to "tap into the body of localized knowledge and capabilities [… This however depends] in a fundamental way, on the ability to establish and maintain effective social links and lines of communication" (Breschi & Malerba, 2001: 820).

The relationship between network structure and organizational output such as profitability (Berg et al., 1982; Hagedoorn & Schakenraad, 1994) and innovation (e.g. Coleman et al. 1966) has already been studied. Whereas the profitability studies did not directly analyze the influence of collaboration on innovation output, most innovation studies concentrated on the adoption or diffusion of innovations rather than on the generation of innovations. Some studies, however, have attempted to analyze the more specific relationship between network structure on the one hand and the generation of innovation on the other. Shan et al. (1994), for instance, discovered a positive influence of inter-firm cooperation on innovation, and more specifically, on the relationship between the number of collaborative relationships that were entered into and innovation output (as measured in terms of biopharmaceuticals patents of startup firms in the biotechnology industry). Powell et al. (1996) found that for biotechnology start-ups, centrality in inter-firm networks was related to subsequent firm growth. However, both studies did not consider the impact of network positions or the involvement of firms in cohesive subgroups in regional clusters on innovation. Therefore, the structural elements in which firms are embedded in regional clusters and the role they play for firms' innovation outputs remains unclear.

Especially in a regional clustered context, links to other firms or other types of organizations within the region can provide the possibility to combine knowledge, competencies and assets. More specifically, (1) the number of ties maintained by a firm can influence the innovation output of a firm – measured, for instance, in terms of patents filed or prototypes developed – because these ties potentially provide the above mentioned benefits regarding the flow of critical information (Ahuja, 2000). Furthermore, (2) the involvement in Simmelian ties, or cliques, and especially, the involvement of cluster firms in overlapping local cliques of different relational dimensions, may be important for enhancing innovation. Overlapping cliques may represent the structural elements that provide the rich social context necessary in the transfer of interdisciplinary, “sticky” knowledge that is said to be involved in innovation processes in regional clusters in high-technology fields.

Direct Dyadic Ties and Innovation Output

Ahuja (2000) proposed and demonstrated that a firm’s innovation output is positively influenced by the number of direct dyadic ties. According to him, three benefits are responsible for this association: knowledge sharing, complementarity of skills from different organizations, and scale economies. Berg et al. (1982) had showed previously that direct ties facilitate the interorganizational sharing of knowledge. The point here is that participating firms collaborating in a technology development project have access to the developed technology, and therefore, obtain a greater amount of knowledge than the individual firm would if the firm developed the technology independently.

As stated above, the simultaneous use of complementary competencies and knowledge bases is increasingly necessary in technological innovation processes. Studies have shown that closely collaborating firms will be more successful in developing and marketing complex goods than firms that operate independently (cf. Meeus & Faber, 2006, for a recent summary of such research). Collaboration facilitates the pooling and joining together of complementary skills from different companies (Arora & Gambardella, 1990). Especially for small and medium sized firms, which are characteristic of regional industry clusters, purchasing, developing and maintaining multiple and broad competencies in a rapidly changing competitive environment demanding complex goods or services is very often infeasible, because the associated costs are too high. This situation often leaves only the development of internally specific competencies and collaboration with other specialized firms as possible options (Mitchel & Singh, 1996). By accessing the competencies of other cluster firms via direct ties, firms can benefit from economies of specialization without too much prior investment in the internal development of these competencies. Therefore, firms can improve their knowledge base and raise the likelihood of their increased innovation performance. As a result, and consistent with prior research, we suggest the following baseline hypothesis:

Hypothesis 1: The more direct dyadic ties a firm maintains within its regional network, the greater the firm's subsequent innovation output.

Firms' Clique Involvement and Innovation Output

Hypothesis 1, building on prior research, focuses exclusively on dyadic ties. That is, innovation outcomes are explained by an organization's ties to other individual members of the network. But network structure is often more complex than this. In line with Simmel's (1950) argument that triads (smallest possible cliques) are fundamentally different from dyads, and that they should be considered as the fundamental unit of analysis in social systems, we believe that cliques in clusters will result in different innovation outcomes than when focusing solely on dyads. According to Simmel (1950: 138) the shift from a dyad to a triad changes individuals' behavior because in triads or larger cliques norms become more important, especially as an effective means of coordination (Coleman, 1990).

Triads differ from dyads on three distinct grounds (Simmel, 1950; Krackhardt, 1999). First, individuals in triads have less individuality because they can be outvoted by the others in the triad. Second, individuals in triads have less bargaining power because threatening to leave the triad has less of an impact to the other triad members than it would have in a dyad, which terminates if one member leaves. And third, generally there is less conflict in a triad because conflicts between two individuals can be resolved or moderated by a third person in a triad. Krackhardt (1998: 24), who defines Simmelian ties as ties embedded in a clique, also argues that such Simmelian ties, embedded in cliques, or co-clique relationships, are more stable, exhibit longer longevity, and promote greater trust.

