DEVELOPING NEW TECHNOLOGIES THROUGH KNOWLEDGE RECOMBINATION: A FIRM LEVEL APPROACH

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INTRODUCTION

This thesis comprises three essays on the role of combinatorial processes in technological innovation. A good deal of consensus has formed around the idea that technological innovation is a problem solving endeavor wherein new solutions are either unique combinations (Schumpeter, 1939; Nelson & Winter, 1982) or new configuration of existing knowledge (Henderson & Clark, 1990). Yet, a lingering question remains as to how firms' should structure their inter-organizational and intra-organizational activities to favor the development of new combinations. This thesis addresses this question, and explores the effect of intrafirm and interfirm knowledge networks on firms innovative output.

The first essay reviews the most influential papers that built on a combinatorial approach to technological innovation, with the aim to assess the state of art and to advance an integrative framework. A co-citation analysis is carried out to detect the main themes of research in this tradition, and to integrate these topics into a coherent framework. The study highlights some limitations of this approach, and discusses future research that is needed to extend these themes, address the limitations, and exploit emerging research opportunities.

The second essay explores the effect of inter-organizational knowledge networks and firm capabilities in the development of new technologies. The study sets out to integrate two well-established, complementary, and yet unrelated views on the process of technology development. On the one hand, inter-firm networks act as "pipes" that funnel different learning opportunities to different network positions and, hence, to different firms. On the other hand, it has been argued that a firm's inventive performance depends on its organizational capabilities, and particularly its assimilative and recombinant capabilities. Integrating these perspectives, the study advances and tests a set of novel testable hypotheses at both the firm- and the network-level the semiconductor industry over the period 1975-2001.

The third essay explores how a firm's internal collaboration network affects its ability to integrate knowledge in the generation of new technologies. Building on the knowledge-based view of the firm, the paper contrasts the relative efficacy of densely connected and brokered (i.e., cluster-and-bridge) structures, showing how the costs and benefits of both structures vary depending on the heterogeneity of a firms' knowledge base. To put our arguments to a test, a novel dataset describing the patent co-authorship networks of 121 semiconductor firms over the period 1992-1998 is presented. The results offer support to our predictions and they yield important implications for the design of organizations.

Table 1 introduces the essays and provides a summary of the research questions, unit of analysis, and key results of each article.

TABLE 1: Summary of the three essays

	Essay 1	Essay 2	Essay 3
Research Questions	▪ What does literature adopting a combinatorial perspective on technological innovation has accomplished so far? ▪ How can studies adopting this approach be integrated into a coherent framework? ▪ How can the combinatorial approach to technological innovation be extended in future research?	▪ What is the relationship between knowledge diffusion and knowledge generation in inter-organizational networks? ▪ How do knowledge network structure and firms' assimilative and combinative capabilities impact technological performance?	▪ How does a firm's internal collaboration network affects its ability to integrate knowledge in the generation of new technologies? ▪ Under which conditions dense and brokered collaboration networks enhance firms' ability to integrate specialized knowledge into new technologies?
Research setting and sample	69 highly cited papers in top management journals that built on a combinatorial approach to technological innovation (1990-2006)	An unbalanced, longitudinal panel of 132 firms in the worldwide semiconductor industry, between 1975-2001.	A novel dataset describing the patent co-authorship networks of 121 semiconductor firms over the period 1992-1998
Unit of analysis	N. A.	Firm	Firm
Research design	A co-citation analysis and a critical assessment of the most influential contributions that built on a combinatorial approach to technological innovation.	An empirical test of hypotheses relating firms' ability to assimilate knowledge from prolific contacts and knowledge network structure on innovation. Visual inspection techniques to display network evolution.	An empirical test of hypotheses relating firms' ability to generate new technologies to the structure of its knowledge network and to its knowledge base heterogeneity.
Key Findings	▪ Research on the role of re/combination in innovation covered three main topics (i) enabling architectures for recombination (ii) recombination as a capability (iii) outcomes of combinatorial processes. ▪ Four major shortcomings and area for development emerged from this perspective: the lack of connection across levels of analysis, the use of recombination as a metaphor, the reification of constructs and limited analysis of performance implications.	▪ A firm inventive performance increases with its ability to assimilate and recombine knowledge from highly prolific contacts ▪ The more an organization brokers structural holes in a knowledge network, the greater its inventive performance ▪ Brokering structural holes and assimilating knowledge from prolific contacts in a knowledge network are substitute mechanisms that drive a firm inventive performance ▪ Self-enforcing, knowledge dynamics explain the patterns of network evolution	▪ On average, brokered collaboration structures tend to enhance firms' ability to develop new technological knowledge, while dense networks tend to depress it ▪ These relationships are altogether reversed for firms whose knowledge base is highly heterogeneous.
Contribution	▪ The review contributes to the field of technology and innovation management by providing an integrated framework that highlights the role of combinatorial dynamics in the development of new technologies ▪ Our critical assessment points out the fundamental limitations and the emerging research opportunities.	▪ The paper extends received inter-organizational network theory showing that, in addition to knowledge conduits, networks encompass knowledge wellsprings ▪ The paper sheds new light on the debate about the putative effects of closed versus brokering networks of knowledge ▪ Our proposed analytical perspective yields a non-trivial insight on the issue of "how collective outcomes might be generated in inter-organizational networks"	▪ The paper extends recent studies in the knowledge tradition by advancing a theoretical framework that illuminate choices regarding the internal organization of a firm knowledge generation activities ▪ The study offers network research new insights on the role of cohesive and brokered structures in the generation of new knowledge ▪ The study enlarges the empirical content of both knowledge based theory and network research

Essay 1

A REVIEW AND A CRITICAL ASSESSMENT OF COMBINATORIAL PERSPECTIVES ON TECHNOLOGICAL INNOVATION

ABSTRACT

A co-citation analysis of the most cited papers that build on a combinatorial perspective identifies three main topics covered by research on the role of re/combination in innovation: (i) enabling architectures for recombination (ii) combinative capabilities (iii) outcomes of combinatorial processes. The paper integrates the three themes into a theoretical model that clarifies the role of combinatorial dynamics in technological innovation and highlights some limitations of this approach. The study then discusses future research that is needed to extend those themes, address the limitations, and exploit emerging research opportunities.

Keywords: technological innovation, recombination, combinative capabilities, co-citation analysis

How do firms generate technological inventions? In more than seven decades of research on technological innovation, a good deal of consensus has formed around the idea that the innovative process is a problem-solving endeavor wherein solutions are discovered through recombination of existing elements. From this combinatorial perspective, innovation stem either from the novel combination of knowledge embedded in existing technological components or from reconfigurations of existing combinations (Gilfillan 1935; Schumpeter, 1939; Usher, 1954; Nelson & Winter, 1982; Basalla, 1988; Henderson & Clark, 1990; Fleming 2001).

In the last two decades, more than 900 peer reviewed academic papers have built upon a combinatorial approach to innovation. The rapid development of this perspective is due in part to the flexibility that the idea of re/combination provides, that may well apply to describe evolutionary processes at different levels of analysis (Nelson & Winter, 1982; Kauffman, 1993). It is also due to its fit with other popular areas of organizational research and practice that have been rapidly growing during that same period: new product development, organizational learning, and industry life cycles.

The large number and broad range of contributions embracing this perspective in technological innovation research raises important concerns about the use of the notion of recombination in this line of research and suggests an assessment of the literature is in order. What does literature adopting a combinatorial perspective on innovation has accomplished so far? Is a combinatorial approach necessary and useful for the development of the innovation field? How different constructs developed in this perspective, such as “architectural innovation” (Henderson & Clark, 1990) “combinative capabilities” (Kogut & Zander, 1992), “modularity” (Ulrich, 1995; Krishnan & Ulrich, 1996) and “flexibility” (Sanchez & Mahoney, 1996), “resource recombination” (Galunic & Rodan, 1998), “integrative knowledge” (Helfat & Raubitschek, 2000), “knowledge integration” (Grant, 1996; Brusoni, Prencipe & Pavitt, 2001) or “recombinant search” (Fleming, 2001) have contributed to our understanding of the process of recombination and how can we integrate these ideas into a reasoned framework? Finally, how can this approach be extended in future research?

Such an assessment is important, because, despite the number and range of studies that built on this approach, the dynamics through which the combinatorial process unfolds and the implications of the idea of recombination remain to a great extent underdeveloped (Fleming, 2001: 118). Several studied used the idea of recombination as a metaphor, so that some of the constructs that have been developed in this tradition are at risk of reification (Thomason, 1988; McKinley, Zhao & Rust, 2000). Reification is problematic because it threatens the validity of these constructs. Not only do constructs such as “combinative capabilities” (Kogut & Zander, 1992), “combinative flexibility” (Sanchez, 1995; Sanchez & Mahoney, 1996), “resource recombination” (Galunic & Rodan, 1998), “recombinant search” (Fleming, 2001) become taken for granted, but researchers increasingly fail to specify the assumptions that underlie the use of this approach. Such problems can only be addressed by exploring the diverse interpretations and applications of the idea of recombination in innovation in heterogeneous streams of research, and investigating its assumptions and building blocks (Rousseau & House, 1994). These insights allow to refine the theoretical model that underlies this approach, and to reconnect it to its network of supporting assumptions.

In this paper, I attempt to conduct such an investigation by providing a synthesis and an extension of the most influential contributions that built on a combinatorial approach to technological innovation. By reviewing these studies, I intend to contribute to the field of technology and innovation management an integrated framework, that explains how combinatorial processes lead to innovative outcomes and that might guide future research. The literature review is based on the bibliometric technique of co-citation analysis (Small, 1974;

White & Griffith, 1981; Veerbek, Debackere, Luwel & Zimmerman, 2002), a powerful and widely used procedure to study the study of scientific disciplines and trends (e.g. Meyer, Pereira, Persson & Grandstrand, 2004; Ramos-Rodríguez & Ruíz-Navarro, 2004; Gartner, Daviddson & Zahra, 2006; Acedo, Barroso & Galan, 2006). This method allows for the determination of the most relevant works that build on a combinatorial perspective in the last two decades, and for the identification of the three major themes covered by these contributions. Such themes, together with a graphical representation of the links between the studies, serve as a basis to clarify the theoretical model of combinatorial innovation. Based on these analyses, I identify the strengths of this approach as well as the weaknesses that I believe have led to oversee the procedural aspect and implications of the idea of recombination. Finally, I begin to explore additional themes that are needed to address those weaknesses and extend our understanding of the role of combinatorial dynamics in innovation.

This paper differs from other bibliometric studies and from most literature reviews in general, in two major ways. First, this review is not based upon a single construct, or specific theme, or on a definite research theory; on the contrary, I take a broad approach to recombination, and I explore how different strategic theories, such as the knowledge based view, the research based view and dynamic capabilities research used this idea to develop new constructs and to explain innovation. Second, this study aims not only to highlight the main themes and emerging model of a combinatorial approach to innovation, but to use these analytical insights to develop a set of criteria to assess and evaluate both existing and potential studies.

This study proceeds as follows. The first section presents the combinatorial approach to innovation, describes the methodology adopted for the literature review and summarizes the main findings of the co-citation analysis, with attention focused on the core themes and on their classification according to two main dimensions. The second section integrates findings from the bibliometric analysis into a theoretical framework, and discusses the strengths and research avenues that need to be developed to integrate the emerging model. Finally, the last section discusses the results of the analysis and highlights the main issues on which future research should focus in order to develop a better understanding of the role of combinatorial dynamics in technological evolution.

COMBINATORIAL PERSPECTIVES ON INNOVATION: REVIEWING TWO DECADES OF RESEARCH

To analyze the role of combinatorial mechanisms in technological innovation, I build on co-citation analysis, a bibliometric technique used to analyze publication patterns in a field or body of literature (Veerbek *et al.*, 2002). This technique is based on grouping together authors or publications that are frequently cited in pairs, the underlying assumption being that two often co-cited documents are related to one another, and address the same broad research questions, without necessarily agreeing with each other (White & Griffith, 1981). By using statistical techniques, co-citation analysis makes it possible to provide a map or visualization of research on a given subject in terms of the main contributions and links between them. Co-citation maps makes it easier to operationalize the notion of consensus (White, 1990), thereby defining a research area intellectual structure (McCain, 1990), and serving to model the research area of invisible colleges (Zuccala, 2006). In this case, this technique makes it possible to identify the connections between the most influential contributions that have *explicitly* or *implicitly* built on a combinatorial approach to technological innovation, in order to systematize them into a coherent framework.

The analysis encompasses five steps: (1) selecting the list of contributions (2) retrieving co-citation frequencies to build the raw co-citation matrix (3) converting the raw co-citation matrix into a correlation matrix; (4) performing factor analysis and multi-dimensional scaling; and (5) analyzing the results.

The unit of analysis is defined in terms of articles that have explicitly or implicitly built on a combinatorial approach to technological innovation. For studies targeted at specific research perspective (as in this case), it is preferable to analyze papers rather than authors so that the results will not be biased by the fact that the same author may have published in different fields (Acedo *et al.*, 2006).

Insert Table 1 about here

Throughout the last century, several outstanding personalities from all fields highlighted the inherent combinatorial nature of innovation (see table 1 for an overview) and described this combinatorial search process vividly. For example, the mathematician Poincarè (1921: 387) offered this account: "Ideas rose in crowds; I felt them collide until pairs interlocked, so to speak, making a stable combination". Einstein also wrote that "combinatory play seems to be the essential feature in productive thought" (quoted in Simonton, 1999: 29). Similarly, new technologies can often be traced to the combination of prior technologies (Gilfillan, 1935; Nelson & Winter, 1982; Basalla, 1988). As Schumpeter (1934) puts it "the essence of innovation is carrying out of new combinations". Yet, the combinatorial approach to the development of novel technological solutions[1] has become popular in mainstream management journals only during the

[1] The combinatorial perspective applies to the emergence of novelty in general (Simonton, 1999; Nelson & Winter, 1982) and thus, both to the idea of *invention* and to the idea of *innovation*. This review, yet, focuses on the process of innovation, intended as the development of novel technological solutions to practically relevant problems. In this respect, our works differs from studies on creativity (e.g., Amabile, 1986; Fleming *et al.*, 2007).

two past decades, with the emergence of evolutionary views of economic change and of new research streams such as the resource-based and knowledge-based views of the firm and dynamic capabilities.

In particular, Henderson and Clark (1990), with their research on the photolithographic alignment equipment industry, pioneered this perspective in management research by introducing the concept of architectural innovation, defined as change the way in which the components of a product are linked together, while leaving the core design concepts (and thus the basic knowledge underlying the components) untouched (p. 10). This paper has been widely cited by following studies, receiving as many as 963 forward cites in the Social Science Citation Index (SSCI) of Thomson-ISI[2] between 1990 and 2007, and can be considered as the path-breaking contribution bringing this idea to the attention of management researchers. For this reason, I sampled for this review all articles citing Henderson and Clark (1990) in two types of publications: top generalist management journals and top journals aimed at the specific community of Technology and Innovation Management[3] researchers. Following the prescription of Brown & Eisenhardt (1995), I also included the most impactful practitioner-oriented journals. Following this approach, I identified 417 papers in the selected outlets in the period between 1990 and the end of 2007, as detailed in table 2.

Insert Table 2 about here

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[2] The Social Science Citation Index (SSCI) of Thomson-ISI, with a time span from 1990 to 2007 is available on-line and covers over 1,700 of the world's leading scholarly social sciences journals in more than 50 disciplines and relevant items from approximately 3,300 of the world's leading science and technology journals, provides access to bibliographic information, author abstracts, and cited references.

[3] I selected the following outlets: Academy of Management Journal, Academy of Management Review, Administrative Science Quarterly, Management Science, Organization Science, Strategic Management Journal, Journal of Management, Journal of Management Studies, Organization Studies, Industrial and Corporate Change, Research Policy, Journal of Product Innovation Management, Sloan Management Review, California Management Review, Harvard Business Review, IEEE Transactions on Engineering Management.

When analyzing a body of research, the usual criterion to establish the core is relevance. In line with previous studies (Acedo *et al*., 2006) I focused on the most relevant pieces on the topic by retaining only those articles that received at least 50 citations by later articles in SSCI. The selection threshold at 50 citations reduces our sample to 69 papers.

