CHAPTER 9

Intangible Capital in Industrial Research: Effects of Network Position on Individual Inventive Productivity

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Keywords: Industrial research, social network analysis, inventive productivity.

Abstract

The paper investigates the effects of collaboration networks on inventive productivity within an industrial research environment. A distinction is made between two kinds of network structures: structural holes offering information brokerage opportunities to individuals and network closures supporting co-specialization of individuals. Hypotheses regarding the effects of network positions on the development of technological know-how are tested based on longitudinal individual-level network data. The analysis provides partial support of both the structural hole and the network closure argument. However, contrary to literature emphasizing innovation via inter-organizational collaboration, the positive effects of ties between the research center and business units are highlighted. The interpretation of these results seems to call for more refined models of firm boundaries to better explain how the research activities are organized within firms.

Introduction

Innovation, along with the associated "creative destruction" that occurs as successful new products, production methods, and ways of organizing economic activity replace old ones, forms the core of competition in the capitalist process (Schumpeter, 1942). Start-ups innovate in order to identify, pioneer, and capture key positions in emerging markets. Incumbents innovate in order to leverage their existing assets, match changing customer preferences, and expand their markets. Thus, understanding the sources of innovation is a high priority for all managers. Indeed, theories of knowledge-based competition and intangible capital are receiving increasing attention (e.g., Grant, 1996; Nahapiet and Ghoshal, 1998).

This paper focuses on one major antecedent of successful innovation – inventive activity – and the related form of intangible capital – technological know-how. The development of technological know-how is investigated within the context of the industrial research laboratory, a form of organizing inventive activities that dates back to the early twentieth century (Mowery, 1990). A stream of research inspired by Schumpeter (1934, 1942) has studied the factors that affect inventive productivity in industrial research. Specifically, Schumpeter surmised that "technological progress is increasingly becoming the business of trained specialists who turn out what is required and make it work in predictable ways" and, as a result, "innovation itself is being reduced to routine" (1942: 132). The stylized context for this routinization of innovation was "the perfectly bureaucratized giant industrial unit" (1942: 134), although in his earlier work he emphasized that inventions are economically irrelevant unless put into practice (1934: 88), and presumed that the new combinations (i.e., innovations) do not generally arise from old firms but from new ones beside them (1932: 66). Thus, some words of caution are in order regarding the present study. First, regularities in inventive activities may not be directly associated with regularities in innovative activities. In extreme cases, some factors that benefit inventive activities may reduce the chance of fully translating the inventions into practical use, i.e., hinder innovation. Second, innovations may arise from different contexts via distinct mechanisms, and as such the dynamics related to industrial research are only a very specific lens to the issue. Nevertheless, investigation of the regularities of inventive activities within the context of industrial research is an important intermediary stage for understanding which, if any, aspects of the innovation process can be routinized, and for identifying boundary conditions for this routinization.

This study aims to contribute to this research agenda by examining the role of collaboration networks as a form of intangible capital in inventive activities. A competence-based approach is used to develop measures for technological know-how internal to the organization (Henderson and Cockburn, 1994, 1996). The innovation network approach provides the rationale to extend the analysis beyond the focal organization (Powell et al., 1996). Finally, the social capital approach is used to integrate the external and internal perspectives (Burt, 2000).

The measures of factors contributing to inventive productivity are based on archival data that is readily available to managers of R&D organizations. Thus, the methods applied in this paper can be adapted for practical research portfolio management purposes. The present analysis quantifies the relative effects of internal and external networks on inventive productivity, providing managers with insight on how to monitor and fine-tune their research organizations.

The research contributes to the existing competence-based strategy literature by applying measures that address the role of individual-level collaboration networks in the development of technological know-how. The network measures are one approach to investigating aggregate firm-specific differences in inventive productivity, i.e., competence, in detail (cf. Henderson and Cockburn, 1994). The empirical results are a direct test, within the specific context of industrial R&D, of the relative importance of competing hypotheses developed in the social capital literature regarding the role of network closures and structural holes as mechanisms of social capital creation.

Theoretical Background and Hypotheses Development

This section develops the hypotheses regarding the sources of inventive productivity drawing on three streams of previous research. First, competence-based perspective emphasizes hard-to-imitate resources, e.g., technological know-how embedded within firm-specific routines and collaboration structure, as sources of competitive advantage. Second, the innovation networks perspective elaborates on access to and absorption of external knowledge as factors critical to inventive performance. Third, social capital literature examines the relative merits of tight collaboration closures and brokerage across closures as mechanisms supporting inventive activities.

The argumentation is based on the following network terminology. *Internal collaboration network* refers to the collaborative ties between members of the case organization, i.e., the personnel of the research center. *Boundary-spanning* refers to network nodes that have connections, i.e., collaborative ties, outside the case organization. *Network closures* are parts of the internal network in which there are tight connections between the nodes. There are a number of different network analysis definitions that define what is "tight enough" for the nodes to be considered to form a closure. *Structural holes* are connections between otherwise separate parts of the network. These separate parts can be network closures, and often the structural hole is bridged by only one node that has connections to each closure. Detailed discussion of network terminology and methods to operationalize the concepts are presented by Wasserman and Faust (1994).

Competence-based perspective on within-firm sources of inventive productivity

The resource-based view of the firm proposes that firms are essentially pools of heterogeneous resources, such as technological know-how (e.g., Wernerfelt, 1984). If the resources are hard to imitate or replicate, the firm's unique resource combinations may provide a source of temporarily sustainable competitive advantage (Amit and Schoemaker, 1993). The firm's ability to develop and apply new resources has been referred to as "competence" (Prahalad and Hamel, 1990), "capability" (Leonard-Barton, 1992) or "dynamic capability" (Teece et al., 1997). In the context of industrial research, research scientists and engineers apply their skills, such as cryptographic expertise or knowledge of data-mining methods, to various R&D projects. The projects yield novel ways to apply technological know-how to produce practical results, i.e., inventions. Inventions, some of which the firms patent, are thus a measure of the technological know-how accumulated.

The resource-based framework can be used to conceptualize firm-level processes of invention and innovation. Schumpeter defined innovation as an activity in which an entrepreneur "carries out new combinations" in the economy (1934: 132). In the realm of industrial research, inventions are the result of R&D personnel carrying out new combinations of technological know-how. Firms and individuals gain experience of those entrepreneurial opportunities they undertake, and the increased knowledge opens up new areas of entrepreneurial activity (Penrose, 1959). The new knowledge, a part of which is tacit, can be embodied in the skills of employees (Polanyi, 1958), or become routinized in the firm's way of operating (Nelson and Winter, 1982). Neither tacit knowledge nor firm-specific routines are easily imitated or replicated by competitors. Technological progress often follows paradigms as the R&D activities cumulatively increase certain performance characteristics of a technology, thus creating technological trajectories (Dosi, 1982, 1988). Given the cumulative, and partially tacit, nature of technological know-how, we posit:

> Hypothesis 9.1. Technological competence is cumulative at the individual level in the sense that previous contribution to inventive accomplishments positively affects the likelihood of producing new inventions.

To a degree, the above hypothesis is confounded by several different mechanisms. First, it is conceivable that the individuals have semi-permanent characteristics that affect their inventiveness (e.g., Amabile, 1988). These characteristics could include specific skills (e.g., ability to communicate ideas clearly), norms (e.g., likes to challenge status quo), psychological features (e.g., creativity), as well as personal history (e.g., highest educational degree completed). Second, there could be differences in "technological opportunity" that affect the fertility of R&D activities between technological fields (e.g., Cohen, 1995). This effect could be either "global," in the sense that all the R&D efforts by various organizations in a given field result in a particularly high or low inventive productivity, or "local," in the sense that a specific organization provides extensive management attention (including, e.g., special incentives) and support (e.g., priority in patenting process) to R&D activities in select fields. Although it is not within the scope of the present study to extensively examine the specific effects of individual characteristics, the hypothesized combined cumulative effect will provide a baseline for investigating the effects of network position on inventive productivity. To a degree, variation in technological opportunity can be controlled by dummy variables of broad technological fields.