Consistent with and building on Burt's structural hole argument, Krackhardt (1999) emphasized that bridging a structural hole can add constraints on the behavioral options an individual possesses. This would be the case if norms of additional triads or other cliques become relevant as a result of the bridging. Even though the broker of a structural hole receives power because s/he controls the flow of information, he or she is now subject to an increased portfolio of norms resulting from the affiliation with multiple cliques. This affiliation results in a decrease of power due to a decrease of the range of action that can be taken.

Building on the idea that triads or cliques matter, how do they relate to output measures, and particularly to the innovation of organizations in clusters? One of the very few studies that analyze cliques and especially the overlap of cliques in relation to output oriented measures was conducted by Provan and Sebastian (1998). Here the influence of cliques and, especially, clique overlap, was analyzed relative to network effectiveness. The results indicated that network effectiveness in networks of mental health agencies was greatest when the network was integrated through cliques of agencies that exhibited multidimensional overlapping links. In a later study, Provan, Milward and Isett (2002) showed that the number of cliques within a nonprofit managed care system increased significantly over time indicating a higher degree of coordination and collaboration. Neither study, however, investigated the possible impact of clique structuring on the organizational innovation process.

Organizations generally, and firms within regional clusters in particular, are actually often embedded in multiple, partially overlapping networks (Powell & Smith-Doerr, 1994). Powell (1985) previously suggested that modeling multiple networks of different relational dimensions is necessary in order to comprehend how different networks influence organizational outcomes. This can actually be achieved by considering firms' involvement in cliques and in their multidimensional overlap.

Clique concepts identify cohesive, and arguably, effective subgroups and larger compounded sub-groupings in complex networks like clusters (see Kilduff & Tsai, 2003: 44-49) and generate subgraphs that overlap (see Everett & Borgatti, 1998), indicating more integrated regions in a network. So conceptually, dyadic ties and involvement in (overlapping) cliques, even though often correlated especially in networks with higher density, measure different aspects of network integration. Whereas the simple counting of dyadic ties takes access to resources into account (especially the knowledge possessed by the linkage partner), consideration of triads/cliques and involvement in overlapping cliques also takes into account exposure to group norms and their implications for the behavior of clique members. For instance, a recent study of the biotechnology sector (Owen-Smith & Powell, 2004) indicated that membership in loosely connected but coherent network configurations, like cliques, conveyed benefits for the generation of innovations to organizations in knowledge-intensive industries.

While cliques are different than dyadic ties, the impact of clique membership on innovation may have only a modest impact on innovation outcomes, as compared to dyadic ties. Where clique membership is likely to matter most is regarding clique overlap. The different knowledge and expertise held by organizations in different societal spheres, such as scientific and commercial, makes network integration in regional high-technology clusters exceptionally important for generating innovative projects. However, it also makes network integration challenging. Innovation in high-technology is often interdisciplinary in nature and, therefore, cluster firms need to simultaneously exploit their ties to regionally based business *and* research partners. It is not sufficient to focus on single ties, since actors of different organizations are involved in complex innovation processes at the same time. Firms that simultaneously explore and exploit regional networks of different relational dimensions are expected to be more successful in transferring knowledge in complex regional innovation activities and are, therefore, likely to be more innovative than other firms in the cluster that maintain only single ties to different partners. Thus, other things being equal, we propose:

Hypothesis 2: The greater a firm's involvement in overlapping cliques of cluster organizations, the greater that firm's subsequent innovation output.

In an interdisciplinary high-tech field such as photonics, we also expect more complex integration measures such as clique membership and clique overlap to be better predictors of organizational innovation outcome than the pure number of direct ties. Specifically, we argue that the benefit to organizations of cliques for acquiring knowledge in a network cluster will exceed that of dyadic ties and that the complexity of clique analysis will more accurately match the rich complexity of the relationships in the cluster than would be the case if only focusing on traditional dyadic measures. Therefore we propose the following hypothesis:

Hypothesis 3: Clique overlap will be a stronger predictor of a firm's innovation output than the number of direct ties the firm maintains.

RESEARCH METHODOLOGY AND SETTING

Social network methods and analysis were used for this research. Its focus is the empirical analysis of network structures, with the goal of trying to explain the relationship between the relational structure in which actors are embedded and actor's behavior or (economic or innovative) output. The basic idea behind structural network analysis is that the configuration of inter-actor links is in some way connected with their actions (Barnes, 1972) and that the links between these interdependent actors "permit the flow of material goods, information, affect, power, influence, social support, and social control. They provide individuals with opportunities and, at the same time, potential constraints on their behavior" (Freeman, 2000: 350).

Before defining our constructs in more detail and presenting our measures, the research context – the photonics cluster in Berlin-Brandenburg – and the sampling of the firms in this context will be described.