I then retrieved the co-citation frequencies in Thomson-ISI SSCI and then compiled the raw co-citation matrix, using UCINET 6. The co-citation matrix is a square matrix; the rows and columns represent the articles included in the sample and each cell of the matrix f_{ij} reports the number of papers that jointly cite paper *i* and paper *j*. Diagonal values are treated as missing. Once this set of papers was obtained, it was necessary to verify that the resulting co-citation matrix was appropriate for bibliometric study. As Rowlands (1999) has observed, in a highly coherent research area, the number of zeros or very low values must be relatively small. Taking this approach and that of White and Griffith (1981), two criteria were established to screen the initial list of documents: (i) the number of total cocitations received (ii) the number of zeros and ones in its line of the matrix. This process eliminated two documents (Malerba, 2002; Zajac, Kraatz & Bresser, 2000). The final core was made up of 67 works that are listed in table 3.

Insert Table 3 about here

The raw co-citation matrix was converted into a correlation matrix, using SPSS Version 17 to calculate Pearson’s correlation coefficient for each cell of the matrix. Correlation coefficients represent a measure of similarity between two papers: the higher the positive correlation, the higher the perceived similarity between the two works (White & McCain, 1998). Using correlation instead of a count of co-citation has two important advantages (Rowlands, 1999). First, it allows for data standardization, thus avoiding the scale effects caused by the number of citations made to the different documents. Secondly, it reduces the number of zeros existing in the matrix, preventing problems in the application of statistical methods. Once the correlation matrix was obtained, I applied two statistical multivariate techniques: factor analysis and multidimensional scaling (MDS).

Factor analysis allowed to identify the factors explaining most of the variance observed and to identify groups of strongly correlated papers so that the structure of research in this area becomes visible. As shown in Table 4, the analysis resulted in three factors, explaining 80.8% of the variance (see the Appendix A for details).

Insert Table 4 about here

By analyzing the contributions loading on each factor, I named the three factors according to the following definitions: (i) Enabling architectures for recombination (ii) Recombining as a capability (iii) Outcomes of recombination. It is important to note that some contribution load on more than one factor: such works represent a bridge between the factors highlighted by this analysis.

Using Euclidean distance as a measure of dissimilarity, MDS provided a representation of the relationships among the contributions shown in Figure 1.

Insert Figure 1 about here

MDS reduces the data space, by positioning the articles on a bidimensional space, and making it easier to interpret the relative positioning of the clusters of contributions. Consequently, in order to analyze MDS maps, both the point placement of the articles and the orientation of the clusters of articles along the two axes have to be interpreted. In the MDS graph, contributions tend to be clustered coherently with the results of factor analysis, and thus in three main groups. The two axes can be interpreted as follows. The x-axis classifies existing studies according to the object of recombination, along a continuum that goes from *immaterial* elements (such as cognitive frames, routines and knowledge elements) to *material* components (product parts and core components), as we move from the left to the right part of the graph. The y-axis juxtaposes a *proactive* approach to recombination where firms actively engage and orchestrate combinatorial processes, to a *reactive* approach, where recombination is to a large extent triggered by factors that are exogenous to the firm. The three factors occupy specific positions in the graph. Factor 2 (enabling architectures) is placed on the lower right part of the graph, as it focuses on the intentional design of technological systems that favor combinatorial dynamics. Factor 3 (outcomes of recombination) is placed on the top right quadrant, to suggest that research has focused on how recombination favors adaptation and organizational survival. Papers loading on factor1 (recombining as an organizational capability) locate on the left hand side of the diagram, since they focus on immaterial factors and, consistently with the capability based approach, support both a proactive and a reactive approach to recombination.

Building on these results, I move now to reviewing the papers loading on each factor together with their contribution to our understanding of the process of recombination underlying technological innovation. Building on the findings of these research themes, I then propose an integrating framework.

Enabling architectures for recombination: modularity research

Factor 2 groups papers that relate to the *structural antecedents* of combinatorial processes. The broad stream of research examines how design choices at different levels of analysis (e.g., technological systems, process technologies, organizational structures, knowledge elements) affect the innovative process and its outcomes. In this respect, this set of papers builds upon earlier works on system decomposability (Simon, 1962; Alexander, 1964) and focuses on *modular structures* (Baldwin & Clark, 1997; 2000) as *enabling architectures* for recombination. System architectures considered by this research range from fully modular –i.e. systems made up by separate subsystem with no interactions between subsystems – over loosely coupled systems up to integrated systems, where each subsystem is tightly connected to all other parts of the system. The contributions loading on this factor cluster around three complementary research themes: definitions of modularity, practices to implement modular designs, and advantages of modularity.

The description of the combinatorial architecture and the definition of modular systems is certainly a challenging task. To characterize modular architectures, extant research focuses on concepts such as decomposability, interdependences and interfaces (Ulrich, 1995; Krishnan & Ulrich, 1996; Browning, 2001). Trying to capture how modular architectures are described and defined by scholars from various disciplines quickly leads to the concepts of modules and the dependencies between them. An often encountered notion of modularity in this set of papers describes modular systems as exhibiting relatively weak interdependencies between subsystems and relatively strong interdependencies within them (Ulrich, 1995; Krishnan & Ulrich, 1996; Schilling, 2000). A major tool developed to describe such interdependencies is a design structure matrix (Steward, 1981) and its various derivatives (Browning, 2001). This approach is followed by references that reflect modularity by the way functions are mapped to components (Ulrich, 1995). In other cases interface standardization becomes the determining modularity at the product level: “Production of components conforming to standard interface specifications also leads to modularity.” (Garud & Kumaraswamy, 1995: 94) or “a modular product architecture [..] is a special form of product design that uses standardized interfaces between components to create a flexible product architecture" (Sanchez & Mahoney, 1996: 66).

The issues of how these architectures can be implemented in technological systems, organizational structures and knowledge structures and how design choices at one level of analysis relate to design choices to other levels of analysis have been extensively debated. Organizational architectures are generally described using intrafirm and interfirm networks (Powell, 1990; Garud & Kumaraswamy, 1995), or giving emphasis to specific aspects, such as centralization or decision making processes. In order to design technological systems that allow recombination and knowledge reuse, "firms need to reorganize their internal and external relationship to reduce the cost of component reuse, while enhancing the associated benefits" (Garud & Kuramaswamy, 1995: 94). In this respect, while some authors suggest that a close match between the structure of the products and governance modes is necessary to favor combinatorial innovation (Sanchez, 1995; Sanchez & Mahoney, 1996; Schilling, 2000), others suggest that the three levels of analysis tend to be somehow dissimilar, so that intra-organizational and inter-organizational structures co-evolve with the structure of technologies and their underlying knowledge (Hobday, 1998; Brusoni *et al.*, 2001). Institutions (Garud & Kumaraswamy, 1993; 1995) play a fundamental role in the diffusion and adoption of architectures that allow recombination, upgradeability and combinatorial technology development at the industry level.

Combinatorial advantages of modular architectures represent the last theme analyzed by papers loading on factor 2. Modularity increases the possible configurations achievable from a set of inputs and allows achieving both mass customization and mass production (Kotha, 1995). By mixing and matching components in modularly upgradeable systems, firms can reduce product development time, leverage past investments, and provide customers with novel technological solutions while maintaining a high degree of continuity and compatibility with their existing products (Garud & Kumarasway, 1995). For that reason, these architecture enact innovative processes that entail economies of substitution (Garud & Kumarasway, 1993), where the partial retention of some technological components makes the cost of developing a new technological system lower that the cost of developing the system afresh. Thus, through the combination of technological subsystems, organizations can balance standardization and differentiation, and face an increasingly heterogeneous demand (Schilling, 2000).

Recombining as a capability: a process based view

Factor 1 is the richest of the three factors extracted in terms of number of contributions and groups studies that have seen recombination as a central *organizational capability*. The broad theoretical framework in which these articles can be positioned is the evolutionary approach (Nelson & Winter, 1982); some of the most salient and widely cited contributions of the resource based view (Galunic & Rodan, 1998), dynamic capability research (Teece, Pisano & Shuen, 1997; Zollo & Winter, 2002) and knowledge based views of the firm (Grant, 1996a; Grant, 1996b, Kogut & Zander, 1992) load on this factor.

These works suggest that the ability to generate novel outcomes through the combination of distinct inputs is a central capability that characterizes organizations. Consistently with an evolutionary view of the firm, this ability depend both on the heterogeneous inputs (routines, resources, knowledge) that a firm has to begin with, and on the processes that a firm put in action to alter its resource process. While the theoretical framework and process differs somewhat across studies, all these works agree that generating new combinations by performing local and distant search (Stuart & Podolny, 1996, Van Der Bosch *et al.*, 1999; Rosenkopf & Nerkar, 2001; Ahuja & Lampert, 2001; Fleming, 2001; Ahuja & Katila, 2001; Katila & Ahuja, 2002), combining and integrating specialized knowledge residing in the mind of individuals (Grant 1996a; Grant, 1996b, Kogut & Zander, 1992) or distributed in groups of individuals (Hansen, 1999; Grant & Baden Fuller, 2004), generating new routines out of existing routines (Edmondson, 1999; Edmondson *et al.*, 2001) or building up new capabilities and competences by combining existing routines (Henderson & Cockburn, 1994; Lei, Hitt & Bettis, 1996; LeonardBurton, 1996; Matusik & Hill, 1998; Lorenzoni & Lipparini, 1999; Helfat & Raubitschek, 2000; Lee *et al*., 2002; Zollo & Winter, 2002) or resources (Galunic & Rodan, 1998) is the central activity performed by organizations.

As the MDS graph in figure 1 highlights, the process through which recombination unfolds is triggered by both firm specific and environmental factors, and thus can be proactive – i.e. enacted by organization based on their slack resources and their ability to enact change processes - or reactive – i.e. resulting from the adaptation of firms to changes in the competitive landscape and in the environment. Relevant phases of combination process are the evaluation of the existing organization, in terms of competencies, knowledge and technologies, the generation of variety by bringing in and integrating internal and external inputs, the selection of a solution and its retention (Nelson & Winter, 1982; Zollo & Winter, 2002).

The development of new combinations is inherently intertwined with the organization's existing knowledge and competences. Organizations command both *component knowledge* (Henderson & Clark, 1990; Henderson & Cockburn, 1994), or knowledge that focuses on "a subroutine or a discrete aspect of an organization's operations (Matusik & Hill, 1996: 684) or on a core product and service, and of *architectural knowledge*, defined as "organization wide routines and schemas for coordinating the various components, both physical and organizational, and putting them to productive use" (Matusik & Hill, 1996: 684). Taken together, both types constitute the basis of an organization *system of knowledge* (Henderson & Cockburn, 1994;

Helfat & Raubitschek, 2000). Due to their path dependent evolutions, organizations develop highly heterogeneous systems of knowledge, competences and capabilities (Helfat & Raubitschek, 2000). Recombination concerns how an organization system of knowledge and the routines embedded within a firm's competences may have to be untangled, altered and integrated with other knowledge elements and routines to create novel concepts, competencies and solutions (Teece *et al.*, 1997; Galunic & Rodan, 1998; Zollo & Winter, 2002). The process entails both *variation*, intended as the use of experimentation and reconfiguration heuristics (Lei *et al.*, 1996; Galunic & Rodan, 1998) and *integration*, whereby novelty is generates through the synthesis of existing knowledge and competences (Brusoni et al., 2001; Grant, 1996a; Galunic & Rodan, 1998). Organizations devise feedback mechanisms to evaluate the internal and external fit between the newly developed combinations (Lei *et al.*, 1996; Helfat & Raubitschek, 2000). Through these cycles, organizational learning takes place. When the feedback is positive, the new combination is accepted and the competences and new knowledge are retained by the organization. This way, the organization may employ such combinations for a number of purposes central to their survival and competitive advantage.

Outcomes of recombination: incumbent failure

Papers loading on the last factor deal with the *outcomes* and implications of failed or successful recombination. As the MDS suggests, most contributions loading on this factor focused on the emergence of novel combinations as determined by factors that are exogenous to the firm, and tried to understand why established organizations fail to adapt to/ develop novel configurations (Henderson & Clark, 1990) at given points of an industry lifecycle. Thus, research focused on survival or adoption as outcomes.

Established firms are bounded by their current managerial cognitive frames (Tripsas & Gavetti, 1997; Tripsas, 2000), by existing markets and design features (Christensen & Bower, 1996; Christensen & Rosenbloom, 1996) or existing designs (Anderson & Tushman, 1990), by the legitimacy of established combinations (Dougherty & Heller, 1994; Garud *et al.*, 2001) and tend to become more inert and fail to develop new combinations. Failure to innovate leads to incumbent failure.

Yet, a few contributions highlight that overcoming these types of inertia is indeed possible. Ahuja and Lampert (2001) suggest that firms can overcome the familiarity, maturity and propinquity traps that hinder the development of innovative combinations by experimenting novel, emerging and pioneering technologies. Exploiting the expertise and insights of key individuals, incumbent can dismantle mature architectures and redeploy their existing combinations and existing experience in new related contexts (Burgelman, 1994; Klepper & Simons, 2002). It is worth pointing that the ability to overcome combinatorial inertia is certainly an example of organizational capability: as a result, the last three papers in the list represent a link between firms' capabilities and outcomes[4].

Seen dynamically, these contributions also suggest that combinative process acts at the level of the industry, and that industry life cycles can be seen as characterized by an initial phase where all actors engage in combinatorial plays of functions and elements to define new products, a moment where a dominant design – or accepted architecture – emerges and a shakeout occurs and a maturity phase, where the actors who survived exploit the design and perform incremental and modular improvements of the existing product (e.g. Anderson & Tushman, 1990; Klepper & Simons, 2002).

[4] Indeed, these papers (Burgelman, 1994; Tripsas & Gavetti, 2000; Ahuja & Lampert, 2001) load both on factor 1 and on factor 3.

COMBINATORIAL PERSPECTIVES ON INNOVATION:

A CRITICAL ASSESSMENT

Accomplishments and shortcomings of the literature to date

This initial analysis has been motivated by three main research questions. First, what does literature adopting a combinatorial perspective on innovation have accomplished so far? Second, how can these contributions be integrated into a coherent framework? Third, how can this approach be extended in future research?

The analysis shows that the combinatorial approach is well established in innovation research and widely used in organizational learning, research based view, knowledge based view and dynamic capability research to describe the process that originates novelty. Summarizing the most influential contribution in this perspective, I consider recombination as the process through which an actor untangles, alters and integrates existing technologies, competences, system of knowledge and routines, to create new stable combinations that address rapidly changing environments. Research in this area contributed to the emergence of the following integrative *framework* of the process combinatorial innovation (Figure 2):

Insert Figure 2 about here

The framework can be interpreted this way. Combinatorial processes start with a set of inputs, which can be traced back to the agent of recombination -i.e. internal- or in the environment. Such inputs may be material (such as physical components, parts, and tangible assets) or immaterial (cognitive frames, knowledge inputs, or competences). Combinatorial processes are largely influenced by the architecture of such inputs. In fact, system partitions and interdependencies determine the size and complexity of the combinatorial space. Then a phase of combinatorial play occurs, which can be experimental – result of combinatorial play of individual bits into a system - or integrative – result of combinative routines designed to combine, integrate and synthesize parts and related knowledge into a whole. That is, this phase entails both variety generation and integration, or syntheses. The combination is then retained or discharged, according to the fit with hard factors (demand, technological performance) or soft factors (fit with organizational culture, objective, managerial cognitive frames, practices or institutional framework). The outcomes affect in turn the set of available inputs and the architectures in use, and provide the basis for future recombination, in a cycle of continuous learning. The results of this process determine a range of performance outcomes, such as organizational survival, financial performance, product strategies and real options.

This framework emerges from distinct models and heterogeneous theoretical roots; yet this combinatorial model of innovation, and the studies I considered for this review, rests on some shared assumptions. First, innovation does not require all components, processes and services that become part of a new combination to be entirely new to the world. Second, the notion of new combinations suggests certain cumulativeness also in innovative processes, which will exhibit path dependent properties. Third, combinatorial dynamics take place at all level of analysis, but collectives and organizations in particular, are the *loci* where combinatorial processes may be systematically applied to the development of technological solutions that foster the production of goods and services.