R&D activities confront uncertainty regarding both emerging business needs and development of competing technological trajectories. As a result of bounded rationality considerations, scientists and engineers resort to selective communication channels and information filters, as well as tacit problem-solving strategies (Henderson and Clark, 1990). Communication channels are formed between groups and individuals with interacting tasks. Individuals focus on information which their previous experience suggests as relevant. Successful solutions to old problems are adapted to new ones with relatively little conscious effort. Henderson and Cockburn hypothesized that R&D scientists and engineers "embedded within particular firms develop deeply embedded, taken for granted knowledge or unique modes of working together that make the group particularly effective" (1994: 65). In terms of social network analysis, a group of individuals with direct connections to each other forms a closure within the broader network (cf. Burt, 2001b). For example, all the members of a research laboratory form one kind of network, and within that network there can be several project teams. The members of those teams, in so far as they work closely together, form closures within the broader network of the research laboratory. Another example of network could be researchers working on some next-generation technology. This network could consist of personnel from several laboratories. Within that network there can be numerous small groups active, for example, in standardization of specific aspects of the technology. Those groups form closures within the broader network. Based on these arguments we propose:

> Hypothesis 9.2. Membership in a closure within the collaboration network positively affects the inventive productivity of the associated individuals.

Close collaboration with other scientists and engineers can facilitate inventive productivity by several mechanisms. First, it provides access to partially tacit knowledge, thus enabling more effective transfer of knowledge between individuals than would be possible otherwise (cf. Nonaka, 1994; Nonaka and Konno, 1998). Second, collaboration is likely to proxy some amount of trust between the collaborators. The trust can be either a prerequisite or byproduct of collaboration; nevertheless, it may support an exchange of ideas, especially in the early phases of the inventive process. Third, the collaborating individuals may develop co-specialized skills and knowledge that as a combination provide fertile ground for inventive activities.

Innovation networks perspective on distributed sources of inventive productivity

Cohen and Levinthal (1989, 1990) note that internal R&D contributes to the firm's ability to evaluate and utilize innovations external to the firm, that is, it provides them with "absorptive capacity." Powell et al. (1996) expand this view by arguing that "the locus of innovation is found within the networks of inter-organizational relationships" (1996: 142) if the knowledge base of an industry is complex and expanding. Informal and formal collaborative relationships, especially in R&D, enable knowledge transfer across organizational boundaries. Thus, individuals and organizations in central network positions have timely access to information of new breakthroughs or obstacles, and are thus better able to leverage their own R&D capabilities.

The innovation networks contribute to inventive productivity via several mechanisms. First, knowledge of the R&D capabilities of potential partners is often hard to acquire without direct ties. Some collaboration, perhaps informal, can act as a prerequisite for the formation of more complex joint arrangements that aim to combine complementary capabilities, reduce risks, or seek synergies in R&D efforts

(Teece, 1992, 1998). Collaboration supports strategic structuring of R&D activities into the most effective make-or-buy variants (Pisano, 1990, 1991). Second, knowledge transfer via collaborative ties may provide insights that lead to new inventions. Inventive productivity is increased almost immediately due to better flow of knowledge (cf. Zucker et al., 1998). Third, the diverse sources of knowledge increase the participants' awareness of future R&D opportunities. Inventive productivity is increased with some delay, as the R&D portfolio starts to reflect the new insights from external sources. Of these arguments, the second and third can be examined at the individual level:

Hypothesis 9.3a. Boundary-spanning network connections positively affect the inventive productivity of the associated individuals.

However, collaboration across organizational boundaries may entail significant communication and coordination costs for the "gatekeepers" (Allen, 1977). The gatekeepers have to resolve differences due to conflicting organizational values, priorities, working practices, and so on. Thus, although the boundary-spanning connections may be beneficial for research groups, the gate-keeping activities may be burdensome at the individual level.

Hypothesis 9.3b. Boundary-spanning network connections positively affect the inventive productivity of research groups.

In addition to direct boundary-spanning network connections, scientific contributions can also be interpreted as "currency of exchange" (Pake, 1986) in the communities of practice furthering technological development (cf. Rappa and Debackere, 1992; Brown and Duguid, 1998). Thus, a less strict operationalization of the boundary-spanning activities could be based on all academic contributions, whether or not those outputs involve cross-organizational co-authorship. In this study, internal networks refer to the collaborative relations between the researchers of the case organization. For example, three researchers jointly producing an invention are considered to be connected to each other in the internal network. This internal network may span organizational boundaries if the act of jointly producing also involves members from other organizations. For example, a researcher can make an invention with a marketing manager from some business unit of the company, or a researcher can produce an academic publication in collaboration with university researchers. Thus, although the connections in the internal network as well as the connections from internal to external network are formed by the same mechanisms, i.e., joint production of inventive or academic outputs, it is still analytically feasible to distinguish nodes of internal network that are tied to the external network, i.e., boundary-spanning network connections.

Social capital perspective on integration of internal and external sources of inventive productivity

Nahapiet and Ghoshal define social capital as "the sum of actual and potential resources embedded within, available through, and derived from the networks of relationships possessed by an individual or social unit" (1998: 243). Whereas the competence-based perspective examines the processes through which new resources are generated and existing resources are utilized in ways that provide competitive advantage, the social capital perspective emphasizes that the exchange and combination of information is embedded in a network of relationships. Burt (2000, 2001a, 2001b) distinguishes between two different network mechanisms that make somewhat contradictory predictions about how social capital can facilitate the creation of competitive advantage. *Network closures*, i.e., parts of networks in which the nodes are closely connected to each other, provide access to information and support the development of trust, common norms, and shared language. *Structural holes* are connections between otherwise separate parts of the network. In so far as different information flows in the different parts of the network, the structural holes offer opportunities for information brokerage. Burt argues that as the "structural holes are gaps between non-redundant sources of information" (2000: 10), contact networks rich in structural holes are the ones that provide entrepreneurial opportunities. For example, within an industrial research center there can be one research group specializing in data-mining methods, and another in user interface design. In so far as these groups do not typically interact, a researcher interested in applying data-mining techniques for user interface optimization could be in a brokerage position that spans this structural hole. Hargadon and Sutton (1997) present a detailed analysis of how a product design company has organized itself to leverage the brokering possibilities.

The closure argument at the individual level of analysis underlies hypothesis 9.2. At the social unit level of analysis, all organizations are network closures to some degree. Thus, hypothesis 9.3 is a structural hole argument. Structural holes, however, can also be examined in the within-firm network structure. Especially in expert organizations, including research laboratories, the individuals possess highly specialized bodies of knowledge. Both the awareness of "who-knows-what" and the appreciation of the kind of problems to which the knowledge could be applied are likely to correspond to the collaboration network structure within the organization. That is, individuals with collaborative relationships tend to be more familiar with each other's areas of expertise than unconnected individuals. An individual with collaborative ties to otherwise unconnected experts thus spans a structural hole in the within-firm network structure. In terms of network analysis, positions of high betweenness centrality provide brokerage opportunities between otherwise disconnected parts of the network (Burt, 2000). Thus we propose:

Hypothesis 9.4a. Information brokerage, in the sense of individual's betweenness centrality within the collaboration network, positively affects the inventive output of the individual.

Table 9.1 Summary of internal and external perspectives on network benefits

	Competence-based internal perspective	Innovation networks external perspective
Closure benefits	Co-specialization; sharing of tacit knowledge	Flow of information is facilitated by co-membership in communities-of-practice
Brokerage benefits	Unique resource combinations	Access to non-redundant sources of information

Both internal information brokerage and external boundary-spanning activities require translation between diverse perspectives and specialized terms, as well as unique routines and working practices. Although it is reasonable to presume that these communication and coordination costs are less notable in within-firm brokerage situations than in boundary-spanning collaboration, information brokerage may also be beneficial at the level of research groups rather than that of individual R&D personnel.