Research Context: Photonics Cluster Berlin-Brandenburg

Generally, photonics[2] is a global R&D intensive industry in which innovations are generated across organizational as well as national boundaries (Hendry et al., 2000). Companies interact with their research and business partners on a global basis because the necessary competencies are often so specific and distributed that only a handful (if any) competitors or research groups in the world can provide state of the art technology (for a recent overview of the optics and photonics industry see Sydow & Lerch, 2007). However, there is also considerable local R&D and commercial interaction and exchange within photonics clusters in specific regions (see, for example, regarding research on German photonics clusters, Cantner & Graf, 2006; Lerch et al., 2006; Schricke, 2007; and on US photonics clusters, Feldman & Lendel, 2008). In order to gain or secure access to valuable knowledge and other resources, photonic companies seek not only global, but also, local partners. These firms seek to establish collaborative relationships, or, as circumstantial evidence shows, to strategically locate in or purchase companies in developed or developing photonics clusters.

To understand the relation between network integration and firm innovation performance, as well as to test dyadic tie- versus clique-based measures of network integration as predictors for organizational outcomes, we analyze relational data from an important photonics/optics industry cluster in Germany: Berlin-Brandenburg. The cluster, which is still being developed, has a history of more than 200 years, punctuated by considerable transformations due to the history of Germany and Berlin. More recently, the cluster has exhibited rapid development. This is due to the establishment, of a formal association in 2000 to take part in a national competition for government funding as part of a strategic national effort to promote optical technologies. After the funding was granted in 2001, a network administrative organization (Human & Provan, 2000) was set up, a more reflexive network organizing progress began, the association's member base grew to what is now more than 90 organizations, and the level of interconnection increased[3]. About half of the association's member organizations were in the "economic sphere" and one third in the "science sphere" (Giddens, 1984), with the rest being supporting organizations like venture capital and consulting firms (cf. Sydow and Windeler, 2003). The members of the association, which were the empirical base in this study, represented about one third of all the organizations that worked in the field of photonics in the region at the time of data collection. More importantly, the association comprised almost all organizations that were strategically important in terms of sales volume, number of employees, and knowledge accumulated or growth realized.

Research Sample: Networks of Firms within the Cluster

Relational data for the Berlin-Brandenburg photonics cluster association's member organizations were obtained for 2005 through 83 semi-structured telephone interviews with the CEOs or directors of these organizations. Nearly all member organizations were included (88.3 %). Of these, 46 were business firms, the rest being research organizations or service providers, banks or consultants. Of the 46 firms in the sample, 37 firms (80.4 %) yielded a full set of relational and attributional data. It is the network activities of these 37 firms that will be the focus of our analysis.

The interorganizational network activities we examined included the relations between each of the 37 optics firms, as well as relations between these 37 firms and the other organizations in the sample of 83 organizations. Relationships were first measured dichotomously in terms of whether they existed or not and then measured along three specific types of relational dimensions: personal, R&D and commercial. It is the latter two interorganizational, rather than interpersonal, relations that will be relevant in the clique analysis. Two matrices were generated. Let Z be an n x n binary asymmetric matrix representing the presence ($Z_{ij}= 1$) and absence ($Z_{ij}= 0$) of relationships between n (= 83) organizations. The second matrix M is a n x n asymmetric matrix representing the presence of a two-dimensional relationship (R&D *and* commercial) between actor a_i and a_j ($M_{ij}= 2$), the presence of a one-dimensional relationship (R&D *or* commercial) between actor a_i and a_j ($M_{ij}= 1$), the absence of a relationship between actor a_i and a_j ($M_{ij}= 0$). Using the cut-off value of 2 and then dichotomizing M generates a binary symmetric matrix representing two dimensional relations.

Organizational outcomes were measured in terms of patents, development of prototypes, and publications in photonics (industry) journals or at industry conferences. In addition, we gathered qualitative data on the development of the cluster as well as on several networks in the cluster with the help of several semi-structured personal interviews, the analysis of documents such as minutes, annual reports, master plans and roadmaps, and participant observation of a broad array of strategy meetings, workshops and colloquia over a period of seven years. The quantitative data were analyzed using UCINET 6 (Borgatti et al., 2002) and SPSS. The qualitative data we collected are drawn on to develop a deeper understanding of the processes that brought about both the network structures and the innovation outcomes within the cluster.

Constructs and their Measurement

The independent variables are firm centrality and firm involvement via overlapping cliques. An innovation index was developed as the dependent variable.