Four major shortcomings and area for development emerged from this perspective: the lack of connection across levels of analysis, the use of recombination as a metaphor, the proliferation and reification of constructs and limited analysis of performance implications.

Crossing and bridging levels of analysis

Most of the studies analyzed in this review build on a shared assumption: combinatorial dynamics take place at all level of analysis, but organizations are the *loci* where new combinations are used and applied to the production of goods and services (Kogut & Zander, 1992; Grant, 1996a). Accordingly, since innovation requires turning creative ideas into commercially viable solutions (Schumpeter, 1939), research focused on firms as agents of recombination and on the process through which they apply old means to new ends (Nelson & Winter, 1982). This provided a greater understanding of the reason why firms exist and on the definition of their boundaries.

Yet, more efforts are needed to reconnect these collective processes to lower level combinatorial practices and activities, and to get a better understanding of how collective and micro-dynamics interact. This step is fundamental for the development of a combinatorial theory of innovation, as all theories in social sciences need to explicitly address what has been called the micro-to-macro problem (Coleman, 1988: 8). That is, explanations of system behaviors need to explain how theoretical predictions at the micro-level translate into propositions at the macro level. Further contributions are needed to address the following questions: what is the link between combinatorial processes at different levels of analysis? To what level of analysis is it necessary to go to find empirical evidence of architectures and recombinant processes? For example, how do individually held convictions that certain elements belong together affect the coupling of such elements within their organization? Do concepts such as modularity or coupling apply also to more immaterial element that affect such as the cognitive frames and architecture held by individuals within organizations? Also, how can these micro-level combinatorial processes be linked to firm level constructs, such as combinative capabilities or architectural knowledge?

Also, the link between individual firms' combinatorial processes and combinatorial dynamics at the level of the industry is an avenue worth further examination. The idea of the division of innovative labor (Arora, Gambardella, & Rullani, 1998) suggests that, when proper architectures are in place, the combinatorial process can be carried on by a number of organizations. The role of inter-organizational relationships in the development of complex combinations has only been partially explored (Garud *et al.*, 1993; Garud *et al.*, 1995; Brusoni *et al.*, 2001). Analyzing how groups of firms manage and orchestrate distributed recombination and integration and how these processes interact with firm level dynamics could be a promising area for future research.

Going beyond the metaphor

Despite the widespread use of the combinatorial approach to innovation, more contributions, both theoretical and empirical, are needed to unpack the black box of combinatorial processes, and delve into the fundamental steps of this process. Our review of works in this tradition suggests a general tendency to treat recombination as a metaphor. The very process of recombination is often poorly described or mentioned, for example, in most empirical works relating given types of inputs to innovative output in mainstream management research, which simply assume combinatorial dynamics to be the underlying mechanisms explaining the input output relationship.

Field based studies could add greater detail to our understanding of each phase of the combinatorial process, and of the different mechanisms enacted by different design choices and architectures. We need to understand whether the model described in figure 2 general, or do we need to adapt it based on the agent or object of recombination. Literature would greatly benefit from observing the separate phases of variation, integration and selection at different levels of analysis, to gain an increased understanding of how such phases differ across levels of analysis and of the interaction between levels of analysis. For example, we need to build a better characterization of the process of selection that clarifies what levels of analysis concurrently explain fit, and to reconnect our characterization of fit to the underlying assumptions of our combinatorial framework. Only clarifying the uniqueness of this idea of fit *vis à vis* traditional market selection mechanisms would clarify the distinctive traits of this approach to technological progress.

Econometric-based tests could also contribute to a more nuanced view of combinatorial models. Recent studies (Fleming, 2001; Fleming, Mingo & Chen, 2007) developed fine grained, patent based measures of combinatorial outcomes, which explain how much a given invention is re-using prior combination or producing a new combination. Such measures could be used to disentangle truly combinatorial outcomes and can be used and extended to other empirical contexts. New measures may be created applying the same logic to data other than patents.

Reification of constructs and their validity

Partially related to the previous point, the ease with which the idea of recombination has been used resulted in a stunning number of contributions ascribing to this perspective. This has resulted in a plethora of constructs, such as developed in the field, such as “architectural knowledge” (Henderson & Clark, 1990), “combinative capabilities” (Kogut & Zander, 1992), “dynamic core competencies” (Lei *et al.*, 1996), “flexibility” (Sanchez & Mahoney, 1996), “dynamic capabilities” (Teece et al., 1997; Zollo & Winter, 2000), “resource recombination” (Galunic & Rodan, 1998), “knowledge integration” (Grant, 1996a, b; Brusoni, Prencipe & Pavitt, 2001), “integrative knowledge” (Helfat & Raubitschek, 2000) or “knowledge base malleability” (Yayavaram & Ahuja, 2008). These constructs greatly contributed to our understanding of how firms enact or react to combinatorial processes that lead to technological innovation.

Yet, the use and abuse of the idea of recombination led to the reification of these constructs. Reification consists in the process by which the initial conceptualization of a construct ceases to be challenged, some of its original assumptions forgotten, and the construct becomes to be used as an “off-the-shelf” component to support researchers’ arguments (Rousseau & House, 1994). Some contributions that advance these constructs locate very closely on the MDS graph, thus suggesting that all these constructs have been used interchangeably by following research, and co-cited in a significant number of works. Yet, these constructs differ somehow with respect to some dimensions (i.e. static-dynamic, inbound-outbound perspective).

Though some attempts to systematize these and related innovation constructs exists (Gatignon *et al.*, 2002), it would be promising to reason on the distinctiveness of such constructs, on the different assumptions behind them, thus providing lines for their development. In what way each construct advances our understanding of how combinatorial dynamics lead to new solutions? This work would help to build proper measure of some constructs, given that most of these pieces are theoretical and even empirical research used very similar proxies or data to operationalize them.

Understanding performance implications

Finally, research in this area would greatly benefit from considering the implication at large of organizational combinative activities. To date, a review of the papers loading on factor 3 (outcomes of recombination) revealed that our understanding of the performance implications of recombination, other than successful or failed adaptation, is limited.

Surely, there have been attempts in this direction. For example, a recent stream of research connected modular designs and organizational combinatorial processes to real options and competitive advantage (Baldwin & Clark, 2000; Kogut & Kulatilaka 2001). More work is needed to understand how firms can actively enact and orchestrate combinatorial strategies and exploit them through product innovation or entry in other markets. Extending our understanding of the process of internal and external selection would pave the way to advancements in this direction.

CONCLUSIONS

The aim of the study was to address three related research questions: what does literature adopting a combinatorial perspective on innovation has accomplished so far? Second, how can these contributions be integrated into a coherent framework? Third, how can this approach be extended in future research? In order to address these questions, a bibliometric assessment of the most cited papers' building upon this research trajectory was performed.

The analysis showed that the combinatorial approach is well established in innovation research, as it well applies to describe evolutionary processes at different levels of analysis. Combinatorial processes have been widely used by different theoretical perspectives (research based view, knowledge based view, dynamic capability) to describe the process that originates innovation and to illuminate a wide range of issues, such as new product development, organizational learning and industry life cycles. The heterogeneous and large body of research building on this approach, though, can be coherently organized around three main themes. Understanding the link between the themes made it possible to gain a deeper understanding of the role of recombination in innovation, as well as of the current limitations of this perspective.

The study makes two important contributions. First, the results of this analysis contribute to research in the technology and innovation management field a framework that integrates and clarifies the relationship between the three core issues that characterize the process of recombination: (i) enabling architectures for recombination (ii) recombining as a capability (iii) outcomes of recombination. The model rests on a simplified picture of recombination, and tries to reconnect the definition and the emerging framework to their network of supporting assumptions. Second, focusing on the current limitations of this approach, I developed a set of criteria to assess and evaluate both existing and potential studies. These lines may be developed to address current limitations and exploit emerging research opportunities.

The approach used in this paper has of course some limitations, which provide possible avenues for further developments of the study. First, the criteria used to identify the core papers of the combinatorial perspective is based on the impact that Henderson and Clark (1990) work had on subsequent research. Obviously, other choices could be possible, such as focusing on a core of initial contributions on the topic, or performing a keyword based search in the selected outlets. In this respect, a thematic analysis of the papers would help to distinguish between contributions where recombination is important to a paper core topic and papers that use it as an embellishment. Similarly, the relevance criterion used in this study favors older documents to the detriment of more recent ones that may be more central to the core of the recombinant approach. Setting year specific thresholds for the selection of the initial contributions would make the results more robust to right truncation biases (Acedo *et al.*, 2006).

Yet, the number of studies in this perspective suggests that combinatorial dynamics have an increasing practical and strategic relevance in technology strategy. Firms face increasingly fragmented markets, which demand timely and targeted innovative products, and severe pressures to maximize efficiency, to remain competitive in the face of worldwide producers (Baldwin &

Clark, 2000). Combinatorial strategies may be a way to reconcile these objectives. As Harold Wester (FIAT head of engineering) puts it "I will no longer reinvent the wheel each time. I will work instead on trying new combinations and on improving the same solution and within existing models. (…). The customer is interested in a fuel-efficient and well-functioning HVAC unit. Whether it's the same between four cars, or it uses solutions developed for other models, he doesn't care. The effort we have to make is to guarantee compatibility and re-use" (Fortune, 2007). Advancing our current understanding of the role of recombination in innovation and of its implications can greatly contribute to understand how companies can implement and profit from combinatorial strategies.

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TABLE 1

Reference	Definition
Poincaré, 1908	“the finest ideas in science (...) are those which reveal to us unsuspected kinship between other facts, long known, but wrongly believed to be strangers to one another. Amongst chosen combinations the most fertile will often be those formed of elements drawn from domains which are far apart”
Poincaré, 1913	“… ideas rose in crowds; I felt them collide until pairs interlocked, so to speak, making a stable combination”
Usher, 1927	“invention finds its distinctive feature in the constructive assimilation of pre-existing elements into new synthesis, new patterns or new configurations”
Einstein, quoted in Simonton, 1999	“…combinatory play seems to be the essential feature in productive thought”
Schumpeter, 1934	"the essence of innovation is carrying out of new combinations (…) development consists primarily in employing existing resources in a different way, in doing new things with them”
Schumpeter, 1939	“innovation combines components in a new way, or it consists in carrying out new combinations”
Penrose, 1959	“The services yielded by resources are a function of the way in which they are used—exactly the same resources when used for different purposes or in different ways and in combination with different types or amounts of other resources provides a different service or set of services … unused productive services are a source of competitive advantage (…) they facilitate the introduction of new combination of resources - innovation - within the firm”
Nelson & Winter, 1982	“… the creation of any sort of novelty in art, science, or practical life - consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence”

TABLE 2

Journal	Number of articles
STRATEGIC MANAGEMENT JOURNAL	79
RESEARCH POLICY	71
JOURNAL OF PRODUCT INNOVATION MANAGEMENT	39
ORGANIZATION SCIENCE	38
MANAGEMENT SCIENCE	35
IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT	25
INDUSTRIAL AND CORPORATE CHANGE	25
ACADEMY OF MANAGEMENT JOURNAL	24
ACADEMY OF MANAGEMENT REVIEW	24
JOURNAL OF MANAGEMENT STUDIES	19
ADMINISTRATIVE SCIENCE QUARTERLY	17
CALIFORNIA MANAGEMENT REVIEW	9
SLOAN MANAGEMENT REVIEW	6
JOURNAL OF MANAGEMENT	5
ORGANIZATION STUDIES	1
Total	417

TABLE 3

List of articles

Selected Papers
Ahuja & Katila, 2001, *Strategic Management Journal* , 22(3): 197-220.
Ahuja & Lampert, 2001, *Strategic Management Journal* , 22(3): 521-543.
Anderson & Tushman, 1990, *Administrative Science Quarterly* , 35(4): 604-633.
Baum & Ingram, 1998, *Management Science* , 44(7): 996-1016.
Benner & Tushman, 2003, *Academy of Management Review* , 28(2): 238-256.
Benner, 2002, *Administrative Science Quarterly* , 47(4): 676-706.
Blanckler, 1995, *Organization Studies* , 16(6): 1021-1046.
Browning, 2001, *IEEE Transaction on Engineering Management*, 48(3): 292-306.
Brusoni et al., 2001, *Administrative Science Quarterly* , 46(4): 597-621.
Burgelman, 1994, *Administrative Science Quarterly* , 39(1): 24-56.
Christensen & Bower, 1996, *Strategic Management Journal* , 17(3): 197-218.
Christensen & Rosenbloom, 1995, *Research Policy* , 24(2): 233-257.
Cockburn et al., 2000, *Strategic Management Journal* , 21(2): 1123-1145.
Dougherty & Hardy, 1996, *Academy of Management Journal* , 39(5): 1120-1153.
Dougherty & Heller, 1994, *Organization Science* , 5(2): 200-218.
Edmondson et al., 2001, *Administrative Science Quarterly* , 46(4): 685-716.
Edmondson, 1999, *Administrative Science Quarterly* , 44(2): 350-383.
Fleming, 2001, *Management Science* , 47(1): 117-132.
Galunic & Rodan, 1998, *Strategic Management Journal* , 19(12): 1193-1201.
Garcia & Calantone, 2002, *Journal of Product Innovation Management* , 19(2): 110-132.
Garud & Kumaraswamy, 1993, *Strategic Management Journal* , 14(5): 351-369.
Garud & Kumaraswamy, 1995, *Strategic Management Journal* , 16: 93-109.
Garud et al., 2001, *Academy of Management Journal* , 45(1): 196-214.
Gatignon et al., 2002, *Management Science* , 48(9): 1103-1122.
Grant & Baden-Fuller, 2004, *Journal of Management Studies* , 41(1): 61-84.
Grant, 1996a, *Strategic Management Journal* , 17: 109-122.
Grant, 1996b, *Organization Science* , 7(4): 375-387.
Hansen, 1999, *Administrative Science Quarterly* , 44(1): 82-111.
Helfat & Raubitschek, 2000, *Strategic Management Journal* , 21(2): 961-979.
Henderson & Cockburn, 1994, *Strategic Management Journal* , 15: 63-84.
Hobday, 1998, *Research Policy* , 26(6): 689-710.
Katila & Ahuja, 2002, *Academy of Management Journal* , 45(6): 1183-1194.
Kessler & Chakrabarti, 1996, *Academy of Management Review* , 21(4): 1143-1191.
Klepper & Simons, 2000, *Strategic Management Journal* , 21(2): 997-1016.
Kogut & Zander, 1992, *Organization Science* , 3(3): 383-397.
Kotha, 1995, *Strategic Management Journal* , 16: 21-42.
Krishnan & Ulrich, 1996, *Management Science* , 47(1): 1-21.
Lee et al., 2001, *Strategic Management Journal* , 22(5): 615-640.
Lei, Hitt & Bettis, 1996, *Journal of Management* , 22(4): 549-569.
Leonardbarton, 1996, *Strategic Management Journal* , 13: 111-125.
Levinthal, 1997, *Management Science* , 43(7): 934-950.
Lieberman & Montgomery, 1998, *Strategic Management Journal* , 19(12): 1111-1125.