Hypothesis 9.4b. Opportunities for information brokerage positively affect the inventive productivity of research groups.

To summarize, technological competence is hypothesized to be cumulative, partly tacit and embedded in routines. Network closures facilitate the use of tacit knowledge and the formation of routines. Both external boundary-spanning activities and internal information brokerage offer opportunities to create novel combinations of diverse sources of expertise, i.e., inventions. However, whether the boundary-spanning and information brokerage activities are beneficial at the individual or group level of analysis is an open empirical question. The synthesized framework is presented in Table 9.1.

The hypotheses are examined at the individual level of analysis. At this level, the collaboration networks are clearly defined, i.e., each individual is a node in the network and ties between nodes indicate collaborative relationships; thus, the use of network measures is feasible. Some of the measures can also be aggregated to the level of technological programs. At the program level of analysis, a number of control variables regarding the research portfolio structure can be introduced. These effects are investigated in Salmenkaita (2001).

Data Sources, Measures and Analysis

This section describes the data sources, operationalization of the measures, and analysis methods.

Case organization and data sources

The main network data comprises the industrial research activities of one major communications equipment corporation in 1995–2000. In 2000, the corporation had sales of 30.376 billion euros (6.191 billion euros in 1995), total R&D expenditures of 2.584 billion euros (425.7 million euros in 1995), and employed some 60,000 people (32,000 in 1995) (Nokia Corporation, 1996, 2001). The company has one corporate research center that serves the business units. The business units have their own R&D activities, mainly at the product development end of the research–development continuum, which are not included in the study. It should be noted that only a small portion of all the R&D effort, slightly over 5 percent in 2000 as measured by person-years, is conducted at the corporate research center. The research center is divided into seven laboratories based on broad technological fields (e.g., software, electronics), and the center operates at several sites in Europe, Asia, and the US. The laboratories are divided into research groups, based on more specific technological disciplines (e.g., software architectures, data mining). The research center explores new technological opportunities and develops technological know-how for both current and future business areas of the corporation.

The research activities are divided into projects, that is, the organization is a matrix of research groups and projects. Funding for the research activities is negotiated on a per project basis, with the majority of funds coming directly from the business units. Following common research management practices, the corporation has also "earmarked" some funding for research that is beyond the current interests of business units (cf. Buderi, 2000). Participation in research collaboration is partly funded by external sources, e.g., European Union Framework Programmes[1] and Finnish National Technology Agency[2].

The years 1995–2000 were a period of significant growth both for the company and for the research center. The growth was primarily internally generated, i.e., there were relatively few acquisitions and no mergers during the period. The research center grew from fewer than 500 to slightly over 1,000 employees during the period. Technological change during the period was rapid. Mobile terminals became increasingly miniaturized, incorporated new features and supported new radio transmission technologies. Communication networks evolved from circuit-switched voice networks to packet-switched data networks with integrated support for Internet protocols. With regard to emphasis on internal growth within a technologically turbulent environment, the case setting is representative of the kind of incumbent firms Schumpeter (1942) and Penrose (1959) envisioned in their theories of economic change and growth of firms.

Corporate research centers play a dual role in internal inventive activities, as well as in monitoring developments in the external environment (Mowery, 1983). Promising inventive outputs are first documented in invention reports, in which the employees disclose their findings to the employer. Thereafter, the employer has an opportunity to evaluate the importance of the findings and seek patent protection for the invention, if appropriate. The patenting process is costly; therefore, a decision to seek patent protection for an invention is a measure of the perceived quality of the invention (Patel and Pavitt, 1995). For the purposes of this study, the author had access to the company's internal database of inventions created by the research center's personnel. Compared to publicly available patent data, this arrangement had several benefits. First, it made it possible to distinguish between inventors from different organizational sub-units (e.g., corporate research center, business units), which is not feasible based on information available in patents. Second, it provided a richer view of the collaborative structure, since inventions that eventually were not patented were also accounted for in examining the collaboration network. Third, it removed the artificial collaborative relationships that are formed when a corporation merges several invention reports into one patent application.

The monitoring of the external environment is often active in the sense that the R&D personnel collaborate with people external to the company, such as in joint projects with university researchers (Debackere and Rappa, 1994). The outputs of the boundary-spanning collaboration include publications and conference presentations, the co-authors of which are from different institutions. This data is available from specialized databases, including Science Citation Index by the Institution for Scientific Information and INSPEC by IEEE, which are used in this research. Science Citation Index covers a broad range of major publications in a multitude of scientific fields, but lacks information about conference activities. INSPEC focuses on electrical engineering and related disciplines and also has coverage of key conferences in these areas. The results of author affiliation-based searches from the Science Citation Index and INSPEC databases were combined, and duplicate entries were manually removed.

The journals and conferences covered by the external publication databases have selective inclusion processes, typically based on peer review. Thus, by examining outputs that have passed the review, a standard of quality regarding the academic and scientific contributions is created. Also, the associated collaborative relationships are likely to entail a significant investment of time and effort between the parties (Cockburn and Henderson, 1998). However, there are some caveats. First, the author–affiliation relationships are not fully recorded on a one-to-one basis in the databases. The standard bibliometric approach to mitigating this problem is to first identify the affiliations of sole authors, and to then apply those author affiliations to database items with several authors in which the same authors also participate. In this study, an internal company phonebook was used to complement this method. Second, some authors can have multiple affiliations and may exercise discretion regarding which affiliations they report to each publication. Thus, an affiliation-based search can miss some relevant items. Unfortunately, complementary individual-based searches, besides being costly compared to a relatively simple affiliation-based search, would create new problems with the data. Specifically, different individuals can have similarly abbreviated names in the databases, or one individual can have differently abbreviated names in the databases.

In total, the databases comprise 2,427 records of inventions and 443 records of academic outputs for years 1995–2000. Of the inventions, 360 (14.8 percent) involved collaboration across research center boundaries, mainly with personnel in business units (331 items). Of the academic outputs, 169 (38.1 percent) involved collaboration across research center boundaries, mainly with researchers at universities

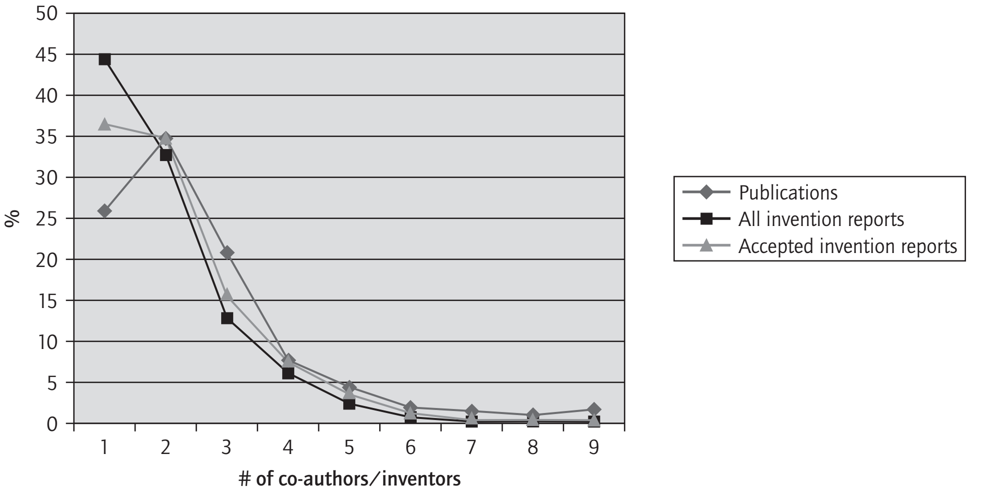

Figure 9.1 Distribution of number of co-authors / inventors; 443 publications, 2,427 invention reports, of which 1,135 accepted for patenting

(145 items). Figure 9.1 shows the distribution of the number of co-authors and co-inventors for publications, inventions and inventions accepted for patenting.