In-degree centrality

In social network analysis, three distinct centrality measures are commonly used (Freeman, 1979): degree centrality (involvement), distance centrality (power), and betweenness centrality (information control). Since we were interested in the involvement of a firm in the network of relationships in a regional cluster as a predictor of innovation, we focused solely on degree centrality. Degree centrality is simply the number of other nodes, or actors (individuals, organizations, etc.) to which a focal actor is adjacent or, put differently, directly connected (Scott, 2000). A node is central if it has more direct connections than other nodes in the network. An individual or organization with low degree centrality is isolated from direct involvement in the network or regional cluster and is cut off from active participation in ongoing flows of information and communication (see also Freeman, 1979).

Degree centrality can also be computed for nodes in directed graphs. In this case, each node will have two measures: in-degree and out-degree centrality. In directed graphs, it makes sense to distinguish between those two measures (Knoke & Burt, 1983). In our sample of cluster organizations, some “senders” of relations appeared to be overoptimistic in their description of their direct ties. In the network of "recipient" ties, however, this effect is leveled out by normal distribution effects. Since we did not focus on prestige, affect, power, or influence effects in this analysis, we decided to use only the in-degree scores as a more reliable indicator of degree centrality. In-degree centrality scores were computed for each organization by summing up the cells in the columns in the binary social network matrix *Z*.

Firm Involvement in Overlapping Cliques

A clique can be defined as a sub-set of at least three actors in which every possible pair of points is directly connected and the clique is not contained in any other clique (Wassermann & Faust, 1994: 254; Scott, 2000: 114). However, since such narrowly specified sub-groupings are quite uncommon in social life, a number of more relaxed concepts have been introduced; specifically, n-cliques, n-clans, and k-plexes.[4] Because of the limitations of these more relaxed constructs (see Scott, 2000: 116-117), we used the stricter graph theoretic concept of the clique. Luce and Perry (1949), as well as Harary (1969), define a clique as a maximally complete sub-graph. However, because a key aspect of our research is clique overlap, our operationalization of cliques allows for multiple clique membership.

Clique overlap, a complementary measure of network integration that captures the idea of more integrated networks in clusters quite well, can be measured as the extent to which members of a clique interrelate with members of other cliques. This can be calculated in a number of ways, by taking only one or several types of relationships into account (Kilduff & Tsai 2003: 47; Provan & Sebastian, 1998: 457). One-dimensional clique overlap scrutinizes how actors are connected in a network of single-dimension relations and how the substructures of their network overlap. Multi-dimensional clique overlap, by contrast, indicates how these actors are tied together in a network of more than one relational dimension – and how these relations overlap with those of other cliques. For example, comparing two networks where in one network two cliques overlap and in the other network where the cohesive subgroups do not overlap, one would expect the diffusion of information, knowledge and innovation to occur more rapidly in the former, where boundary spanners – individuals or organizations – function as bridges between the otherwise separate cliques (Hanneman, 2001: 77).

Firms' involvement in overlapping cliques was measured by first generating a social network matrix *M* that included both R&D and commercial relations. The multiplex matrix was then inclusively symmetrized, since the potential of unanswered ties that exist between the cluster organizations should be included in the analysis. Using UCINET 6, 120 overlapping cliques of at least 3 actors (triads or higher) were identified. The individual firm's involvement in overlapping multiplex cliques was derived from the diagonal of the actor-by-actor co-membership UCINET 6 output. Thus, a clique was considered to have overlapping membership if all of its members shared both R&D and commercial relations.

Z-Standardized Firm-level Innovation Index (InnoIndex)

Innovation in general can be measured in a number of ways. Common measures are the number of patents or new products brought onto the market by either a firm or a number of cooperating actors in a given period of time (e.g. Hagedoorn & Schankenraad, 1994; Shan et al., 1994; Stuart, 2000). A large number of scholars stress the usefulness of *patents* as a highly relevant measure of the innovation output of organizations, because of the direct relation of patents to inventiveness, the fact that patents represent an externally validated measure of technological novelty (Griliches, 1990), and because patents have economic significance, since they award the patent holder with property rights (Kamien & Schwartz, 1982). However, we take a more critical stance, because patents as a measure of innovation output have a number of limitations, especially in the optics/photonics field. Use of patents is generally problematic because it is more indicative of an invention rather than an innovation, showing only the right of an actor to produce and market the patented product or service rather than providing direct evidence about the actual use and exploitation of the patent. Moreover, there are often significant time-lags between inventing, patenting, and marketing a product or service that are difficult to deal with in empirical research. Furthermore, quite a number of innovations are not patented at all in order to keep the innovation secret and because the patenting procedure is too demanding, especially for small and medium sized firms as those in the Berlin-Brandenburg cluster. As a result, firms differ in their tendency to patent their innovations (Cohen & Levin 1989; Griliches 1990).