Lorenzoni & Lipparini, 1999, *Strategic Management Journal* , 20(4): 317-338.
Madhavan et al., 1998, *Strategic Management Journal* , 19(5): 439-459.
Matusik & Hill, 1998, *Academy of Management Review* , 23(4): 680-697.
McGrath. 2001, *Academy of Management Journal* , 44(1): 118-131.
Meyer & Utterback, 1993, *MIT Sloan Management Review* , 34(3): 29-47.
Meyer et al., 1997, *Management Science* , 43(1): 88-111.
Mezias & Glynn, 1993, *Strategic Management Journal* , 14(2): 77-101.
Mitchell & Singh, 1996, *Strategic Management Journal* , 17(3): 169-195.
Ocasio, 1997, *Strategic Management Journal* , 18: 187-206.
Rosenkopf & Nerkar, 2001, *Strategic Management Journal* , 22(4): 287-306.
Sanchez & Mahoney, 1996, *Strategic Management Journal* , 17: 63-76.
Sanchez, 1995, *Strategic Management Journal* , 16: 135-159.
Schilling, 2000, *Academy of Management Review* , 25(2): 312-334.
Sorensen & Stuart, 2000, *Administrative Science Quarterly* , 45(1): 81-112.
Stuart & Podolny, 1996, *Strategic Management Journal* , 17: 21-38.
Suarez & Utterback, 1995, *Strategic Management Journal* , 16(6): 415-430.
Takeishi, 2001, *Strategic Management Journal* , 22(5): 403-433.
Teece et al., 1997, *Strategic Management Journal* , 18(7): 509-533.
Tripsas & Gavetti, 2000, *Strategic Management Journal* , 21(2): 1147-1161.
Tripsas, 2000, *Strategic Management Journal* , 18: 119-142.
Ulrich, 1995, *Research Policy* , 24(3): 419-440.
Utterback & Suarez, 1993, *Research Policy* , 22(1): 1-21.
Van den Bosh et al., 1999, *Organization Science* , 10(5): 551-568.
Wade, 1995, *Strategic Management Journal* , 16: 111-133.
Wolfe, 1994, *Journal of Management Studies* , 31(3): 405-431.
Zollo & Winter, 2002, *Organization Science* , 13(3): 339-351.

TABLE 4

Factor Analysis

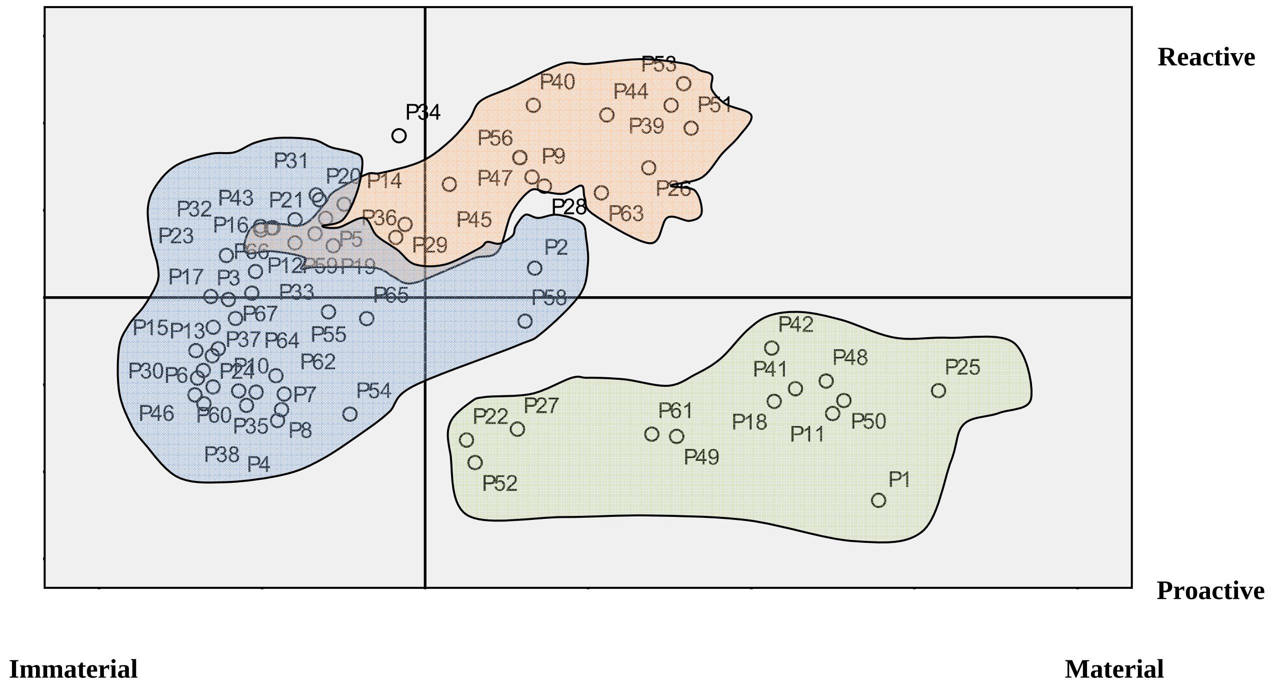
	Factors		
	1	2	3
Galunic and Rodan, 1998	0,979		
Lei, Hitt and Bettis, 1996	0,976		
Van den Bosh et al., 1999	0,974		
Grant and Baden-Fuller, 2004	0,968		
Kogut and Zander, 1992	0,967		
Grant, 1996b	0,966		
Matusik and Hill, 1998	0,964		
Grant, 1996a	0,952		
Lorenzoni and Lipparini, 1999	0,944		
Hansen, 1999	0,944		
Henderson and Cockburn, 1994	0,942		
Zollo and Winter, 2002	0,938		
Helfat and Raubitschek, 2000	0,936		
Lee et al., 2001	0,925		
Cockburn et al., 2000	0,911		
Baum and Ingram, 1998	0,885		
Leonardbarton, 1996	0,883		
Ahuja and Katila, 2001	0,870		
Blanckler, 1995	0,869		
Mitchell and Singh, 1996	0,854		
Ocasio, 1997	0,811		
Teece et al., 1997	0,806		
Ahuja and Lampert, 2001	0,784		
Levinthal, 1997	0,770		0,576
McGrath. 2001	0,761		
Benner and Tushman, 2003	0,753		
Rosenkopf and Nerkar, 2001	0,746		
Katila and Ahuja, 2002	0,746		
Fleming, 2001	0,714		
Sorensen and Stuart, 2000	0,708		
Takeishi, 2001	0,689	0,551	
Edmondson, 1999	0,677		
Dougherty and Hardy, 1996	0,640		0,569
Madhavan et al., 1998	0,640		
Edmondson et al., 2001	0,629		

	Factors		
	1	2	3
Kotha, 1995		0,951	
Sanchez and Mahoney, 1996		0,893	
Schilling, 2000		0,876	
Krishnan and Ulrich, 1996		0,867	
Garud and Kumaraswamy, 1995		0,865	
Sanchez, 1995		0,865	
Ulrich, 1995		0,853	
Garud and Kumaraswamy, 1993		0,853	
Meyer and Utterback, 1993		0,850	
Brusoni et al., 2001		0,833	
Hobday, 1998		0,825	
Browning, 2001		0,800	
Anderson and Tushman, 1990			0,892
Tripsas, 2000			0,830
Garcia and Calantone, 2002			0,824
Gatignon et al., 2002			0,807
Klepper and Simons, 2000			0,806
Lieberman and Montgomery, 1998			0,802
Christensen and Bower, 1996			0,776
Christensen and Rosenbloom, 1995			0,776
Suarez and Utterback, 1995			0,757
Utterback and Suarez, 1993			0,755
Burgelman, 1994	0,577		0,730
Wade, 1995			0,692
Tripsas and Gavetti, 2000	0,628		0,688
Garud et al., 2001			0,664
Mezias and Glynn, 1993			0,591
Dougherty and Heller, 1994			0,588

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

FIGURE 1

Multidimensional scaling



References

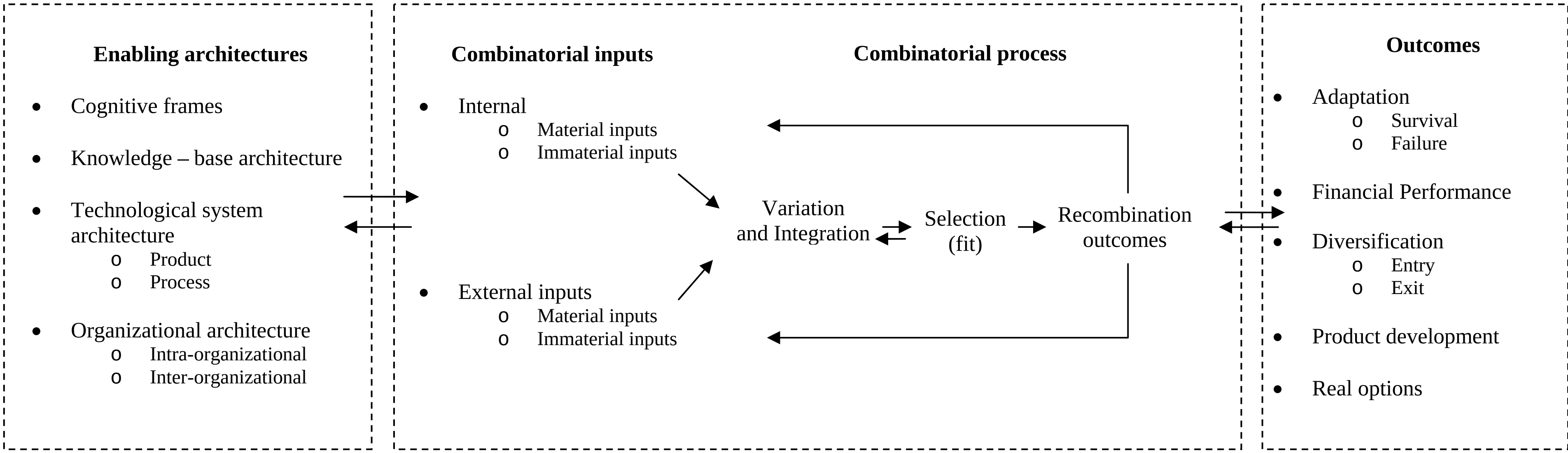
P2	Madhavan et al., 1998	P34	Benner, 2002
P3	Baum and Ingram, 1998	P35	Grant and Baden-Fuller, 2004
P4	Matusik and Hill, 1998	P37	Leonardbarton, 1996
P6	Galunic and Rodan, 1998	P38	Kogut and Zander, 1992
P7	Hansen, 1999	P46	Henderson and Cockburn, 1994
P8	Lorenzoni and Lipparini, 1999	P54	Blanckler, 1995
P9	Edmondson, 1999	P55	Mitchell and Singh, 1996
P10	Van den Bosh et al., 1999	P57	Lei, Hitt and Bettis, 1996
P12	Sorensen and Stuart, 2000	P58	Kessler and Chakrabarti, 1996
P13	Helfat and Raubitschek, 2000	P59	Dougherty and Hardy, 1996
P14	Klepper and Simons, 2000	P60	Grant, 1996b
P15	Cockburn et al., 2000	P62	Grant, 1996a
P17	Ahuja and Katila, 2001	P64	Levinthal, 1997
P19	Fleming, 2001	P65	Teece et al., 1997
P20	McGrath. 2001	P67	Ocasio, 1997
P21	Rosenkopf and Nerkar, 2001		
P22	Takeishi, 2001		
P23	Ahuja and Lampert, 2001		
P24	Lee et al., 2001		
P28	Edmondson et al., 2001		
P30	Zollo and Winter, 2002		
P32	Katila and Ahuja, 2002		
P33	Benner and Tushman, 2003		

P5	Lieberman and Montgomery, 1998
P16	Tripsas and Gavetti, 2000
P26	Garud et al., 2001
P29	Garcia and Calantone, 2002
P31	Gatignon et al., 2002
P36	Anderson and Tushman, 1990
P39	Utterback and Suarez, 1993
P40	Mezias and Glynn, 1993
P43	Burgelman, 1994
P44	Wolfe, 1994
P45	Dougherty and Heller, 1994
P47	Christensen and Rosenbloom, 1995
P51	Wade, 1995
P53	Suarez and Utterback, 1995
P56	Christensen and Bower, 1996
P63	Meyer et al., 1997
P66	Tripsas, 2000

P1	Hobday, 1998	P41	Meyer and Utterback, 1993
P11	Schilling, 2000	P42	Garud and Kumaraswamy, 1993
P18	Krishnan and Ulrich, 1996	P48	Ulrich, 1995
P25	Browning, 2001	P50	Garud and Kumaraswamy, 1995
P27	Brusoni et al., 2001	P52	Sanchez, 1995
P49	Kotha, 1995	P61	Sanchez and Mahoney, 1996

FIGURE 2

A combinatorial view of technological innovation: an integrative framework



APPENDIX A

The extraction method I used was principal component analysis and I used varimax rotation of the extracted factors to interpret the results. The number of extracted factors was fixed by studying the screeplot rather than by using Kaiser's criterion. Kaiser's criterion for factor extraction is accurate when there are less than 30 variables with communalities after extraction higher than 0.7 or, in the case of more than 230 with communalities, after extraction higher than 0.6. Since we do not fit in either case, having 67 variables with communalities, after extraction, all higher than 0.73, the use of the screeplot is justified.

Three papers did not load on any factor (Benner, 2002; Wolfe, 1994; Kessler & Chackrabarti, 1996).

Essay 2

NETWORKS AS PIPES AND WELLSPRINGS: EXPLORING THE LINK BETWEEN FIRM AND NETWORK DYNAMICS IN THE INVENTIVE PROCESS

ABSTRACT

This paper sets out to integrate two well-established, complementary, and yet unrelated views on the inventive process. On the one hand, it has been argued that a firm's ability to generate new technological inventions is related to firm's network position. This argument rests on the presumption that inter-firm networks act as "pipes" that funnel different learning opportunities to different network positions and, hence, to different firms. On the other hand, it has been argued that a firm's inventive performance depends on its organizational capabilities, and particularly its assimilative and recombinant capabilities. We develop a model that integrates arguments from both views. By so doing, we generate a set of novel testable hypotheses at both the firm- and the network-level. Based on an analysis of the semiconductor industry over the period 1975-2001, our hypotheses are corroborated.

Keywords: inventiveness, inter-organizational networks, recombination, assimilative capabilities

The dynamics by which firms generate technological inventions can hardly be understood without taking into account the organizational field within which those dynamics unfold (Tushman & Rosenkopf, 1992; Davis & Marquis, 2005). Firms extensively derive ideas for new technologies from other firms, and quite often the frontier of technological knowledge is advanced by a concatenation of inventions that cut across organizational boundaries (Utterback, 1974). Accordingly, firms' inventive performance depends to a relevant degree on their ability to assimilate the technological knowledge residing outside their boundaries (Cohen & Levinthal 1990, 1994; Lane & Lubatkin, 1998; Van Den Bosch, Volbreda, & De Boer, 1999; Zahra & George, 2002), and this is particularly true in organizational fields where technologies are complex, dispersed, and rapidly expanding. Because one important way in which firms acquire external knowledge is by engaging in collaborative relationships with other firms (Hamel, 1991; Ahuja, 2000; Hoang & Rothaermel, 2005), a sizeable body of research has studied the inventive process by conceiving firms as nodes interconnected by a network of collaborations (e.g., Ahuja, 2000; Stuart, 2000; Zaheer & Bell, 2005).

Research in this area has typically conceptualized inter-organizational networks as "pipes", or "channels", funneling different knowledge streams and hence different opportunities for learning and innovation, to different network positions (Powell, Koput, & Smith-Doerr, 1996; Podolny, 2001; Owen Smith & Powell, 2004). This perspective proved very useful in explaining how the inventive process is influenced by the uneven structure of knowledge diffusion in a field. For example, Powell and colleagues (1996) analyzed the commercial biotech field to show that exposition to the knowledge circulating through an inter-organizational alliance network leads to increased rates of learning and innovation. Similarly, Ahuja (2000) found that the inventive performance of the firms operating in the international chemical industry is systematically related to the position firms occupy within the network of alliances. Extending this argument, other studies suggested that the value of being exposed to the knowledge circulating through an inter-organizational network is contingent on partner characteristics (Stuart, 2000; Zaheer & Bell, 2005; Hoang & Rothaermel, 2005).

The emphasis this line of inquiry has placed on the role of knowledge diffusion *across* firms has corresponded to a tendency to abstract away from the role the firms themselves play in the inventive process. The diffusion of technological knowledge throughout a network, however, is driven by two mechanisms that are strictly inherent to the level of the firm. First, technological knowledge can diffuse from a firm to another only if the former *generates* new technological knowledge. Second, technological knowledge can diffuse to a firm from another only if the former is able to *assimilate*[1] that external knowledge. The networks-as-pipes metaphor evokes a somewhat passive image of the firm as a recipient of the knowledge that accrues to its network position. However, both to generate and to assimilate knowledge firms must build costly and hard to develop organizational routines, practices and processes (Blackler, 1995). In fact, it has been argued that the most important function of the firm lies in its capacity to build and govern such capabilities and that variance across firms with respect to these capabilities is a key source of firm performance differentials (Kogut & Zander, 1992).