For the network analysis, *an internal collaboration matrix* was constructed for each year from 1995 to 2000 by combining the co-inventor relationships from the internal invention report database and the co-author relationships from the external database. The internal collaboration matrix is a square matrix in which the nodes represent collaboration relationships among those R&D personnel that have participated in at least one invention report or publication in a given year. The size of the internal collaboration matrix increased from 137 in 1995 to 445 in 2000. In Figures 9.2 and 9.3, illustrations of the structure of the internal collaboration matrix are presented for years 1997 and 1998, respectively. The matrices are hierarchically clustered using Johnson's hierarchical clustering by applying the single link (minimum) method on the similarity data. The algorithm finds nested partitions of the nodes of the matrix, starting from all nodes in different clusters, and then joins together those nodes that are most similar. The figures illustrate that there are some areas in the collaboration network where dozens of researchers have overlapping collaborative relationships. In addition, there are many smaller collaborative clusters, and a number of the researchers remain unconnected in terms of collaborative ties.

The databases were also used to construct *an external collaboration matrix* for each year from 1995 to 2000. The external collaboration matrix is an affiliation matrix in which the nodes represent collaborative relationships between the R&D personnel and external institutions. Specifically, the number of collaborative ties for each researcher with both business units and other organizations was recorded separately.

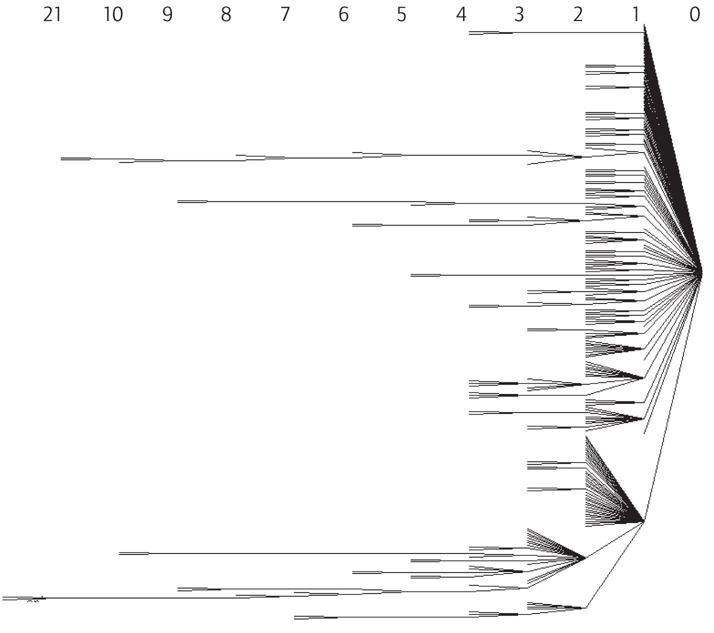

Figure 9.2 Cluster presentation of the internal collaboration matrix; year 1997

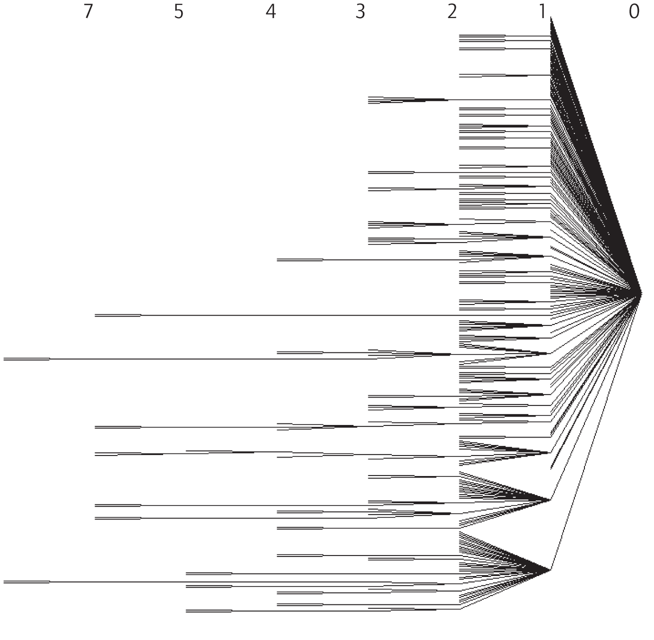

Figure 9.3 Cluster presentation of the internal collaboration matrix; year 1998

In 1995–2000, some 4,000 man-years of research were conducted at the research center. However, a significant share of this effort produced deliverables other than inventions or publications, and was therefore not accounted for in the data sources used in this study. Specifically, the data sources involved 1,717 observations of 881 individuals. The observations were arranged in longitudinal panel format, and all one-year "holes" in the panel were identified. Thus appended, the data set under analysis consists of 1,820 researcher/year observations.

Some technology development tasks, especially in the field of software technologies, result in relatively few potentially patentable outputs. Industrial research often involves a great deal of consulting (Kline and Rosenberg, 1986). Consulting can be critical to the firm's ability to appropriate the technological expertise, but results in few academic or inventive outputs. Moreover, industrial research is not devoid of managerial responsibilities. Even though senior technological experts might prefer to spend their time on inventive activities and scientific research, practical project and personnel management duties may consume a significant share of their attention (cf. Katz and Allen, 1997). Lastly, previous studies have observed that an "induction period" in tasks requiring highly specialized expertise can take up to one year or more before the person assigned to the task is able to fully contribute to new knowledge creation (cf. Katz, 1997). The effects of this induction period are more noticeable in fast-growing organizations, and in those that frequently recruit new graduate students instead of head-hunting seasoned experts. Both conditions apply to the case organization during the observation period.

Measures

Individual technological productivity is measured based on invention reports patented by the company. Inventive productivity *INV_P* is the sum of contributions to invention reports in a given year by a researcher, with each qualified invention report providing a contribution of one to the sum. For inventions produced by several collaborators, equal contribution by each individual was presumed. Thus, collaboration as such does not increase inventive productivity, i.e., two researchers producing a total of two inventions are allocated an inventive productivity of one regardless of whether each of the two inventions is the product of a single inventor or of the two inventors collaborating on both inventions.

Based on *INV_P*, an inventive stock variable, *INV_S*, of individual technological know-how is constructed by adding *INV_P* to past stock *INV_S* on a yearly basis. To allow for gradual obsolescence of technological know-how, the invention stock measure is depreciated yearly using a depreciation rate of 0.25 (cf. Henderson and Cockburn, 1996). The values of *INV_S* for the first year of observation (1995) in this study were based on archival data that covers the whole history of the research center from 1987. Therefore, it was not necessary to estimate starting stock values (cf. Henderson and Cockburn, 1996: 58).

Analogous to inventive productivity and stock measures, academic productivity *ACA_P* and academic stock *ACA_S* variables were constructed based on individual contributions to publications and conferences. Academic outputs are indicators of the individual's ability to contribute to the frontiers of knowledge in their fields.

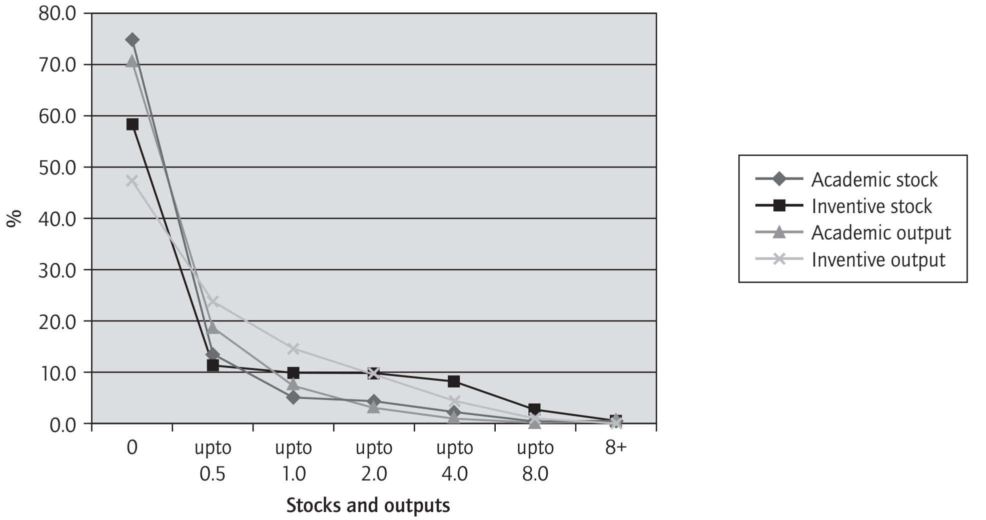

Figure 9.4 Distribution of inventive and academic stocks and outputs; n = 1,820 person-year observations