The actual number of *new products* or services brought onto the market, however, has its limitations as well. For instance, this measure may exhibit no or only modest levels of innovativeness. The relevance of this limitation depends on the research design and the industry setting. This problem will be most acute in inter-industry studies, as there is likely to be significant variance across industries (Levin et al., 1987; Cohen & Levin 1989). Restricting a study to only one industry or, as in our case, even to a single industry sector should minimize these problems, because the factors influencing the patenting propensity of firms are expected to be stable within such a confined context (Basberg, 1987; Cohen & Levin, 1989; Griliches, 1990).

Because of the limitations that use of patents and products entail as a measure of innovation output, we generated a *firm-level innovation index* that applies a collection of different measures in order to make our innovation construct more robust. Specifically, we generated a firm-level innovation index using three z-standardized measures of each firm: patent frequency, number of developed prototypes, and publications.

We obtained yearly patent counts for each sample firm for 2005 and 2006 in order to include the time-lag between collaborative invention and filing for a patent. We only counted German patents for two reasons: First, the large majority of the firms in the sample are small companies that, if at all, primarily patent in their home (German) market. Second, considering worldwide, US, European, German, and other country's patents would lead to double counting of patents. To collect the number of successful patent applications or granted patents we used the database of the DEPATIS-Systems of the German Patent and Brand Office (Deutsches Patent- und Markenamt). Most patent applications are ruled upon within one and a half years. So, patents applied for in 2005 should have been granted by mid-2007, which was when final patent data were collected for the study. Additionally, we collected the number of developed prototypes and the number of publications in scientific journals and at conferences in 2005/06 in the 2006 interviews. Finally, we z-standardized the three measures and generated an average z-standardized innovation output score (InnoIndex) for each sample firm. Table 1 represents the measures and the timeframe they cover.

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Because innovative outputs like publications, patents, and prototypes are likely to correspond to innovative collaborative activity preceding the application for a patent, the completion of a prototype, or the presentation of a novel technology in a journal or at a conference, we used a one year lead as well as the data of the particular year in which the relations were measured. Thus the innovation index for 2005/06 is regressed against the 2005 values of the other covariates.

Control Variables

The most commonly used control variables in studies of innovation are firm age, size, and the R&D intensiveness of the firm. Older firms are expected to have had more time for R&D and product development and to have accumulated more "absorptive capacity" (Cohen & Levinthal, 1990), and for that reason alone, should have a higher innovation output. Although some prior research has shown little or no such association between the firm's (start-up) age and its innovation output (Powell & Brantley, 1992; Shan et al., 1994), we expect a firm's age to have a positive effect on its innovation output.

It is also common to check for firm size effects in the analysis of innovative productivity (e.g. Cohen & Levin, 1989). It is expected that larger firms will have more resources available to be used in R&D and innovation processes. Additionally, R&D intensiveness is likely to influence the innovative outputs of firms. The more resources that are committed to R&D in a firm and the more people in a firm who have an R&D background, the more likely the firm is to produce innovative output.

Company size (SIZE) was simply measured in terms of the number of full-time employees as of December 2005. This number was derived from the telephone interviews. Company age (AGE) was measured as the number of years since its founding in the region. The information for this measure was obtained from the cluster association's database. Finally, company R&D intensiveness (R&D %) was measured in terms of the percentage of R&D personnel in the firm's employee base as of December 2005. The information for this measure was also collected in the interviews.

Other control variables like diversification (Cohen & Levin, 1989), R&D expenditures, technological opportunity in specific industry sectors in which a firm is active, international research presence, and technological distance between partners (Ahuja, 2000) may also be relevant but data for these variables were not obtained.

EMPIRICAL RESULTS

In the Berlin-Brandenburg optics cluster, the level of interaction within the cluster association's member base was high. The network of relations between the members evolved quite dramatically from one that was fragmented and with low visibility in 2000 to a dense, complex network in 2005 (see Figure 1).

Table 2 presents a correlation matrix, including means and standard deviations of the variables used in the analysis.

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We tested hypotheses 1 and 2 applying a regression equation model that modeled the influence of the network variables in-degree centrality and firm involvement in overlapping cliques and the control variables on firms' innovation output (see model 4 in Table 3).

----- INSERT TABLE 3 ABOUT HERE -----

Hypothesis 1, positing that the number of direct ties would be positively related to innovation output, was supported using zero order correlations ($r = 0.434$, $p<0.01$). However, the relationship was not supported in the regression analysis ($B = -0.107$; n.s.). In sharp contrast, hypothesis 2 was, supported in both the correlation analysis ($r = .480$, $p<0.01$) and in the regression equation ($B = 0.087$; $p<0.05$). In other words, firms with high involvement in multidimensional overlapping cliques of cluster organizations seem to have a significantly higher level of innovation output than firms that are involved in few overlapping cliques. For the three control variables used – age, size and R&D intensiveness – only size had a positive significant relationship with innovation output in the correlation analysis ($r = 0.320$, $p<0.05$), but this relationship was not supported in the regression equation ($B = 0.004$; n.s.).