Our contention in this paper is that a vantage point can be gained by better explicating the relation between the network structure of knowledge diffusion, on the one hand, and the firm-level processes of knowledge generation and assimilation, on the other. Extending the metaphor mentioned earlier, we suggest that in addition to pipes funneling knowledge among firms, inter-firm networks encompass knowledge wellsprings, i.e. firms that by their knowledge recombination activities continuously generate and renew the knowledge flowing through the

[1] Throughout the paper, we follow Zahra and George (2002: 189) in defining knowledge assimilation as a firm's ability to "analyze process, interpret, and understand the information obtained from external sources." As such, a firm's knowledge assimilation capabilities constitute a key component of firm's absorptive capacity (Cohen & Levinthal, 1990, Zahra & George, 2002; Lane, Koka & Pathak, 2006).

network at any point in time. By more explicitly relating the network-level dynamics of knowledge diffusion to the firm-level mechanisms of knowledge assimilation and generation, the paper aims to achieve a fourfold objective.

First, on a general level, the paper illuminates the understudied link between firms and networks in the inventive process. By so doing, our study responds to the call for mechanism-based organizational research that takes explicitly into account the duality inevitably existing between firms and inter-organizational fields (Davis & Marquis, 2005). Similar to other areas of organizational research, most extant studies of the inventive process focused *either* on the firm *or* on the inter-firm network. Accordingly, two lines of inquiry have developed largely independent of each other. By contrast, this paper represents an attempt to integrate important notions and theoretical arguments from both research traditions, with the end to gain novel insights about, and systematize our understanding of, the inventive process. The paper shows that firm- and network-level mechanisms do interact at some crucial junction of the inventive process, and much can be learned by more carefully exploring these interactions.

Second, the paper furthers our understanding of how inter-firm network structure relates to firm performance. Namely, it has been shown that over time network structures tend to stabilize and reproduce themselves (White, 1981, Walker, Kogut, & Shan, 1997), so that once a firm has gained a favorable network position, it will tend to benefit from it indefinitely in the future (Podolny, 1993). By contrast, our proposed analytical perspective emphasizes that even if network structures stabilize, the knowledge circulating through those structures is continuously transformed and renewed by the firms populating the network. Accordingly, we will argue and show that net of positional benefits, the knowledge a firm can assimilate and recombine at any point in time through its network, crucially depend on the inventiveness of its network contacts at that specific point in time.

Third, the paper sheds new light on the important debate about the putative effects of closed versus brokering networks of knowledge (Brass, Galaskiewicz, Greve, & Tsai, 2004). Prior research has extensively debated whether a firm's inventive performance is facilitated when the firm occupies a brokering position within the knowledge network or, conversely, when it occupies a closed position. To date, however, the empirical evidence is mixed. For example, Ahuja's (2000) study of the international chemical industry shows that firms' inventiveness increases when firms have many technical collaboration ties to densely connected contact firms; similarly, Rowley and colleagues (2000), Obstfield (2005) and Uzzi and Spiro (2005) provide evidence that network closure improves creativity and firm's knowledge generation. On the contrary, several studies (Baum, Calabrese, & Silverman, 2000; Ruef, 2002; Zaheer & Bell, 2005) find that networks giving access to diverse knowledge has a positive effect on inventiveness. This paper shows that which of the two positions is most beneficial depends on the firm ability to assimilate knowledge from inventive contacts. Namely, occupying a brokering position is advantageous to the extent that a firm draws from slow innovators; however, when a firm's assimilates knowledge from technologically prolific contacts, being embedded in a closed network facilitates the recombination of their rich technological spillovers.

Fourth, by concurrently treating the inventive process at both the firm- and the network-level, our proposed analytical perspective yields a non-trivial insight on the issue of "how collective outcomes might be generated in inter-organizational networks" (Provan, Fish & Sidow, 2007: 480). Namely, we provide some evidence that inter-firm networks have an inherent tendency to partition into dense clusters of either technologically prolific or technologically sterile firms. Furthermore, we show that the technologically prolific clusters coalesce towards the core of the network, while the technologically sluggish clusters remain mostly confined within its periphery.

To further explain and test our arguments, we proceed as follows. We begin by elaborating our view of the inventive process in the context of inter-firm networks and, accordingly, we present a model of knowledge networks encompassing both "pipes" and "wellsprings". Against the background of this network model, we then develop our hypotheses. To disentangle empirically knowledge generation and knowledge assimilation dynamics, and hence to operationalize our proposed model of knowledge network, we focus on a field where the bulk of technological developments gets systematically codified and patented – the semiconductors field between 1975 and 2001. In that context, we are able to follow Zahra and George's suggestion to model firms' ability to assimilate each other's knowledge based on cross-firm citation patterns (Zahra & George, 2002: 199). Having discussed the empirical context, the operationalization of the variables, and the statistical methods, we present the results of our analyses. We conclude the paper by elaborating on the implications and limitations of the study, and by pointing out which steps may be taken in order to extend this line of research.

THEORETICAL FRAMEWORK

Recombinant capabilities

How do firms generate new technological knowledge? A good deal of consensus has formed around the view that the inventive process is a problem-solving endeavor wherein new knowledge is generated by recombining existing knowledge in novel ways (Fleming, 2001). According to this notion, new technical solutions are discovered through recombination of knowledge embodied in existing technological components (Gilfillan, 1935; Schumpeter, 1939; Usher, 1954; Nelson & Winter, 1982; Fleming, 2001) or through reconfigurations of existing technological architectures (Henderson & Clark, 1990). Through knowledge recombination, firms discover new technological trajectories (Schumpeter, 1939), or new ways "to exploit [their] knowledge of the unexplored potential of the technology" (Kogut & Zander, 1992: 391).

As firms' recombinant capabilities evolve in a path-dependent fashion, firms tend to develop distinctive knowledge bases as well as distinctive trajectories of technological accumulation (Patel & Pavitt, 1997; Tsai, 2001; Jacobides & Winter, 2005). Accordingly, firms vary widely in their inventive performance (Ahuja, 2000; Katila & Ahuja, 2002; Yayavaram & Ahuja, 2008), and this variance is apparent both across and within technological sectors (Dosi, 1982). Although firms' ability to creatively recombine knowledge from within their own technological base is strategically pivotal (Tsai, 2001; Nerkar & Parachuri, 2005; Miller, Fern & Cardinal, 2007), however, a large and increasing share of their recombinant inputs are taken from other firms (Powell *et al.,* 1996). Hence, "firm-level technological trajectories influence, and are influenced by, trajectories of other firms" (Rosenkopf & Nerkar, 2001: 291). This notion prompts the question of how firms can integrate externally generated technological knowledge into their own technological trajectory – or, said otherwise, of how technological knowledge diffuses across firms in the inventive process.

Assimilative capabilities

To integrate external technological knowledge into their own technological trajectory, firms must learn to analyze, interpret, and understand other firms' technological trajectories (Zahra & George 2002; Hoang & Rothaermel, 2005). Accordingly, having access to externally generated knowledge is in general not enough to internalize it. To the contrary, specialized and costly organizational routines, practices and processes must be developed in order to both make sense of, and act upon, the heuristics embodied in the knowledge generated by other firms (Leonard-Barton, 1995). In the absence of such "assimilative capabilities" (Zahra & George, 2002), technological knowledge cannot diffuse across firms. For example, in the semiconductors field most newly generated technological knowledge is made publicly accessible through patents or products fact sheets. Nevertheless, to be able to assimilate at least part of that knowledge, firms must invest significant resources in monitoring and analyzing as closely as possible the technological developments of no more than a few competitors (Di Biaggio, 2007).

Focusing on the technological trajectories of selected external sources facilitates the development of assimilative capabilities in at least two important ways. First, firms' technological trajectories are highly path-dependent (Patel & Pavitt, 1997). As a consequence, there is a scale advantage in concentrating one's attention and learning investments on the technological trajectories developed by specific firms. Second, assimilating knowledge from another firm tends to progressively reduce the technological distance from it (Tushman & Rosenkopf, 1992), which in turn progressively decreases the costs of further knowledge assimilation. Consistent with this view, Todorova and Durisin (2007) argued that a firm can internalize knowledge generated by another firm either by reconfiguring its technological base to fit the external knowledge or, conversely, by reconfiguring the external knowledge to fit its technological base. Either way, repeatedly assimilating knowledge from another firm reduces the technological distance from it.

As firms build their assimilative capabilities, therefore, they become embedded in a network of source firms whose technological trajectories they understand and from which they can learn and draw recombinant inputs. From the perspective of the firm, this knowledge network delineates a firm's search zone within the overwhelmingly vast body of technological knowledge residing outside its boundaries. Ideas and discoveries generated outside this knowledge network are overlooked because a firm is not equipped to either monitor or comprehend them (Zahra & George, 2002). From the perspective of the field, this knowledge network is the evolving substrate on which inventions and recombinant inputs diffuse across firms (Brown & Duguid, 1991; 2001).

Knowledge networks as "pipes" and "wellsprings"

The two previous sections argue that the structure through which technological knowledge diffuses is inherently related to firm-level capabilities. Technological knowledge diffuses across firms to the extent that firms learn how to assimilate each other's knowledge. Furthermore, firms differ in their recombinant capabilities and this has an impact on the volume of knowledge they pump into the network. We now turn to developing a network model that makes it possible to better take into account these considerations. Figure 1 provides a visual representation of our network model.

Insert Figure 1 about here

The example considers the "ego-network" of firm A, i.e., (i) A itself, (ii) A's direct contacts (B, C and D), (iii) the ties between A and its direct contacts, and (iv) the ties among A's contacts. In the figure, node sizes indicate the amount of new technological knowledge each firm generated during a given time interval *t*. In most network representations of inter-firm networks, a tie represents a collaborative relationship among two firms. By contrast, in our model a tie indicates a firm's capacity to assimilate knowledge generated by another firm. While our choices of operationalization will be described in detail in a later section, it may be useful to anticipate that empirically, we will assume dyadic assimilative capacities to depend on the frequency with which a firm has assimilated knowledge from another firm over the past (few) years. Accordingly, in the example in Figure 1, prior to *t* firm A has accumulated a great deal of experience in assimilating knowledge from firm B, resulting in a large capacity to assimilate the knowledge B generates during *t*. Conversely, A's capacity to assimilate knowledge from C and D is small *albeit* positive, reflecting A's limited experience in assimilating knowledge from the trajectories developed by those firms. Hence, unlike models of inter-firm collaboration, in which a firm either has or does not have a tie to another firm, our model allows *valued* ties. Also note that the absence of ties is as informative as their presence in our model, signaling which firms *do not* have the assimilative capabilities needed to draw from each others' inventions. In Figure 1, for example, firm B has developed no assimilative capacity *vis-à-vis* D, implying that B is highly unlikely to make use of any of the knowledge D has generated during *t*.[2] Finally, note that whereas models of inter-firm collaboration networks assume ties to be *symmetric*, our model allows *asymmetric* ties as well. For instance, in Figure 1, A's capacity to assimilate knowledge from B is much larger than B's capacity to assimilate knowledge from A. Against the background of our network model, in the next section we develop a set of testable hypotheses. Subsequently, we will provide a formal treatment of our network representation, allowing us to further sharp-focus both our concepts and their empirical operationalization.

HYPOTHESES

We have argued that the knowledge diffusing through a network is continuously generated and renewed by the firms populating the network. A straightforward implication of this argument is that the volume of novel external knowledge a firm can creatively recombine at any point in time, and hence its inventive performance, depend on how technologically prolific are

[2] This last point is important because it sets a clear demarcation between our model and models of technological knowledge prevalent among economists (see, e.g., Weitzman, 1996). Models in economics assume that an invention is a public good (i.e., the knowledge embodied in the invention can be assimilated at negligible costs) if it is both accessible and well-articulated in a codified language. By contrast, our model assumes that even when knowledge is well-articulated and publicly accessible, firms are able to assimilate that knowledge only insofar as they understand the technological trajectory on which the invention builds.

the firms in its ego-network at that point in time. There are two reasons for this conjecture. First, the greater the technological output generated by the firms in a focal firm's ego-network, the larger the pool of external knowledge the focal firm is equipped to understand and assimilate; hence, the greater the likelihood that the focal firm will discover recombinant inputs that enhance its technological production (Fleming, 2001). Second, firms whose technological trajectories grow fast may have identified new valuable veins of technological development, or may have triggered what historian Nathan Rosenberg called "compulsive sequences" of solutions to technical bottlenecks (Rosenberg, 1977). In that case, firms with the assimilative capabilities needed to exploit such opportunity-rich veins of technological development during the early phase of their expansion will have a distinct advantage over firms that do not (yet) have those capabilities. Therefore, irrespective of a firm's position within the network, we expect its inventive performance to be boosted when a firm's direct contacts are generating technological knowledge at a fast pace. By the same token, we expect a firm's technological production to decelerate as the firms in its ego-network generate fewer technological inventions.

Hypothesis 1: The more a firm has the capability to assimilate knowledge from technologically prolific contacts, the higher the firm's inventive performance.

Inter-firm networks tend to organize as "small worlds" – networks characterized by dense clusters separated by structural holes and received research has shown that the inventive potential of firms is enhanced when they are positioned at the junction between clusters (Burt 1992; Baum *et al.*, 2000; Obstfield, 2005; Uzzi & Spiro, 2005). The established explanation for this finding is that firms that broker across clusters are exposed to a broader variety of knowledge compared to firms that are squarely positioned within a dense cluster (Burt 2004; Fleming, Mingo, & Chen, 2007). While access to diverse knowledge flows is the causal mechanism deemed responsible for the beneficial effect of brokerage on inventive performance, however, extant research has almost exclusively focused on the structural holes inherent in the network of collaborative relationships among firms (McEvily & Zaheer, 1999; Baum *et al.*, 2000; Ahuja, 2000). Our contention is that the structural holes argument can be straightforwardly applied to our model of inter-firm knowledge networks.

In our proposed model of knowledge network, dense clusters correspond to "sub-networks" within which firms have developed an extensive capacity to learn from and build on each other's knowledge. Hence, the more a firm is embedded within a dense cluster in the knowledge network, the more it will draw from redundant and mutually interwoven technological trajectories. Conversely, a firm that is positioned at the junction between clusters is one that has developed the capabilities needed to assimilate knowledge across loosely related technological trajectories and, therefore, one that can recombine more varied knowledge inputs. For these reasons, our second hypothesis is that:

Hypothesis 2: The more a firm brokers structural holes in the knowledge network, the higher the firm's inventive performance

Our proposed model of inter-firm knowledge networks also suggests that there is a fundamental limit to the advantages of brokering structural holes, however. Building on the premise that networks act as knowledge "pipes" in an organizational field, the brokerage argument posits that firms bridging otherwise unconnected clusters are exposed to a broad spectrum of diverse knowledge inputs, which enhances their inventive performance. But as we argued, firms are not mere recipients of the knowledge that accrues to their network position. To the contrary, to rip the benefits of knowledge diversity firms must be able to effectively integrate that knowledge into their technological base. As mentioned, this means that firms must either reconfigure elements of the assimilated knowledge to fit their technological base or, conversely, that they must reconfigure elements of their technological base to fit the assimilated knowledge (Todorova & Durisin, 2007). Firms can handle only limited recombinant complexity (Fleming, 2001; Fleming & Sorenson, 2004), however, and the complexity of such recombinant efforts increases with knowledge variety.

Based on these arguments, we contend that when a firm brokers between technologically prolific contacts these limits are soon reached, as the recombinant complexity to be handled goes through the ceiling when multiple distinct technological trajectories develop at a fast pace. Accordingly, we expect brokering firms to be able to realize the knowledge-variety benefits inherent in their network position only to the extent that their contacts generate new knowledge relatively slowly. Conversely, we reckon that firms should be able to more easily exploit even very fast technological developments made by their contacts when the latter are tightly related to one another in a dense cluster and, hence, their technological trajectories overlap to a greater extent. In the latter case, the new knowledge generated by a focal firm's contacts should be easier for the firm to recombine and, thus, the advantage of a technologically prolific ego-network should be ripped more fully. These arguments lead us to our third hypothesis.