Production of academic outputs involves both formal (e.g., peer review) and informal interaction with the scientific community. The interactions, and especially the informal ones, may involve transfer of knowledge regarding the latest developments in the field. Because of these factors, publication counts can be used as indicators of investment in absorptive capacity (Cockburn and Henderson, 1998). Many academic outputs involve co-authorship of individuals from different institutions. In these instances, the flow of knowledge across organizational borders is likely to be more intense, although not all co-authorships reflect joint research and problem-solving but may, instead, indicate sharing of data or research instruments, for example. The distributions of inventive productivity and stock, as well as academic productivity and stock, are presented in Figure 9.4.

A number of definitions for identifying cohesive subgroups, or closures, within networks have been developed in social network analysis literature (for review, see Wasserman and Faust, 1994: 249–90). The most common definitions for cohesive subgroups within symmetric networks include cliques, n-cliques, n-clans, and n-clubs (Mokken, 1979). Cliques are maximal complete sub-graphs of three or more nodes. The definition is very strict in that the absence of a single tie between network nodes prevents the sub-graph from being a clique. N-cliques, n-clans and n-clubs are definitions that aim to capture the "clique-like" structures that frequently appear in empirical network data. An n-clique is a maximal sub-graph in which the largest geodesic distance between any two nodes is no greater than n. This definition is somewhat loose in terms of identifying cohesive subgroups. For example, two nodes belonging to the same n-clique may have no path connecting them that includes only n-clique members. N-clans and n-clubs are n-cliques that have restrictions that make them more cohesive (Wasserman and Faust, 1994: 260–62).

Specifically, n-clans are n-cliques with a diameter no greater than n. In this study, 2-clans are used as the network definition of cohesive subgroups.

Although n-clan is a reasonably robust definition for a cohesive subgroup within network in terms of connections among nodes, the definition does not account for different strengths of the ties. For example, the definition does not distinguish between three collaborators with one joint output and three collaborators with numerous joint outputs. In practice, the definition allows rather indiscriminate cohesive subgroups to be identified based on single, perhaps ad hoc, acts of collaboration. To better capture the deeply embedded ways of working together, the internal collaboration matrices were dichotomized using a tie-strength of two as cut-off value before the cohesive subgroups were identified. Thus, individuals were considered to be collaborating closely if they were involved in two or more joint outputs in a given year. Individual membership in one or more n-clans is indicated in the binary variable *SCLANB* for each year.

In order to measure opportunities for information brokerage, a measure which identifies those individuals who have connections to otherwise unconnected individuals is required. Betweenness centrality is based on calculating the shortest paths and geodesics among all the nodes in the network (Wasserman and Faust, 1994: 188–92; Freeman, 1979). In the case of several equally short paths between two nodes, the paths are presumed equally likely to be used. In this case, the betweenness index for a network node is the sum of estimated probabilities that the network node is between other nodes. Specifically, let g_{jk} be the number of geodesics connecting nodes j and k, and $g_{jk}(n_i)$ the number of geodesics that contain node i. In this case, node betweenness index for node i is

$$C_B(n_i) = \Sigma_{j<k}\, g_{jk}(n_i)/g_{jk}.$$

The betweenness index is normalized using the number of potential geodesics of the network, thus limiting the value of normalized betweenness centrality *NBETW* to between 0 and 1. That is, normalized network betweenness index for node i is

$$C'_B(n_i) = C_B(n_i)/[(g-1)(g-2)/2].$$

Boundary-spanning across organizational boundaries is measured based on individuals' participation in collaborative outputs in which at least one collaborator was from an external organization. *TIE_EXT* is the number of boundary-spanning opportunities in which the external organization was a university, research institute, or company. *TIE_BU* is the number of opportunities in which the external organization was a business unit of the same company.

The overlapping n-clan membership indicator matrix (n-clan * individual) is used to identify individuals with at least one common n-clan membership (individual * individual). Based on shared n-clan memberships, potential spill-over effects of *NBETW*, *ACA_P*, *TIE_EXT*, and *TIE_BU* measures are studied. Specifically, measures *MNBETW*, *MACA_P*, *MTIE_EXT*, and *MTIE_BU* are calculated for each individual by taking the maximum values of respective individual measures over the individuals sharing n-clan membership.

To allow for the varying role of patent protection in different technological fields, dummy variables are defined based on broad technological areas (laboratories of the research center, e.g., software, electronics, mobile networks). These dummies may also capture laboratory-wide differences in management practices, as well as variance in technological opportunity between the fields. It should be noted that the administrative practices and specialized personnel for protecting intellectual property were the same for all the laboratories during the study period.

Routines provided in UCINET 5 are used for calculation of all the network measures (Borgatti et al., 1999). Descriptive statistics are presented in Table 9.2.

Analysis

The dependent variable, individual inventive productivity *INV_P*, can receive non-negative values. Unlike many patent count studies made at higher levels of aggregation, the dependent variable is not tied to integer values (cf. Hausman et al., 1984). The hypothesized inventive productivity function is of the form

$$\mathbf{y} = f(\mathbf{x}, \mathbf{n}, \mathbf{c}, \mathbf{c} * \mathbf{n}')$$

where $\mathbf{x}$ is a vector of inputs to the inventive process that includes the individual's inventive stock, $\mathbf{n}$ is a vector of network measures, $\mathbf{c}$ is a binary measure of membership in a network closure, and $\mathbf{n}'$ is a vector of network measures related to the network closure. Previous studies have often assumed the patent counts to be generated by a Poisson process (e.g., Henderson and Cockburn, 1994, 1996). As for most patent count data, "the mean is equal to variance" property of the Poisson distribution is not followed by the present invention report data. To partially allow for the skewed distribution of the dependent variable, a logarithmic transformation is performed.

The regression analysis is divided into five models. Model 1a includes the stock variables *INV_S* and *ACA_S*, academic productivity *ACA_P*, as well as the technological area dummies. Models 1b and 1c add network variables (*SCLANB*, *NBETW*, *TIE_BU*, and *TIE_EXT*) and variables related to potential spill-over effects within closures (*MACA_P*, *MNBETW*, *MTIE_BU*, and *MTIE_EXT*), respectively. In model 2, which is an alternative to model 1c, the independent variables *INV_S*, *ACA_P*, and *ACA_S* are also entered in logs, with appropriately coded dummy variables indicating zeros. Model 3 investigates the effects of academic stock by including the cross-terms *ACA_S*SCLANB*, *ACA_S*NBETW*, *ACA_S*TIE_BU*, and *ACA_S*TIE_EXT* in model 1b. Model 4 is otherwise comparable to model 1b, but the dependent variable is academic rather than inventive productivity. Lastly, in model 5 the network variables of model 1b are lagged by one year. Thus, this is the only model in which the dependent and independent variables do not interact indirectly via the collaboration network being constructed from the outputs that also constitute the dependent variable.

The hypothesized effects of the variables on inventive productivity are summarized in Table 9.3.