For a comparison of the two network integration measures, three additional regression models were calculated. Model 1 in Table 3 only includes the control variables, none of which were significant predictors of innovation. The second and third models include the control variables and either the centrality measure alone (model 2) or only the clique overlap measure (model 3). In model 4 we added both the centrality and clique overlap measures to model 1. In model 2, centrality was only slightly predictive of innovation ($p<0.10$). In contrast, clique overlap (model 3) was a strong predictor of innovation ($p<0.01$), explaining considerable additional variance over model 2 ($\Delta R^2 = 0.119$). When both centrality and clique overlap are added to the equation (model 4), clique overlap remains a significant predictor ($p<0.05$), although little additional variance is explained ($\Delta R^2 = 0.001$). Thus, based on the regression analyses, hypothesis one received weak support but hypotheses two and three, which focused on clique overlap, were strongly supported.

----- INSERT TABLE 4 ABOUT HERE -----

Examining part correlations (see right column in Table 4) that indicates the proportion of Y uniquely predicted by each variable in a model can be used in a comparison of the predictability of measures. In the regression analysis displayed in Table 4 (model 4), the proportion of InnoIndex that was predicted uniquely by the variable “firm involvement in overlapping cliques” is much higher than the variable “in-degree centrality”. So at least in the model applied in this analysis, the use of overlapping cliques as a measure of network integration appears to be a stronger predictor than in-degree centrality or the simple count of a firm’s direct ties and hypothesis 3 is supported.

DISCUSSION AND CONCLUSION

This paper examined the relationship between the network integration of firms in a regional photonics cluster in Germany and proposed that firms’ centrality in the cluster and involvement in overlapping multidimensional cliques enhance firm-level innovation output. Interestingly, after including several control variables, only a weak positive relationship between the number of direct ties a cluster firm maintained within a cluster and its innovation activity was found. However, firms’ involvement in overlapping multidimensional cliques was strongly and positively related to a cluster firm’s innovation output, as predicted.

Despite the focus of much network research on dyadic ties and tie strength, it may well be the case that the simple counting of the number of relationships is not a good enough measure for network integration. This finding highlights the necessity to consider and analyze networks (triads or larger cliques) in clusters as opposed to dyadic relations as loci where innovation activity occurs in knowledge-intensive innovation processes. The complex social space provided in the photonics cluster we studied, which was reflected by the presence of multiplex overlapping cliques, provided an arena where context-laden and “sticky” knowledge can be transferred in complex regional innovation activities across the different social spheres and disciplines. The multidimensional clique overlap measure used in this study may actually be able to capture this important relational dimension of the innovation process.

By concentrating on triads/cliques in the analysis of innovation outcomes of firms in regional clusters, the old Simmelian argument is revived, which suggests that in triads, group norms become an effective means of coordination, changing individual’s behavior. This in turn fosters the development of more trustful relationships, which is said to be one of *the* preconditions for inter-organizational exchange of knowledge leading to innovation processes in regional clusters (Cooke et al., 2004; Asheim & Gertler, 2005).

With regard to control variables, it was shown that a cluster firm’s size was positively related to innovation output. This finding is in line with the Schumpeterian argument that larger (start-up) firms should have more resources available for research and development activities. This argument can be extended to a relational dimension: larger cluster firms may also have more resources available for building collaborative interorganizational relationships, or networks in clusters. And absorbing or accessing resources within a particular cluster via such relationships may in turn increase the cluster firm’s innovation output, thereby enhancing its growth even further. Other firm-specific factors may also influence innovativeness, especially for companies in a regional cluster. Factors such as absorptive capacity, however, were not taken into account in this study because the focus of the analysis here was on regional clusters and the network integration of firms in such clusters rather than on the learning properties of organizations per se (see Argote, 1999).

Such firm-specific factors may well influence the capability of firms to transfer or absorb the information and knowledge that is said to be "in the air" in clusters (Marshall, 1890).

Though the control variables size, age and R&D intensiveness capture at least some firm-level differences, this is certainly a limitation of the present study. A further limitation of the study is the small number of firms in the sample though the 37 firms included in the analysis are likely to be representative of at least the total number of firms included in the association that constitutes the formal part of the Berlin-Brandenburg cluster.[5] Collection of a complete set of relational *and* attributional data for firms that are part of a particular cluster is desirable but difficult to accomplish. However, we believe that this analysis, even though limited in scope, provides some interesting insights into the analysis of the relationship between firms' structural embeddedness in clusters and firm-level performance.