Hypothesis 3: The more technologically prolific are a firm's contacts, the more the presence of structural holes among them hampers the firm's inventive performance; by the same token, being connected to technologically prolific contacts is especially beneficial when these contacts are densely connected among each other.

Hypothesis 1 claims that a firm's inventive performance depends on the inventive performance of the firms in its ego-network. Extending this claim to the level of the inter-firm network suggests that there may be an endogenous tendency of firms to partition into either technologically prolific or technologically sluggish clusters. Our reasoning is as follows. As said, in our conceptualization a dense cluster identifies a sub-network wherein firms have developed a capacity to effectively build on each other's technological knowledge. Therefore, any increase in the inventive performance of a firm embedded within a dense cluster will enhance the inventive performance of all other firms in the cluster. As a result, the volume of new recombinant inputs these other firms are able to assimilate and recombine, and hence the volume of knowledge output that they are able to pump back into the cluster will increase. This will fuel a self-reinforcing cycle of knowledge generation within the cluster. By the same reasoning, however, a decrease in the inventive performance of a firm embedded within a dense cluster will reduce the knowledge inputs available to all the other firms in cluster, which may engender a negative self-reinforcing cycle. As a result of these opposing dynamics, we conjecture that the densely clustered areas of the network will have a tendency to partition into either technologically prolific or technologically sluggish. Furthermore, we expect that because the prolific clusters generate more and more knowledge, part of which will spill over to other areas of the network, they will become increasingly central and coalesce towards the core of the network. By the same argument, we expect that because sluggish clusters are bound to contribute increasingly less to the technological development of the organizational field, they will become confined in the periphery of the knowledge network. These arguments lead to two interrelated hypotheses.

Hypothesis 4a: Densely connected clusters of firms exhibit either a predominantly high or a predominantly low inventive performance

Hypothesis 4b: The technologically prolific clusters tend to be located towards the core of the network; conversely, the sluggish clusters tend to be located towards the periphery of the network

DATA AND MEASURES

The semiconductors field

To test our hypotheses, we chose to focus on the inter-firm knowledge network of semiconductor device designers and manufacturers over the period 1975-2001. This setting lends itself to analyzing how the inventive process unfolds through inter-firm knowledge networks for multiple reasons. First, the semiconductors field is characterized by rapid technological growth and the competitiveness of semiconductor firms is to a considerable degree dependent on their inventive performance (Macher, 2006). Second, technological growth has been largely cumulative (Hall & Ziedonis, 2001), which made it possible for the field to progressively stabilize in the face of fast-growing technological developments. Third, public disclosure of technologies is a standard practice among designers and manufacturers of semiconductors (Braun & MacDonal, 1978); therefore, the locus of learning and innovation lies in the inter-firm network of knowledge flows. Fourth, patent data provide abundant, detailed, and quite reliable information about the dynamics of technological growth in this context.

While most studies of the semiconductor field focused exclusively on US-based firms, we chose to expand consideration to European and Asian firms as well. The reason is that although many among the important semiconductor firms are indeed based in the US, the expansion of the industry "would no doubt have been smaller if the technological and scientific leadership of the United States had not come under challenge by the emergence of international competition" (Langlois & Steinmueller, 1999: 19). By concurrently analyzing the role of European, Asian, and US firms, we therefore hope to provide a more complete and accurate representation of the inventive process in the semiconductors field.

Similarly, we reasoned that focusing exclusively on so-called Integrated Device

Manufactures (IMD), as many extant studies have done, could result in too narrow a definition of the semiconductors field for the purpose of our research. IMDs are firms specialized in the design, manufacture, and commercialization of semiconductor devices and, undoubtedly, they play a key role in the semiconductor field. However, for the purpose of understanding the process of technological growth, two more organizational forms need to be taken into consideration as well: so-called “fabless” companies, which specialize exclusively in designing semiconductor devices and contract out their manufacture; and, large, vertically integrated firms (such as IBM, Motorola and Philips), which produce semiconductor devices primarily to incorporate them in other products. While the strategic position of IMDs, fabless, and vertically integrated firms are somewhat distinct, inter-firm learning is plentiful among all three organizational forms and all three contribute in important ways to the development of technological knowledge applied to semiconductors. Accordingly, in our study we expand consideration to all three organizational forms.

Sample and Data collection

We analyze the semiconductors field between 1975 and 2001. To select our sample, we used the following procedure. We first identified a list of semiconductor device designers and producers through authoritative specialized market data providers[3]. We then used the Directory of Corporate Affiliation to detect the subsidiaries of each firm in the sample. Financial and economic data about these firms and their subsidiaries were retrieved from three data sets: COMPUSTAT Global, COMPUSTAT North America, and Osiris. Further, we consulted business directories (*Hoovers Premium*, Who owns Whom US, UK and Asia), industry sources

[3] We relied on the annual *Profiles of IC Manufacturers and Suppliers* published by Integrated Circuit Engineering Corporation (ICE), a semiconductor industry market research firm, on the online reports published by Gartner Research ,by *Electronic Business* and through data Semiconductor Industry Association.

(ICE annual volumes) and prior research (Hall & Ziedonis, 2001) to identify each firm's founding date, and to establish whether a firm should be categorized as "integrated device manufacturer", "fabless", or "vertically integrated producer". All remaining organizational types (i.e., foundries, components producers, and service providers), were categorized as "others".

To collect patent data on this sample of firms, we used two independent data sets: the NBER Patent and Patent Citations Data Set (Hall, Jaffe, & Trajtenberg, 2002), and the National University of Singapore's NUS Patent Data Set (Lim, 2004)[4]. Within these data sets we identified semiconductor-related patents based on the list of USPTO patent subclasses developed by Macher (2006). We first counted the number of patents granted in any of these subclasses to each of the identified firms and subsidiaries, and we selected only on those firms that had at least one patent each time window, and a minimum of 5 patents in our observation period.

Finally, consistent with our inclusive definition of the semiconductor field, we chose to include in our sample all firms that accounted for at least 1% of the total patents in the selected semiconductor-related subclasses. By this selection criterion we cast a wide net, with the end to achieve two related goals. First, consistent with the view that technological knowledge grows cumulatively and interdependently across firms, we wanted to include in our analysis as large as possible a share of the firms participating in the inventive process. Second, by guaranteeing that only negligible sources of technological development are left outside our sample, we met a necessary condition for correctly estimating network autocorrelation models (Lenders, 2002), a point to which we will return later. Summing up, as a result of the procedure just described we were able to retrieve an unbalanced panel of financial, economic, and patent data for 156

[4] The updated NBER data set comprises information on all the patents granted by the US Patent and Trademark Office (USPTO) between 1975 and 2001. The information in the NUS data set is largely overlapping with that in the NBER data set, and its coverage period extends to 2004. Concurrently using the NBER and NUS data sets made it possible to cross validate our data. Precisely, we retrieved detailed patent data for all our semiconductors companies over the period 1975-2001 and we traced forward citations to these patents up to the end of 2004.

semiconductor firms over the period 1975-2001.

Tracing the inter-firm knowledge network

Inter-firm knowledge networks played a key role in the semiconductor field since its inception. As semiconductor firms soon recognized that the value of learning from competitors was far greater than the costs of knowledge leaking, a policy of extensive knowledge codification and disclosure became commonplace in the field, particularly through practices such as patenting and publication of product fact sheets (Braun & Macdonald, 1978: 54-55). The strengthened IPR regime that characterized the last couple of decades of the industry did not diminish the importance of networks of practice, and evidence shows that semiconductor firms still copiously learn "from the inventive efforts of others" (Langlois & Steinmueller, 1999: 22).

As suggested by Zahra and George (2002), we analyzed the evolving pattern of cross-firm patent citations to trace the capacity of a firm to assimilate technological knowledge from other firms. A vast body of research has employed patent data to analyze the process of technological diffusion (see, among others, Henderson & Cockburn,1994; Fleming, 2001; Rosenkopf & Nerkar, 2001). Patent data have received so much attention because they provide detailed large-scale information about several interesting aspects of patented inventions, and because they offer complete coverage over relatively long time periods in computerized form. A key bit of information is contained in the so-called patent's *prior art*. A focal invention's prior art indicates all the existing inventions from which the focal invention has drawn, and thereby it provides an informed account of the knowledge recombination entailed in generating the focal invention. Numerous scholars used this information to investigate technological knowledge diffusion at various levels of analysis, including inventors (Nerkar & Paruchuri, 2005), organizational subunits (Miller *et al.*, 2007), firms (Mowery, Oxley & Silverman, 1996), and countries (Jaffe, Trajtenberg, & Henderson, 1993). In this paper, we used patent citation data to trace the evolving network through which technological knowledge diffuses and gets creatively recombined among semiconductor firms.

While patent citation data have been usefully employed as indicators of technological knowledge diffusion in a wide variety of empirical studies, two validation studies have shown that patent citations should be regarded as a "valid but noisy measure of technology spillovers" (Jaffe, Fogarty and Banks 1998: 183; Jaffe, Trajtenberg, & Fogarty, 2000); accordingly, analyses based on patent citation data must be designed and interpreted with vigilance. The literature has identified two main limitations associated with using patent citation data.

The first limitation is that although citing all relevant prior art is a legal obligation for a patent applicant, "... inventors, their employers, attorneys, and patent examiners all have input to the citation process" (Miller *et al.*, 2007: 314). As a consequence, the choice of which patents (not to) cite may be partly strategic, for example reflecting an attempt to prevent litigations. Taking a patent's citations as indicative of the technological knowledge utilized by an inventor to generate that specific invention may therefore result in both type I and type II errors (Alcacer & Gittelman, 2006). To gauge the magnitude of this problem in the context of our data, we exploited data available since 2001, which disentangle the patent citations made by an inventor from those added during the patent examination process. We devised an empirical test[5] to compare the pattern of intrafirm citation pattern using inventor citations only and using all

[5] Precisely, we randomly sampled 10% of the patents granted to each firm in our study population in year 2001. This resulted in a subsample of 540 patents, accounting for 2285 citations to patents generated by the firms in our population. To check if this subsample was representative of the patents in our sample in the same year we performed a t-test of both the mean number of backward citations and of the number of claims made per patent: neither variable differed across the two groups. We then coded each citation in the subsample to indicate whether it was added by the examiner or, conversely, it was reported by the inventor. On these basis, we built two separate networks. One network was constructed based on all citations; the other network was based on the citations made by the patent's inventor(s) only. We used a Quadratic Assignment Procedure to assess the degree of similarity (or difference) among the two resulting networks (Simpson, 2001). The results showed that the network based on the patent citations made by the inventors is 0.832 correlated ($p<0.001$) with the network based on all citations.

citations. The similarity in citation patterns between inventor-only and all citations, is much higher than that reported for most of the studies for which this check has been made (Alcacer & Gittelman, 2006; Criscuolo & Verspagen, 2008). Therefore, we feel confident that the patent citation data we observe in our study reflect with reasonable accuracy actual patterns of inter-firm technological knowledge assimilation.

The second main limitation associated with using patent citation data is that because not all technological knowledge gets patented, not all technological knowledge flows can be captured by patent citations. While this limitation is inherent in patent data, we think that this is unlikely to engender a significant problem in the context of our study. Indeed, one reason for choosing to test our arguments in the semiconductors field is that in that context, the propensity to codify and patent technological inventions is much higher than in most other sectors (Hall & Ziedonis, 2001); moreover, research has shown that semiconductor firms customarily analyze the patents granted to other firms to benchmark their own products (Di Biaggio, 2007) and to discover new avenues of technological development (Lim, 2007)[6]. As a consequence, the share of technological knowledge diffusion captured by patent citations is likely to be larger in our study than in most studies where patent citations have been usefully utilized.

It should also be noted that unlike many extant studies, our approach does not rest on the assumption that patent citations measure all the technological knowledge diffusing among semiconductor firms. Rather, our study rests on the much weaker assumption that a firm's capacity to assimilate knowledge from another firm is proportional to the frequency with which the former has drawn from patents generated by the latter in the (recent) past. In the next section, we discuss in detail how we use patent citation data to measure firms' assimilative capacities.

[6] Lim (2007), in his study of the development of copper interconnect technology for semiconductor chips, provides evidence that all players in the field extensively sourced knowledge from IBM technical documents, scientific publications and patents. IBM was considered, in the late 90s, the forerunner in that technological area.

Instantiating our network model

Having described the data, we can now turn to developing the visual illustration of Figure 1 into a network model. Formally, a network N_t during time interval t is a four-tuple, $N_t = \langle J_t , L_t, V_t, A_t \rangle$, which consists of a finite set of nodes, $J_t = \{i,\dots,k,q,\dots,j\}$; a finite set of arcs (i.e., directed ties) between the nodes, $L_t = \{l_{ik,t}, \dots, l_{qj,t}\}$; a function $V_t(.)$ mapping arcs on pertaining arc values h (i.e., tie weights); and, a function $A_t(.)$ mapping nodes on node values. Nodes represent firms, and their values represent firms' inventive performance during t; arc value, w_{ij}, represents the capacity of the right-hand subscript firm to assimilate knowledge generated by the left hand firm; hence, "loops" represent the extent to which a firm has developed a capacity to exploit its own internal knowledge trajectory (Nerkar & Paruchuri, 2005).

As said, our goal is to model the network through which technological knowledge gets assimilated and recombined by the firms operating in the semiconductor industry from 1975 and 2001. Consistent with prior studies (e.g., Schilling & Phelps, 2007), to capture the evolution of this inter-firm knowledge network we partitioned the observation period into nine 3-years interval. We use patents application year to assign patents to each time window. As it has been argued, a time interval of three years roughly corresponds to the time that a semiconductor product remains up to date; for example, each next-generation computer memory lasts approximately 2.5 years (Stuart & Podolny, 1996). Hence, in our model, w_{ijt} indicates i's capacity to assimilate the inventions generated by j during a 3-year window t. We reasoned that w_{ijt} should be comparable across both larger firms, which cite thousands of patents every year, and smaller ones. To this end, we followed a consolidated practice in network research (e.g., Burt, 1992), and row-normalized the firm-to-firm citation matrix; hence, w_{ijt} expresses the *proportion* of citations i

makes to patents generated by *j* during *t*, and $w_{ijt} \in [0, 1]$. Unlike collaboration networks, our data make it possible to account for the fact that w_{ijt} is in general asymmetric. Hence, in our model, *i*'s capacity to assimilate *j*'s knowledge can be different from *j*'s capacity to assimilate *i*'s knowledge. Another advantage of our data is that we can treat w_{ijt} as a continuous variable, making it possible to account for the fact that the degree of assimilative capacity of a focal firm varies across contacts depending on the level of experience the focal firm has accumulated with each of them. Therefore, w_{ijt} reflects the current assimilative capacity of *i vis-à-vis* its contacts *j* as a function of how frequently *i* has drawn knowledge from *j* in the past.

We reckoned that ideally, w_{ijt} should reflect the fact that the capacity of a firm to assimilate knowledge from other firms develops over time as a function of both learning by experience (Cohen & Levinthal, 1990; Fleming 2001) and forgetting (de Holan, Phillips, & Lawrence, 2004). That is, the greater is the experience *i* has accumulated with drawing knowledge from *j* up to *t*, the greater should be w_{ijt}; however, the less recent is this experience, the lower should be its marginal contribution to w_{ijt}. To account for these facts, we adopted three alternative operationalizations of w_{ijt}: (i) we operationalized w_{ijt} as the proportion of citations *i* has made to patents generated by *j* during *t*. This operationalization emphasizes the importance of recent experience, while it disregards the experience accumulated in earlier time periods. (ii) we operationalized w_{ijt} as the proportion of citations *i* has made to *j*'s patents from 1975 (the beginning of our observation period) up to *t*. This operationalization accounts for both recent and less recent experience, and it assumes that they both contribute equally to a firm's current absorptive and recombinant capacities (i.e., it disregards forgetting). (iii) we operationalized w_{ijt} as the proportion of citations *i* has made to *j*'s patents from 1975 up to *t*, where the weight of each citation decreases at a decreasing rate with the time elapsed between the citation and *t* (Burt, 2000)[7]. As (iii) adheres most closely to received theory on the dynamics of experience and forgetting, we utilize it for the analyses reported in the main text.