Table 9.2 Descriptive statistics

Variable	Minimum	Maximum	Mean	Std. Deviation	Correlations 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 INV_P	0	12.58	0.549	0.939	1														
2 INV_S	0	12.67	0.678	1.343	0.29	1													
					0														
3 ACA_P	0	4.99	0.192	0.424	0.013	0.147	1												
					0.573	0													
4 ACA_S	0	6.26	0.208	0.559	0.067	0.381	0.331	1											
					0.004	0	0												
5 SCLANB	0	1	0.190	0.400	0.32	0.201	0.062	0.046	1										
					0	0	0.008	0.052											
6 NBETW	0	9.985	0.078	0.451	0.248	0.153	0.076	0.056	0.215	1									
					0	0	0.001	0.017	0										
7 TIE_BU	0	11	0.270	0.840	0.304	0.144	−0.022	0.029	0.139	0.168	1								
					0	0	0.338	0.224	0	0									
8 TIE_EXT	0	4	0.160	0.460	−0.075	0.024	0.4	0.181	0.002	0.023	0.002	1							
					0.001	0.314	0	0	0.922	0.336	0.926								
9 MACA_P	0	3.65	0.129	0.458	0.189	0.171	0.282	0.087	0.575	0.171	0.058	0.078	1						
					0	0	0	0	0	0	0.013	0.001							
10 MNBETW	0	9.99	0.176	0.850	0.222	0.091	0.037	0.018	0.422	0.52	0.119	−0.023	0.316	1					
					0	0	0.119	0.454	0	0	0	0.322	0						
11 MTIE_BU	0	11	0.360	1.340	0.309	0.147	0.041	0.02	0.544	0.206	0.317	−0.01	0.386	0.403	1				
					0	0	0.08	0.384	0	0	0	0.656	0	0					
12 MTIE_EXT	0	3	0.086	0.350	0.119	0.093	0.128	0.037	0.497	0.14	0.077	0.238	0.599	0.305	0.343	1			
					0	0	0	0.119	0	0	0.001	0	0	0	0				
13 SCLANB*ACA_S	0	3.97	0.051	0.291	0.252	0.429	0.209	0.471	0.354	0.149	0.078	0.052	0.321	0.146	0.184	0.203	1		
					0	0	0	0	0	0	0.001	0.027	0	0	0	0			
14 ACA_S*NBETW	0	5.59	0.030	0.277	0.159	0.223	0.108	0.226	0.161	0.524	0.14	0.08	0.15	0.347	0.176	0.124	0.377	1	
					0	0	0	0	0	0	0	0.001	0	0	0	0	0		
15 ACA_S*TIE_BU	0	8.25	0.069	0.472	0.174	0.217	0.124	0.29	0.102	0.166	0.493	0.046	0.116	0.118	0.21	0.116	0.273	0.368	1
					0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	
16 ACA_S*TIE_EXT	0	10.49	0.079	0.578	−0.012	0.108	0.344	0.472	−0.002	0.034	−0.001	0.525	0.069	−0.003	−0.004	0.117	0.19	0.135	0.11
					0.616	0	0	0	0.921	0.149	0.971	0	0.003	0.914	0.849	0	0	0	0

N = 1820
Pearson correlation
Sig. (2-tailed)

Table 9.3 Summary of variables and hypothesized effects on inventive productivity

Variable name	Proxy for	Definition	Hypothesized effects
INV_P	Output of new (technological) knowledge	# of invention reports accepted for patenting	Dependent variable
INV_S	Accumulated technological knowledge capital	Stock of *INV_P* calculated using a 25% annual depreciation rate	Positive (Hypothesis 9.1)
ACA_P	Output of new (scientific) knowledge; measure of absorptive capacity	# of journal and conference contributions	
ACA_S	Accumulated scientific knowledge capital	Stock of *ACA_P* calculated using a 25% annual depreciation rate	
SCLANB	Access to individuals with co-specialized skills and knowledge	Membership in a network closure (n-clan); binary variable	Positive (Hypothesis 9.2)
NBETW	Ability to broker information	Betweenness centrality in the internal collaboration matrix	Positive (Hypothesis 9.4a)
TIE_BU	Access to diverse sources of knowledge	# of network ties in the external collaboration matrix towards business units	
TIE_EXT	Access to diverse sources of knowledge; measure of absorptive capacity and gate-keeping	# of network ties in the external collaboration matrix towards other organizations	Positive (Hypothesis 9.3a)
MACA_P	Access to latest scientific knowledge; measure of absorptive capacity	Maximum of *ACA_P* of closure members	
MNBETW	Ability to broker information	Maximum of *NBETW* of closure members	Positive (Hypothesis 9.4b)
MTIE_BU	Access to diverse sources of knowledge	Maximum of *TIE_BU* of closure members	
MTIE_EXT	Access to diverse sources of knowledge; measure of absorptive capacity and gate-keeping	Maximum of *TIE_EXT* of closure members	Positive (Hypothesis 9.3b)
TECH_AREA DUMMIES	Cross-sectional variation in technological opportunity and importance of patenting	Dummy variables (8) for broad technological areas	

Results

The regression results for individual level data are presented in Table 9.4. In model 1a, inventive stock is a significant predictor of inventive productivity. Neither academic stock nor productivity has a significant effect on inventive productivity. In model 1b, the network measures are added. The inventive stock variable remains as a significant predictor of inventive productivity. Network positions of high betweenness centrality, which support structural hole arguments, are associated positively with inventive productivity. In addition, memberships in network closures are associated with inventive productivity. Ties to business unit personnel are associated positively with inventive productivity. However, ties to individuals outside the company are associated negatively with inventive productivity.

Model 1c includes the network measures related to potential spill-over effects within network closures. The coefficients for variables introduced in the previous models retain their signs and significance. Neither brokerage opportunities nor academic productivity seems to provide spillovers to close collaborators. Both internal and external ties are associated with spillovers with regard to inventive productivity – positive in case of internal business unit ties and negative in case of external ties.

Model 2 provides the same results as model 1c, with two exceptions. First, academic productivity has a positive effect on inventive productivity, but the dummy variable denoting an academic productivity of zero also has a significant positive coefficient. Second, the negative sign of the coefficient for external ties is no longer significant.

In model 3, academic stock in combination with membership in a network closure is associated positively with inventive productivity, whereas the other cross-terms do not have significant effects.

In model 4, academic stock has a strong positive effect, inventive stock a relatively weak but statistically significant positive effect, and inventive productivity has no effect on academic productivity. As with model 1b, membership in a network closure and brokerage positions have a positive effect. However, as can be expected based on the collaboration patterns related to inventive and academic outputs, external ties are positively and business unit ties negatively associated with academic productivity.

In model 5, inventive stock has a positive effect on inventive productivity, whereas academic stock and productivity do not. Of the lagged network variables, brokerage positions and ties to business units have positive effects. Interestingly, past membership in a network closure does not have a positive effect on inventive productivity.

Overall, the regression results support hypothesis 9.1 regarding the cumulative nature of technological knowledge capital. However, it should also be noted that of all the research personnel, only a subset actively produces outputs of the kinds measured in this study. The hypothesized cumulative nature of the knowledge capital can also be interpreted as a hypothesis of the membership dynamics of that active subset. That is, the stronger the positive association between technological knowledge capital stock and inventive productivity, the more stable the "inventive core" of research personnel. The core–periphery dynamics have been discussed in