The empirical finding that network integration, especially as measured by involvement via overlapping cliques, is strongly related to firm-level innovation in a cluster, has important implications for network and cluster theory as well as for managerial practices in regional high-technology clusters. As far as the former is concerned, the finding underlines the necessity to take networks of relationships into account for an understanding of how innovation outcomes in general, and firm-level innovation output in particular, comes about in regional clusters (see also Sydow & Lerch, 2007, for more qualitative evidence on the Berlin-Brandenburg case). Increasingly, these networks of relationships are referred to as "social capital" (Adler & Kwon, 2002). While the results of our empirical study seem to support Coleman's conceptualization of social capital that is based upon network density, it remains important that these structures – networks in clusters – are actually used and reproduced in everyday innovation activities. This is another important limitation of the research presented here. Methodologically even more demanding than capturing this practice or process dimension is to take the recursive interplay between network integration and firm innovation into account. The likelihood that networks of interorganizational relationships are not only ‘good’ for innovative outcomes but that innovative behavior of firms also fosters the building and maintenance of network relationships is quite likely, at least from a structuration perspective (Giddens, 1984; Sydow & Windeler, 2003). Under favorable circumstances, this recursive process may even become self-reinforcing because of positive feedback loops (Meeus & Faber, 2006).

For managerial practice in interorganizational networks in general and in regional clusters in particular, the finding implies that management should organize social space in ways that can be used for building collaborative interorganizational relationships that resemble cliques and, even more importantly, reflect clique overlap. In the cluster studied, the formal governance structure of the cluster as well as a broad range of activities – including events like “Members Introduce Themselves” or the yearly “Networking Days” – provided the social space necessary to get to know and to trust each other, to start to exchange knowledge and to collaborate in joint projects. This space, then, has actually been used by the agents for building networks of cooperative relationships and carrying out innovative projects. Under particular circumstances, the management may even succeed in triggering and sustaining a self-reinforcing governed by positive feedback.

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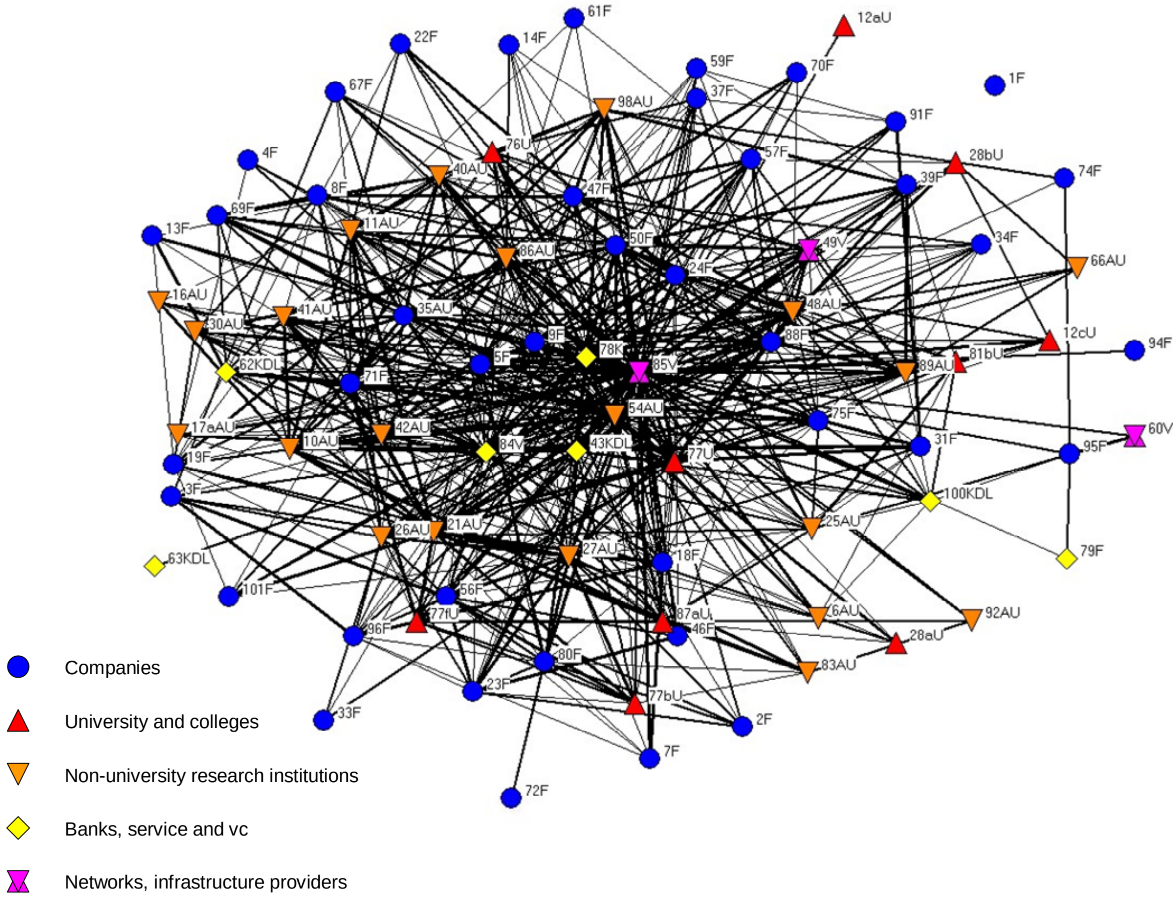
FIGURE 1
Network of Photonics Association Members in Berlin-Brandenburg in 2005 *



*) Displayed relations represent symmetric, potentially multiplex relations.