As a consequence of these choices, we characterize the evolution of our inter-firm knowledge network as a time series of nine subsequent weighed and directed networks. Against the backdrop of this model, we can now explicate the measures entailed in our hypotheses.

Measures

Dependent variable. To measure our dependent variable, *firms' inventive performance*, we followed a consolidated tradition (e.g., Alcacer & Gittelman, 2006; Sampson, 2007; Yayavaram & Ahuja, 2008) and calculated for each firm a citation-weighed patent count. For an invention to be patented, it must consist of knowledge that is new, non trivial, and useful; furthermore, if a patented invention engenders subsequent inventions, it will be cited. Accordingly, a widely used and validated indicator of technological inventiveness consists of counting the number of patents granted to a firm, weighed by the number of citations each of this patents received within a given time interval. As an indirect validation that this measure well quantifies inventive performance, citation-weighed patent counts were found to be very highly correlated with both the economic and the social value of inventions (Trajtenberg, 1990; Harhoff, Narin, Scherer, & Vopel, 1999). Furthermore, citation-weighed patent counts were directly validated as a measure of inventive performance by studies in which surveys were administered to inventors and technical experts (Albert, Avery, Narin, & McAllister, 1991; Jaffe *et al.*, 2000). In our study, to measure the inventive performance of a firm we counted the number of patents the firm generated during each of the nine 3-year time intervals described earlier, weighed by the

[7] Formally: ii) $w_{ijT} = \sum_{t=1}^{T} w_{ijt}$ and iii) $w_{ijT} = \sum_{t=1}^{T} \frac{1}{T-t+1} w_{ijt}$, where weights decrease with time at a decreasing rate. (i) and (ii) provide an upper and a lower bound with respect to (iii); hence, we used them as robustness check.

number of forward citations (excluding self-citations) each patent received within 5 years from its application[8].

Independent variables. To model a firm's *contacts' inventive performance*, we adapted models of network autocorrelation. Network autocorrelation models are used to estimate the extent to which the outcome variable of a focal node in a network varies as a linear combination of the outcome variables of its network contacts (Leenders, 2002). Typically, to each of the network contacts is assigned a weight, reflecting the strength of its connection to the focal node. For example, network autocorrelation models have been used to estimate the extent to which the attitude of a focal person on specific political issues co-vary with the attitudes of her friends, where the influence exerted by each friend is assumed proportional to the strength of her friendship to the focal person (Mardsen & Friedkin, 1993). We use an autocorrelation model to estimate the degree to which the inventive performance of a focal firm *i* during *t* is influenced by the inventive performance of its network contacts, *j*; furthermore, we weigh the influence of each contact firm by our measure of tie strength described above, w_{ijt},. Following Doreian, Teuter and Wang (1984) and Leenders (2002), network autocorrelation can be computed as:

$ay_{it} = \sum_{\substack{i=1 \\ i \neq j}} w_{ijt} y_{jt}$, where y_{jt} is a vector indicating the inventive performance of each contact firm, *j*, belonging to the ego-network of focal firm *i*; w_{ijt} is a weight specifying the impact that the inventive performance of each contact *j* has on the performance of the focal firm, *i*. Let us clarify the measure with a simple example. Let us consider the network in Figure 1. Let 20 and 70 be the inventive performance of node A and B, respectively. Let us suppose that node C has cited node A 20 times and node B 30 times. The measure of contacts inventive performance for node C will

[8] The number of forward citations received throughout the entire period by each firm is highly correlated with the citations obtained with a 5 years threshold (Spearmans' rho correlation of the rank orders turned out to be as high as 0.982). This indicates that truncating citation counts at 5 years from application provides a robust measure.

be computed as follows: $Contacts\ Inventiveness_{Ct} = \frac{20}{20+30} \times 20 + \frac{30}{20+30} \times 70 = 50$

To gauge the extent to which a firm brokers *structural holes*, we took the additive inverse of Burt's well known measure of constraint (Burt 1992: 54-55). The constraint score was computed as follows: $c_{ij} = (p_{ij} + \sum_q p_{iq} p_{qi})^2$, for $q \neq i, j$. The total in parentheses is the proportion of *i*'s relations that are directly or indirectly invested in connection with contact *j* (Burt, 1992). The network constraint measure approaches 0 when ego networks are unconstrained and reaches the maximum of 1 when they are fully constrained. All network-analytic measures were computed with UCINET VI (Borgatti, Everett, & Freeman, 2002).

To measure how the effects of structural holes on a firm's inventiveness change with the inventive performance of its contacts, we constructed a multiplicative term. To reduce multi-collinearity, we mean-centered the constituent variables (Aiken, West, & Reno, 1991).

Controls. We controlled for a number of variables that may affect firms' inventive performance. Centrality in a network of knowledge flows has been shown to affect firms' innovative performance (Powell *et al.* 1996). To control for this effect, we computed a firm's network centrality as the number of direct contacts in its ego network (Ahuja, 2000).

A firm's inventive performance may vary according to a number of firm specific covariates. A firm's *size* may affect both the scope and the scale of its technological activities (Henderson & Cockburn, 1994). We measure firm size as the natural logarithm of the number of employees. *Age* may affect a firm's inventive performance because older firms tend to be more inert than younger ones (Cyert & March, 1963). We measure age as firm age at the middle year of each time window. *R&D intensity* has been often been used as a measure of input in the process of technological generation (Ahuja, 2000; Katila & Ahuja, 2002). We computed *R&D*

intensity as the ratio between a firm's R&D expenditure and its net sales[9]. Previous studies have hypothesized that the economic performance of a firm may have both positive (Katila & Ahuja, 2002) and negative (Cyert & March, 1963) effects on its inventive performance. We measure a firm's economic performance by its *ROA*. We use the lagged number of patents granted to each firm in each time window to control for *knowledge base size* effects (Yayavaram & Ahuja, 2008). A firm that produces general technologies, which are useful in several application sectors, is more likely to be cited than a technological specialist. To control for the degree of *generality* of a firm's knowledge base, we used Hall *et al.*'s generality index (2002). Prior research has shown that technological diversification (Hoskisson & Hitt, 1988) can have a positive effect on inventiveness, as it increases the opportunities for exploiting knowledge internally, or a negative effect, because the top management team in a diversified firm may have a poorer understanding of R&D and be less likely to invest in R&D. To control for these effects, we computed a firm's *technological diversification* as one minus the sum of the squared share of patents in each USPTO patent class. Forward citation frequencies may vary across technological sectors and subsectors independently of firm-specific factors. For example some technological areas may have inherently higher growth potential than others (Dosi, 1982). To control for these effects we use a *technological fertility* variable (Ahuja, 2000), defined as the average citation rate of each technology class in which a firm has patents in a given year, times the number of firm's inventions that belong to that technology class in that year. This is then summed over all technology classes for each firm. Since the focus of this study is on the inter-firm knowledge network, all our measures are computed excluding *self-citations*. Yet, in our models, we control for the extent to which a firm relies on its own previous knowledge, we computed for each firm in each time interval the ratio of backward self-citations to total citations.

[9] When R&D, sales or employment data were not available, we used imputation techniques to estimate the value based on existing data using STATA *ice* function. A total of 74 values were imputed.

Finally, we account for a number of country-, type- and time -varying effects. Differences may exist across countries in patenting propensity. This possibility was controlled for by a dummy variable *US*, which was set to one if a firm's country is the United States, and zero otherwise. Similarly, we constructed a set of three dummy variables to indicate if a firm is an integrated device manufacturer (*IDM*), a vertically integrated firm (*Vertically integrated*), or a fabless firm (*Fabless*). The category Other was used as reference category. We also introduced a set of *time windows dummies*, to control for exogenous shocks and other time-varying effects.

RESULTS

The unit of analysis in our study is the firm-period and, thus, the data have an unbalanced panel form. The dependent variable is a count variable which takes on only nonnegative integer values. The linear regression model is inadequate under these conditions because the distribution of residuals will be heteroscedastic and non-normal. Moreover, the variable presents overdispersion (rejection of Poisson model at $p<0.0001$). Since a Hausman test rejects random effects specification at $p<0.0001$, we used a fixed-effects negative binomial regression analysis (Cameron & Trivedi, 1986).

To visualize the networks, we used NetDraw (Borgatti *et al.*, 2002). Figure 2 provides a representation of the network of knowledge flows in the semiconductor field between 1975 and 2001.

Insert Figure 2 about here

We report summary statistics and correlations in Table 1.

Insert Table 1 about here

To assess potential problems of multi-collinearity, we calculated variance inflation factors (VIF) based on the pooled data. VIF values ranged from 1.51 to 7.75 (mean 3.78). Conventionally, VIF scores are regarded as indicative of multicollinearity problems when their value is greater than 10.

For twelve firms we have data for no more than one three-year window. Because our analyses are based on fixed-effect estimations of inventive performance, these firms had to be dropped. Lastly, for twenty-four firm-period data points we were able to gather information about firms' patenting activity, but not about their sales, R&D expenditure, and employment. This is because those firms were technologically active but not (yet) publicly traded. Given that these observations did not meet the requirements for imputation, we decided to drop them as well. As a consequence of these choices, our econometric analyses are based on an unbalanced panel of 132 firms, yielding a total of 633 firm-period observations.

Insert Table 2 about here

In Table 2, we report the results of our analyses. Model 1 is a baseline model including a set of covariates that according to received research, may affect firms' inventive performance. Of these, firms' age, R&D intensity, size of patent portfolio, technological generality, technological diversification do indeed have a significant positive effect on firms' inventiveness. Furthermore, as one would expect, the results indicate that firms that have developed a competence in technological areas characterized by greater technological fertility tend to be more inventive. All other control variables show little or no association with our dependent variable. In model 2, we introduce the variable *contacts inventive performance*, to gauge the extent to which a firm has focused its assimilative capacity on technologically prolific contacts. In line with hypothesis 1, the inventive performance of a focal firm is positively and significantly associated with its ability to assimilate knowledge from inventive contacts (β=*0.40; p<0.001*). In other words, the more the firms on which a focal firm has focused its assimilative capacity in the past become technologically prolific, the more the focal firm itself becomes technologically prolific.

Model 3 introduces a variable measuring the extent to which firms broker structural holes in the network of inter-organizational knowledge flows, which we hypothesized to be positively related to firms' inventive performance (H2). In line with received theory, the effect of structural holes brokerage is positive and significant (β=*0.42; p<0.001*). Hence, firms that develop the capabilities needed to assimilate knowledge from across unrelated clusters exhibit superior inventive performance. Model 4 introduces the interaction term between *structural holes* and *contacts inventive performance*. Hypothesis 3 was that the positive effect of having developed an assimilative capacity across structural holes declines with the extent to which a firm's contacts produce new knowledge. Also this hypothesis is corroborated, as the coefficient of the interaction term is negative and statistically significant (β=*-0.22; p<0.05*). The log-likelihood statistics provide evidence that each model provides a statistically significant improvement in fit.

Insert Figure 3 about here

In the graph reported by Figure 3, we use the estimated regression coefficients to visually represent the interaction effect between contacts' inventiveness and structural holes brokerage, on inventive performance. For ease of presentation and interpretation, we used the log-linear form of the negative binomial models (i.e., where the log of the conditional mean function is linear in the estimated parameters). As can be seen, the effect of brokering structural holes on a firm's inventive performance is positive when the firm's contacts generate technological knowledge relatively slowly. However, the more rapidly a firm's contacts develop their technological trajectories the harder it becomes to recombine knowledge from them and, eventually, the effect of brokering structural holes turns negative. Thus, for a firm at the mean of both constituent variables, a one standard deviation increase in the inventive performance of its contacts leads to a 42 percent increase in its own inventive performance. For the same firm, a one standard deviation increase in structural holes leads to a 35 percent increase of inventive performance. Yet, for a firm with a high focus on technologically prolific contacts a one standard deviation increase in structural holes reduces its inventive performance by 24 percent.

We also hypothesized that because within dense clusters firms either mutually enhance or mutually hinder each others' inventive performance, the network should tend to partition into clusters of technologically prolific and technologically sluggish firms (H4a). Furthermore, we argued that the prolific clusters should progressively coalesce towards the center of the knowledge network, while the sluggish clusters should remain confined in the periphery (H4b). Given that a formal statistical test of these hypotheses is hard to conceive, we chose to investigate them by visual inspection - a methodological strategy that has been gaining increasing scientific footing in social network analysis (Moody, McFarland, & Skye Bender-deMoll, 2005). To bring evidence in support of our hypotheses, we used the Gopher drawing algorithm implemented in NetDraw. The Gopher function draws the nodes of a network closer together in a 2-dimensional space based on a multi-dimensional scaling algorithm, so that nodes that are strongly tied to one another and to common third parties are clustered together. If our hypotheses are correct, this algorithm should show prolific firms as clustered together towards the center of the graph, while sluggish firms should cluster at the fringe. Conversely, assuming that the clustering structure of the network is unrelated to firms' inventive performance implies that technologically prolific and technologically sluggish firms should be randomly scattered across the represented space. Because these hypothesized outcomes presume that the network has stabilized, we focus our attention on the last window in our observation period (1999-2001).

Insert Figure 4 about here

In Figure 4, black triangles represent the 25% least inventive firms and hollow squares represent the 25% most inventive firms. All remaining firms and all ties have been removed. In line with Hypothesis 4a, firms do group together in either prolific or sluggish clusters, and to us it seems quite evident that this phenomenon goes well beyond what could be expected from a random process. Similarly, as predicted by Hypothesis 4b, the technologically prolific firms have to a very large extent coalesced towards the center of the network, while the clusters of sluggish innovators are mostly confined in peripheral network positions.

Sensitivity analyses

We assessed the robustness of our results in several ways. As previously described, we used a network operationalization based on the weighted sum of the inter-firm citation patterns, where assimilative capacities are assumed to depreciate at a decreasing rate over time. We also computed the measure in two extreme cases of instantaneous depreciation and no depreciation: results hold. To check the robustness of our dependent variable, we also operationalized inventive performance as simple patent counts, regardless of how many citations these patents received. Both the direction and the significance of the estimates of interest are consistent with those presented above. Similar results to those presented in Table 2 are obtained when we adopt a SIC-based measure of diversification (i.e., a dummy valued 1 if the firm has other business lines than semiconductors, 0 otherwise) or when we exclude from the analysis the controls with highest VIF. We also ran the model lagging all non-network variables by one time period and estimated "pre-sample" fixed effect estimators (Blundell, Griffith, & Van Reenen, 1995). Our findings are robust to these changes.

DISCUSSION AND CONCLUSIONS

It is by now widely recognized that a firm's inventive performance depends on its ability to assimilate and recombine externally generated knowledge. Also, most scholars agree that which and how much external knowledge a firm is able to assimilate depends on its position within the network of knowledge flowing throughout a field. The present article improved our understanding of these important notions in multiple ways. The vast majority of received research on these topics has focused on the knowledge accessed through, and funneled by, a particular form of collaboration, typically R&D alliances. We expanded the focus of this line of inquiry by analyzing the role of the knowledge network delineated by firms' assimilative capacities. Namely, we studied the knowledge network that weaves together firms' technological trajectories as they build upon each other's patented knowledge. Such knowledge networks do not necessitate direct interaction or collaboration among firms. Nevertheless, our contention was that they shape the patterns of inter-firm knowledge diffusion to an important extent.

Based on this presumption, we conjectured that received theory on the role of inter-firm network structures could be usefully extended to illuminate how knowledge networks affect firms' inventive performance. This conjecture was corroborated, as we showed that the brokerage of structural holes is an important determinant of firms' inventive performance also in the context of inter-firm knowledge networks. While our hypothesis was based on received theory, the implications that derive from it are somewhat different. Structural holes theory claims that brokering structural holes in a collaboration network provides access to more heterogeneous knowledge, which in turn explains why actors in brokering positions tend to be more inventive (Burt, 2004). Reflecting the prevalent focus of network researchers on inter-firm collaborations, extant studies have taken this principle to imply that in order to become more inventive, firms should seek to collaborate with partners that don't collaborate with each other (Baum *et al.*, 2000; Ruef, 2002). Our study, by contrast, used the structural holes argument to emphasize that in order to become more inventive, firms must develop the organizational capabilities needed to assimilate knowledge from firms that are unable to learn from each other. To the extent that these organizational capabilities can be built exclusively by means of direct collaboration ties, the two perspectives offer a similar recommendation. Nevertheless, firms assimilate useful technological knowledge generated by other firms in many other ways, including reverse-engineering, reviewing patents, scanning newsletters and technical journals, and attending professional workshops and conferences (Brown & Duguid, 2002; Di Biaggio, 2007). Indeed, a distinguishing trait of the knowledge-based economy is that a large share of knowledge gets diffused through codified documents, such as the patents analyzed in this paper (Carnabuci & Bruggeman, forthcoming). Hence, distinguishing the precise causal mechanisms that link inter-firm knowledge networks to the process of technological invention seems relevant from the perspective of both positive and normative theory building.