Table 9.4 Regression results, OLS-model

	Equation						
	(1a)	(1b)	(1c)	(2)	(3)	(4)	(5)
Intercept	0.375**	0.285**	0.281**	0.0908	0.291**	0.0734**	0.348**
	(.022)	(.021)	(.021)	(.050)	(.021)	(.013)	(.035)
INV_S	0.0716**	0.0457**	0.0457**	0.132**	0.0398**	0.0144**	0.0609**
	(.008)	(.007)	(.007)	(.028)	(.007)	(.004)	(.010)
INV_P						0.00231	
						(.006)	
ACA_P	–0.00263	0.00405	0.00576	0.142*	–0.00101		0.03859
	(0.023)	(.023)	(.024)	(.058)	(.023)		(.030)
ACA_S	–0.0173	–0.00524	–0.00589	0.0551	–0.0307	0.100**	–0.0106
	(.018)	(.017)	(.017)	(.046)	(.020)	(.010)	(.023)
SCLANB		0.238**	.242**	0.242**	0.210**	0.0409**	0.0112
		(.022)	(.030)	(.029)	(.023)	(.014)	(.036)
NBETW		0.0990**	0.0941**	0.0977**	0.105**	0.0340**	0.0567*
		(.019)	(.022)	(.022)	(.022)	(.012)	(.024)
TIE_BU		0.114**	0.108**	0.105**	0.119**	–0.0167**	0.0263
		(.010)	(.011)	(.011)	(.012)	(.006)	(.015)
TIE_EXT		–0.0612**	–0.0463*	–0.0280	–0.0635**	0.181**	–0.0411
		(.020)	(.021)	(.021)	(.022)	(.011)	(.031)
MACA_P			–0.00462	0.00655			
			(.026)	(.026)			
MNBETW			0.00475	0.00395			
			(.013)	(.013)			
MTIE_BU			0.0177*	0.0188*			
			(.008)	(.008)			
MTIE_EXT			–0.0763*	–0.0740*			
			(.032)	(.032)			
SCLANB*ACA_S					0.141**		
					(.037)		
ACA_S*NBETW					–0.0273		
					(.039)		
ACA_S*TIE_BU					–0.0163		
					(.022)		
ACA_S*TIE_EXT					0.0116		
					(.019)		
N	1820	1820	1820	1820	1820	1820	913
R-sqr	0.168	0.304	0.308	0.313	0.309	0.357	0.186

* Significant at the 5% level.
** Significant at the 1% level.
Standard errors in parentheses.
All models include 8 dummy variables for technological areas.
In model 2, ACAS, INVS and ACAP are entered in logs with appropriate coded dummy variables.
In model 5, SCLANB, NBETW, TIE_BU and TIE_EXT are lagged by one year.

the learning literature regarding "communities of practice" (Brown and Duguid, 1991, 1998).

From the knowledge capital perspective, both academic outputs and inventions qualify as indicators of the ability to contribute to the frontiers of knowledge. Consequently, both academic and inventive stock measures should have similar positive effects on inventive productivity. Interestingly, the academic stock variable is insignificant as a predictor of inventive productivity in all the models. This suggests that the "inventive community" is distinct from the more general "community of individuals in the frontiers of knowledge". Model 1c also includes academic outputs as one of the potential sources of spillovers between individuals within a network closure. If this variable had positive effects on inventive productivity, we could interpret production of inventive and academic outputs as forms of co-specialization among research personnel. However, this interpretation is not supported by the data.

Brokerage opportunities do not seem to provide spillovers to close collaborators. Assuming a static network structure, brokerage opportunities could be interpreted as a form of intangible capital appropriable by the individual. In practice, however, the network structure is dynamic. The brokerage performed by an individual will increase the knowledge flow between the previously separated parts of the network, and in so far as joint efforts seem beneficial (as indicated by the positive effects on the individuals initially active in brokering), a closure encompassing both sides of the structural hole can emerge. Thus, brokerage can be an important mechanism in the evolution of network structures, even if the brokerage does not seem to offer spillover benefits in the static investigation of networks. In fact, in model 5 prior brokerage position has significant positive effects, whereas previous membership in a network closure does not. Thus, the results support an interpretation of brokerage positions as a form of intangible capital, while the closures are associated with the realization of the value of potentially complementary knowledge capital stocks (cf. Burt, 2001b).

Both internal and external ties are associated with spillovers – positive for internal business unit ties and negative for external ties. This seems to reflect a relationship between inventive productivity in industrial research and the relatedness of research activities to the firm's main operations. Research activities in which business unit personnel participate seem to be especially productive, as measured by inventions qualified for patenting. Several factors may contribute to this finding. First, the patenting process is selective and inventions related to existing operations may be more likely to be perceived as important enough for patenting. Indeed, of the 2,096 inventions that did not involve co-inventors from business units, 43.5 percent were accepted for patenting, compared to 67.4 percent of the 331 inventions with at least one co-inventor from a business unit. Second, business unit personnel may choose to invest their time and effort in collaborating only with exceptionally capable researchers. The correlation between inventive stock and business unit ties is 0.144 (significant at the 0.001 level), whereas the correlation between academic stock and business unit ties is 0.029 (not significant). This suggests that individuals with proven, perhaps firm-specific, inventive capabilities are indeed sought-after collaborators within the firm. Third, inventions are not equal in importance (e.g., Scherer and Harhoff, 2000) or degree of novelty (e.g., Ahuja and Lampert, 2001). In so far as business units are more involved with technologies based on already established paradigms and follow-up inventions in those areas are less costly to produce (in terms of research and engineering effort or cognitive capabilities, including attention) than more radical breakthroughs, the results may reflect the limitations of using only non-weighted invention counts as a productivity measure. These limitations and related future research opportunities are further discussed in the conclusions.

Hypothesis 9.2 of the positive effects of network closures is supported by the analysis. The quantitative data used is not detailed enough to allow us to make causal interpretations regarding the way in which network closures contribute to inventive productivity. However, the insignificance of prior closure membership as a predictor of inventive productivity in model 5 should be noted. This would suggest that closure membership as such is not a form of intangible capital, but rather the individual's ability to identify potential collaborators and initiate joint efforts with them. In general, organizations facilitate joint activities by offering common experiences, shared norms, language, and objectives (Nahapiet and Ghoshal, 1998). The level of social capital generated within different organizations is likely to vary according to firm-specific differences in organizational routines. Moreover, differences in organizational routines may cause semi-permanent differences in the rate at which individuals form collaborative network closures. A study of these differences, however, would necessitate cross-organizational observations not available in this study. Rather, the present analysis should be considered as affirmation of the important role of internal collaboration networks regarding inventive activities in an industrial research environment. Further research should examine the formation dynamics of specific network closures (cf. Kreiner and Schultz, 1993), as well as factors in organizational design that facilitate or hinder the underlying mechanisms.

Hypotheses 9.3a and 9.3b are supported, but with a different interpretation than envisaged based on previous studies (e.g., Henderson and Cockburn, 1994; Liebeskind et al., 1996). Underlying the hypotheses is a presumption that inventive capacity is distributed among research personnel, and that boundary-spanning network connections would provide a rich flow of external knowledge resulting in increased inventive productivity. However, the inventive and academic outputs are produced by somewhat distinct groups of individuals, as only inventive, not academic, stock is a predictor of inventive productivity in the models. The regression results reflect corresponding differences in collaboration practices. Specifically, collaboration with business unit personnel is relatively common in inventive activities, and collaboration with external personnel is often associated with academic outputs. Thus, innovation in the corporate research environment under study is associated positively with boundary-spanning ties to the business units, not toward external innovation networks.

With regard to hypotheses 9.4a and 9.4b, the regression results support individual-level benefits of brokerage (9.4a), but the benefits do not seem to spill over to collaborators (9.4.b). However, as was already mentioned, these results refer only to a static view of network structure. In a dynamic network, a potential spillover effect could be the formation of new network closures. That is, brokerage offers benefits to the organization by contributing to the renewal of collaboration clusters. This potential benefit is of increased importance if collaboration closures including experts from multiple areas are especially effective in R&D (Ancona and Caldwell, 1992).

Conclusions

The quantitative results provide some points of departure with regard to the routinization of inventive activities and associated boundary conditions. The inventions are not isolated flashes of genius, but a rather systematic output of continuous work by R&D professionals. Although there are some peaks in the inventive output of a small subset of the research personnel, the inventive capability is spread over a large number of researchers. The majority of inventions are collaborative, involving two or more co-inventors. Moreover, the collaborative relationships overlap in some areas, with the overlapping collaboration clusters involving dozens of researchers. From these patterns two propositions emerge.

First, as inventive outputs involve collaboration and previous contributions to inventive outputs are positively associated with inventive productivity, organizations that aim to routinize inventive activities benefit from mechanisms that support the formation of collaboration clusters. Collaboration clusters are needed to realize the complementarities of technological know-how possessed by the individuals. Also, collaboration clusters are avenues by which new individuals are introduced to the tacit and firm-specific elements of the technology. In addition, the more systemic the underlying technological knowledge, the relatively more beneficial these mechanisms can be hypothesized to be.