TABLE 1
Measurement of Relations, Firm Attributes and Innovation Output

Measure	Time (span covered)
Firm’s Relations	End of 2005
Firm Age	As of 2005
Firm Size	End of 2005
R&D %	End of 2005
Patent Frequency*	2005 and 2006
Number of Developed Prototypes*	2005 and 2006
Publications*	2005 and 2006

*) Z-standardized measures were mutually used to derive the variable InnoIndex

TABLE 2
Descriptive Statistics: Means, Standard Deviations and Correlations

Variable	Mean	S.D.	1.	2.	3.	4.	5.
1. InnoIndex	0.00	0.68					
2. In-Degree Centrality	0.24	0.13	0.434**				
3. Firm Involvement in Overlapping Cliques	3.54	3.93	0.480**	0.646***			
4. Age	14.57	19.15	0.146	0.263+	0.284*		
5. Size	31.89	45.73	0.320*	0.347*	0.064	0.337*	
6. R&D %	44.38	28.32	-0.227+	-0.357*	0.036	0.142	-0.329*

*** p<0.001; ** p<0.01; * p<0.05; + p<0.10

TABLE 3

Regression Analysis: Predictors of Firm Innovation Output

Independent Variables	Model 1	Model 2	Model 3	Model 4
In-Degree Centrality		1.808+ (0.908)		-0.107 (1.171)
Firm Involvement in Overlapping Cliques			0.084** (0.026)	0.087* (0.036)
Age	0.003 (0.006)	0.000 (0.006)	-0.002 (0.006)	-0.002 (0.006)
Size	0.004 (0.003)	0.003 (0.003)	0.004 (0.002)	0.004 (0.003)
R&D %	-0.004 (0.004)	-0.001 (0.004)	-0.004 (0.004)	-0.004 (0.004)
F	1.578	2.281+	4.146**	3.216*
R^2	0.125	0.222	0.341	0.342

N = 37. Non standardized linear regression coefficient B and standard errors (in parentheses).
*** p<0.001; ** p<0.01; * p<0.05; + p<0.10.

TABLE 4

Regression Analysis: Comparison of Standardized Coefficients

Independent Variables	Beta	Part correlation
In-Degree Centrality	-0.021	-0.016
Firm Involvement in Overlapping Cliques	0.498*	0.392
Age	-0.055	-0.058
Size	0.261	0.260
R&D %	-0.159	-0.158
F	3.216*	
R^2	0.342	

N = 37. Standardized linear regression coefficient Beta and part correlation for model 4. Dependent variable: InnoIndex.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.10$

ENDNOTES

1 An alternative view posits that advantages can be derived from social structure through brokering opportunities resulting from an “open” social structure (Burt, 1992). In this view, the bridging of structural holes facilitates obtaining information and control advantages over others. Interestingly, these different perspectives have diverse, even contradictory normative implications for the design of networks, including networks in clusters. While Coleman’s (1988) position would recommend building dense interconnected networks as the optimal social structure, Burt’s stance would argue for disconnected actors and non-redundant relations connecting the broker to other network participants exclusively.

2 “Photonics is the science of the harnessing of light. Photonics encompasses the generation of light, the detection of light, the management of light through guidance, manipulation, and amplification, and most importantly, its utilisation for the benefit of mankind” (Aigrain, 1967, c.f. European Technology Platform Photonics21, 2006: 11). The very dynamic world photonics market in 2005 (228 billion euro) was bigger than the world semiconductor market (200 billion euro) and is expected to grow on average with annual growth rates of about 7.6% (Mayer, 2007).

3 Earlier research indicates that interorganizational interaction in the cluster may have reached a saturation level. In 2005 the level of connectivity within the network was about the same as 2003. Specifically, the overall density of the photonics cluster association members’ network of relations increased from 21.47 % in 2000 to 28.77 % in 2003 and levelled out at 28.20 % in 2005. Over the years, firms, as compared to the other types of organizations in the network, moved from the periphery to more central positions, indicating a more intensive involvement in cluster activities (Lerch et al 2007).

4 In an n-clique n (usually n=2) is the maximum path distance at which members will be regarded as connected (Scott, 2000); in an n-clan the diameter of an n-clique is limited to n (Mokken, 1979), and k-plexes are sets of points in which each point is adjacent to all except k of the other points (Seidman & Foster, 1978).

5 The insights gained from our qualitative research makes us assume that there was no systematic reason for firms to accept our invitation to take part in the quantitative study.