Second, the knowledge required to identify beneficial collaboration opportunities may involve a significant tacit element. Consequently, internal brokerage, i.e., individuals who by their collaboration connect otherwise unconnected clusters within the organization, is valuable for the organization. Internal brokerage provides immediate benefits when previously unrecognized opportunities between complementary bodies of technological know-how are realized via new combinations. In addition, internal brokerage contributes to the renewal of the organization's internal collaborative structure. Thus, mechanisms that support internal brokerage are beneficial to both inventive productivity and the organization's internal adaptation aimed at better realizing inventive opportunities.

From the perspective of social network analysis, both membership in a collaboration network closure and a brokerage position are plausible candidates for intangible capital for an individual. The analysis, however, provides support only for brokerage as a form of intangible capital, whereas closures are instrumental in promoting individual-level technological know-how in various combinations. Although important for the overall inventive productivity, the benefits of closures seem to be fully captured in the individual-level knowledge capital measures. That is, without closures the inventive productivity would be diminished, but in the long term the closures as such do not enhance inventive productivity beyond the effects of accumulating individual-level knowledge capital stocks.

Regarding the routinization of inventive activities, both collaboration closure formation and internal brokerage are candidates for analytically interesting and operationalizable repeating processes. The processes are complementary, but the mechanisms that support each one may have conflicting features. Closure formation provides grounds for what Henderson and Cockburn (1994) call "component competence." Internal brokerage, in turn, is related to "architectural competence" (Henderson and Clark, 1990). Component competence is largely based on routine, even tacit, problem-solving strategies, the development of which requires close interaction among researchers for an extended period of time. A research organization that supports the accumulation of component knowledge is likely to have a relatively stable internal structure with well-defined areas of expertise and responsibility. Architectural competence is related to the organization's ability to combine its component competences in a flexible manner according to current needs, perhaps with little regard for established communication channels and decision-making routines. For a research organization, the initiation and successful completion of projects that require cross-disciplinary contributions are "core architectural competence." The present analysis suggests that knowledge capital measures, and not those of network closure, account for component competence at the individual level. However, internal brokerage seems to provide benefits distinct from knowledge capital, thus supporting conceptualization in which combinatory or architectural ability is also examined separately at the individual level.

The role of absorptive capacity is somewhat puzzling, at least with regard to the ways in which it has been operationalized in previous studies (e.g., Cockburn and Henderson, 1998). Specifically, neither academic outputs and stocks of academic (scientific) knowledge capital nor external ties from co-authorship relations are associated with increases in inventive productivity. This is in stark contrast to previous studies that have elaborated on the importance of scientific norms and external collaboration networks as sources of inventive productivity and overall competitive advantage. The present study, to the best of the author's knowledge, is the first one to simultaneously examine the two types of knowledge capital (academic/scientific and inventive/technological) in detail at the individual level. Nevertheless, it seems rather implausible that the conflicting results merely reflect more precise operationalization, but rather indicate that a contingency argument of the sources of inventive productivity is in order. That is, the previous studies have focused on biotechnology and the pharmaceutical industry, whereas the current study falls under the domain of communications, including Internet, technologies. In the pharmaceutical sector, patent protection is especially strong since a single patent can, in many instances, almost completely prevent "inventing around." Moreover, patent protection in pharmaceuticals is relatively broad, since a single patent can offer protection to a marketable end-product. In contrast, there are often multiple ways to implement a given feature in complex communications systems, which makes "inventing around" of other patents feasible. Furthermore, communications products are typically protected by a number of complementary patents, and in this sense the protection offered by a given patent is rather narrow. Taken together, there is a fundamental difference in how "systemic" or "atomistic" the technology in these different industries is (cf. Teece, 1992).

Based on variance in the systemic nature of technology, a contingency argument for the mechanisms of absorptive capacity can be proposed. If the technology is comparatively atomistic, the firms should align their internal structure and decision-making mechanisms to correspond to the external sources of knowledge, and cultivate extensive networks of external collaborative ties. Thus, the internal structure is optimized to process (i.e., seek innovations from inventions based on external knowledge) the wide variety of knowledge from external sources, whereas most knowledge generation and exploration is performed within the external networks. Internal structure is comparatively static, corresponding to component competences, whereas norms supporting external collaboration provide flexibility via access to diverse sources of knowledge, and changing network configurations external to the firm provide variation in knowledge, i.e., potential inventive opportunities. However, if the technology is comparatively systemic, the mechanisms for absorptive capacity must respond to different challenges. Specifically, many inventions involve re-combinations across component competences, and singular inventions offer less innovation potential. Thus, the evaluation of innovation potential related to external knowledge requires coordination across component competences, and even in cases where high innovation potential is perceived, complementary inventions may be required. Therefore, internal flexibility is required in ways that the external networks are unable to provide.

These arguments should not be interpreted as suggesting that absorptive capacity is of little value to firms inventing and innovating with systemic technologies. Rather, there are boundary conditions for mechanisms of absorptive capacity that have received little attention in previous research, one of which is the systemic nature of technology. As indicated by the strong positive effects of technological knowledge capital on inventive productivity in this study, the specific skills and knowledge of individual researchers are of importance whether or not the technology is systemic. Thus, instead of facilitating the flow of knowledge across organizational boundaries, firms can facilitate the flow of individuals across both internal and external organizational boundaries in order to promote invention and innovation. Indeed, empirical surveys have found that in many engineering-oriented industries, firms rate access to skilled personnel, not specific pieces of knowledge, as the major benefit provided by universities (Freeman and Soete, 1997).

The present study suggests several practical considerations for managers of research organizations. First, collaboration closure formation and internal brokerage were presented as recurring processes that contribute to the organization's inventive output. The rate at which the processes operate can be examined based on the collaborative relationships implied by inventive and academic outputs. By being aware of these processes and by tracking longitudinal changes in them, managers can be mindful of trends in organizational inventiveness resulting from factors such as changes in the organization's size, maturity, or norms supporting collaboration. Second, the results related to absorptive capacity should alert managers to the contingencies that systemic or atomistic technologies set to the utilization of external innovation networks. Specifically, the guidelines and recommendations for collaboration provided, based on experiences from firms in domains of atomistic technologies, should not be carelessly applied to firms involved with systemic technologies. It was also argued that internal flexibility – even at the cost of efficient routines – is at a premium when inventions in systemic technologies are pursued. In addition, firms can invent in both systemic and atomistic technologies or technological domains can gradually change their nature as a result of factors such as the establishment of de facto standards. In these cases, firms must either facilitate simultaneously different kinds of innovation processes or dynamically change their routines according to the changes in technological domains.

Although the longitudinal data used in this study partly mitigates the challenges of validity, a replication of the study at multiple organizations would be valuable. In addition, the study could be extended to examine the characteristics of inventions in more detail. Several authors have noted that technological inventions tend to be generated by "local search" (e.g., Stuart and Podolny, 1996; Rosenkopf and Nerkar, 2001). It seems rather plausible that the localness of search is a function of internal and external collaboration practices. Thus, research that combines data of technological trajectories with network measures related to the inventors' collaborative positions might provide insights into trade-offs between incremental and radical inventive activities (cf. Trajtenberg et al., 1997; Hansen et al., 2000; Ahuja and Lampert, 2001).

Lastly, the study raises some issues that are relevant to innovation policy. The implications of the atomistic vs. systemic nature of technologies were discussed from the perspective of firms involved in inventive activities. Similar contingency arguments, however, are likely to apply to research carried out at universities. Moreover, policy instruments, e.g., technology programs, that aim to encourage university–industry cooperation are subject to these considerations. Further research is required before attempting to draw any policy conclusions. In the mean time, however, policymakers should remain alert to differences in the dynamics of inventive activities between technological domains.

Notes

1 See, for example, Fifth Framework Programme FP5 at http://www.cordis.lu/fp5/.
2 http://www.tekes.fi

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