In addition to enlarging the empirical content of received theory, our study contributed a number of novel theoretical insights. On a general level, we argued and showed that a vantage point can be gained by explicitly recognizing that the network-level process of knowledge diffusion and the firm-level mechanisms of knowledge assimilation and recombination are inherently interwoven. Extending a well-know metaphor in the literature on inter-firm networks, we argued that knowledge networks consist of both "pipes", along which knowledge diffuses throughout a field, and "wellsprings", i.e. firms that continuously generate and renew the knowledge circulating through the network. By conceiving and modeling knowledge networks in this way, we were able to derive and empirically test three original hypotheses about the inventive process. First, we demonstrated that the more a focal firm focuses its assimilative capacity on technologically prolific firms, the more it will itself become technologically prolific. Hence, in addition to the structural conditions characterizing a firm's position within the knowledge network, the inventive performance of a firm at any point in time, is a function of the inventive performance of the firms in its ego-network at that point in time.

Second, we shed new light on the important debate about the putative effects of closed and brokering network structures (Brass *et al.*, 2004), making it possible to better understand and qualify received network-structural explanations. In particular, we showed that due to their limited recombinant capacity, the extent to which firms can rip the structural benefits inherent in brokering network positions varies inversely with the rate at which firms' contacts generate new knowledge. Namely, for firms positioned within highly innovative regions of the knowledge network, the complexity of recombining knowledge across structural holes is so high that knowledge brokerage becomes detrimental. Conversely, firms embedded within dense clusters are significantly better at exploiting even very fast technological developments made by their contact firms, as their technological trajectories overlap to a greater extent.

Third, concurrently treating the firm and the network level made it possible to provide a nontrivial insight on the understudied issue of "how collective outcomes might be generated in inter-organizational networks" (Provan *et al.* 2007: 480). Specifically, we showed that because within dense clusters the knowledge generation process is driven by self-reinforcing cycles, inter-firm knowledge networks tend to partition into clusters of technologically prolific and technologically sluggish firms. Furthermore, the clusters of technologically prolific firms tend to coalesce towards the center of the network, while the clusters of technologically sluggish firms exhibit a tendency to remain confined towards the periphery. Scholars have recently began to investigate the effects of core-periphery structures on firms' inventive performance, and results indicate that it is a line of inquiry worth further investigation (Cattani & Ferriani, 2008). *Albeit* supported by no more that suggestive evidence, our findings indicate that cross-level and co-evolutionary dynamics play a crucial role in the relation between core-periphery structures and firms' inventive performance.

These results have important practical implications, most notably regarding how companies can manage their knowledge network to enhance their inventive performance. Our findings show that a firm's inventive performance is driven by its capability to assimilate the technological knowledge generated and made publicly available by other firms. The results presented suggest that an important way to develop such capability is to systematically monitor and follow the inventive activity of technologically prolific firms. Managers should invest to strengthen their firms' monitoring capabilities, as well their ability to predict which firms are going to be more technologically prolific. To both these ends, quantitative analytical frameworks and measures such as the ones advanced in this study may serve as a useful guide.

Our result concerning how the effects of structural holes on a firm's inventiveness change with the inventive performance of its contacts, suggest the intriguing idea that there are two different strategies through which firms can benefit from the knowledge circulating in their field, and enhance their inventive performance. One path, ideal for firms that are either good or lucky enough to position themselves within clusters with high potential for technological growth, is to focus on exploiting and developing the existing trajectories within the cluster. This, in turn, suggests that firms surrounded by technologically prolific contacts may be better off by favoring the emergence of knowledge sharing across their contacts. This notion resonates in the words a vice-president of AT&T used to describe the early stage of the semiconductor field: "We realized that if this thing [the transistor] was as big as we thought, we couldn't keep it to ourselves and couldn't make all the technical contributions. It was our interest to spread it around. If you cast your bread on the water, sometimes it comes back angel food cake" (Langlois & Steinmueller, 1999: 22). A second possible path to increasing a firm's inventive performance, conversely, pertains to firms that find themselves locked within technologically sluggish clusters. For these firms, our analyses suggest that the only way to significantly improve technological performance is to broker knowledge from remote regions of the knowledge network. Both strategies entail both risks and costs. On the one hand, seeking network closure in order to handle fast technological growth is likely to entail disclosure of valuable private knowledge and exposure of one's resources to severe risks of expropriation and free riding. On the other hand, brokering knowledge from unrelated areas of the knowledge network means incurring the high fixed costs associated with learning outside one's knowledge base, as well as the legitimacy costs associated with dis-embedding and re-embedding knowledge across domains. How to strike a balance between the benefits and costs of these two strategies is a question that will certainly prove hard to answer for managers and organizational students alike; yet, addressing this question seems highly relevant for both.

Our study has some worth mentioning limitations, which in turn signal potentially fruitful research opportunities. A first limitation is that by focusing on the knowledge network signaled by patent citations, we focused away from the collaborative ties that may be involved in such flows. Received theory suggests that collaboration networks, and more generally the communities of practice that develop across organizations, are a subset of the broader knowledge network through which firms access technological knowledge (Brown & Duguid, 1991; 2001).

But, to the best of our knowledge, no one has yet investigated empirically the exact relationship between these different types of learning strategies. Manipulating knowledge and collaboration networks is likely to require different strategies and capabilities, as the creation and dissolution of collaboration ties may depend on different mechanisms, and entail different kinds of inertial pressures, than do the creation and dissolution of partner-specific assimilative capacities. Future research should be designed to better disentangle these differences. Are there differences in the extent to which firms invest in one kind of network instead of the other? What implications do these different strategies entail for the inventive performance of both individual firms and the fields they are embedded in? Currently, we do not have an answer to these questions.

A second, related limitation of our study is that it heavily relies on patent data, which, as we explained in detail, are known to be valid yet noisy proxies of both technological generation and technological diffusion. While for large-scale studies like ours there hardly exist alternative measures of those constructs, valuable insights and a further validation could be gained by complementing our patent-based analyses with process-oriented qualitative investigations of the interwoven dynamics of knowledge diffusion, absorption and recombination that putatively explain our findings. Also, it would be important to investigate the extent to which the mechanisms we studied extend into the process of technological innovation. While our focus in this paper was confined to the generation of technological knowledge, the process of technological innovation requires that technological knowledge be turned into commercially valuable products. As we have not addressed this topic in the paper, we currently do not know if and to what extent our arguments can be extended to explain performance differentials in technological innovation at large. Future research should investigate this possibility.

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FIGURE 1

Example of knowledge combinative patterns across firms

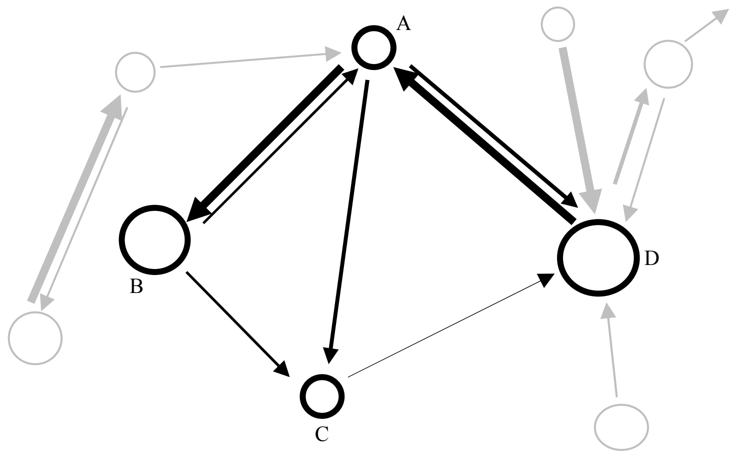
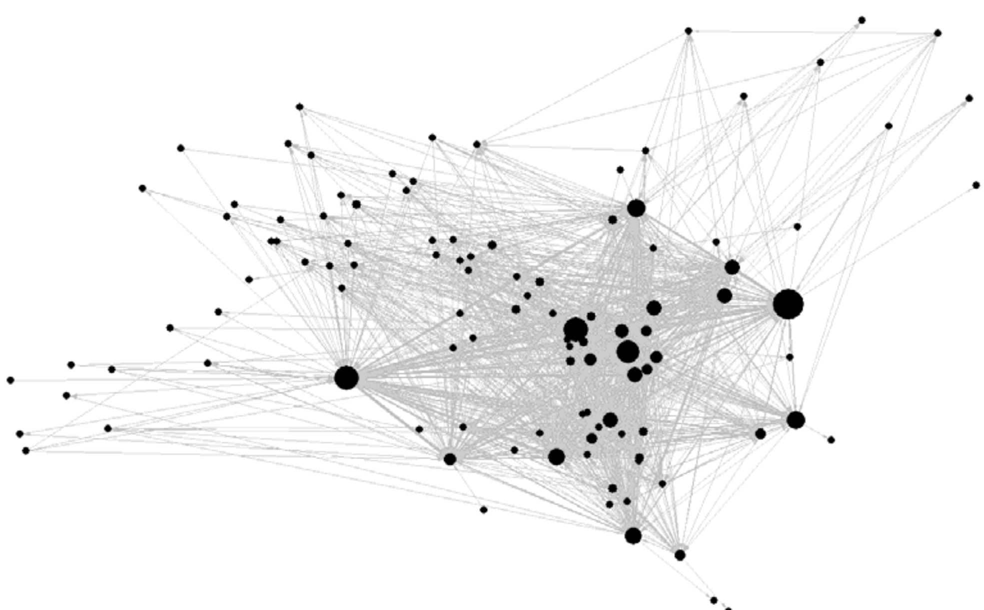


FIGURE 2

Network of knowledge flows between semiconductor players 1975-2001[10]



[10] 10% weakest ties have been removed to ease graph interpretation.

FIGURE 3

Interaction effect between structural holes and contacts inventive performance

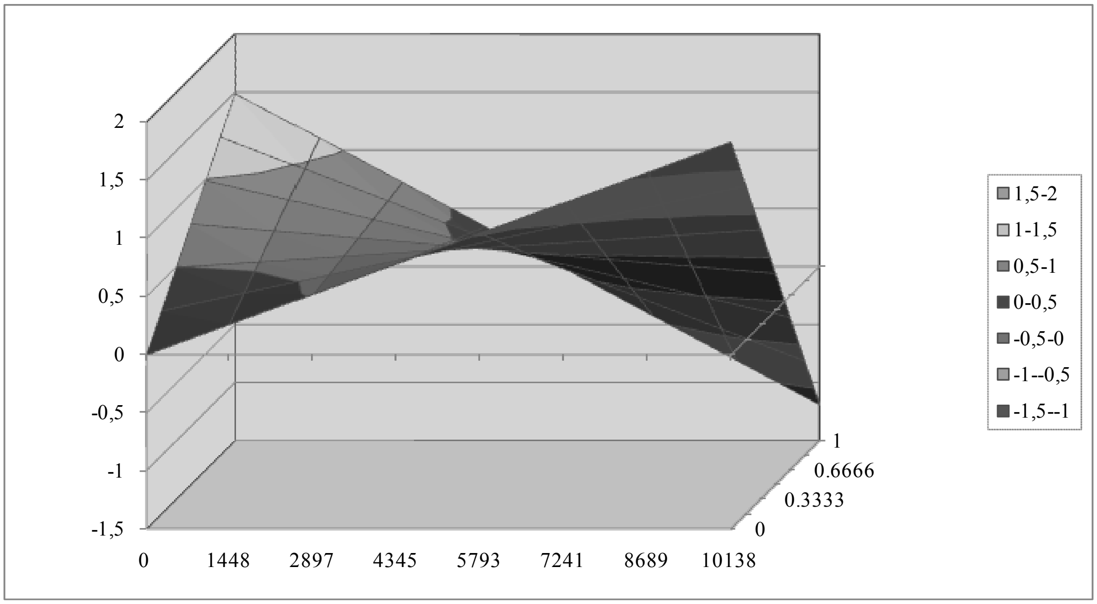


FIGURE 4

Period 1999-2001: Clusters of high-growth and slow-growth firms

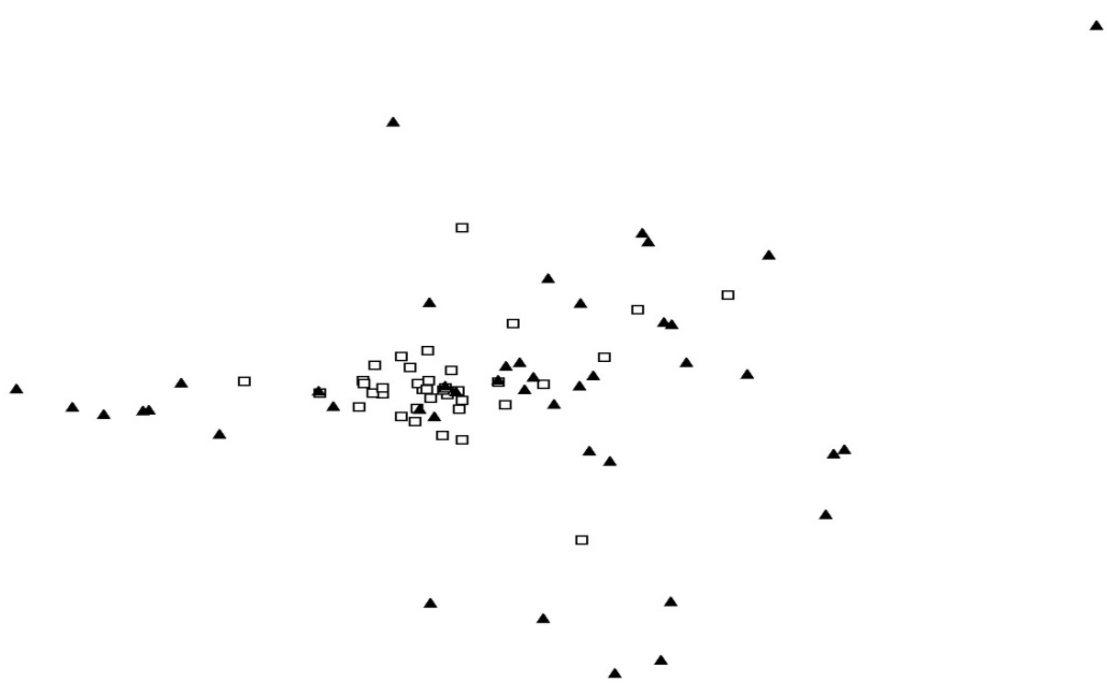


TABLE 1

Correlation matrix (significance levels in parenthesis)

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Inventive Performance	1																
2	Contacts Inventive Performance	0.36*	1															
3	Structural Holes	0.16*	0.26*	1														
4	Performance	0,06	0,00	-0,01	1													
5	Age	0.48*	-0,02	0,08	0,11	1												
6	Size	0.51*	0,04	0.19*	0.17*	0.58*	1											
7	R&D Intensity	-0,02	0,02	0,02	-0,04	-0,02	-0,06	1										
8	Knowledge Base Size	0.81*	0.19*	0.21*	0,07	0.59*	0.57*	-0,03	1									
9	Knowledge Diversification	0.42*	0.28*	0.41*	0.14*	0.44*	0.64*	-0,07	0.47*	1								
10	Knowledge Base Generality	0.14*	0.23*	-0,04	0,09	0,07	0.21*	0,01	0,04	0.30*	1							
11	US	-0.27*	-0,10	-0,09	-0,06	-0.39*	-0.35*	0,03	-0.32*	-0.35*	-0,09	1						
12	Technological Fertility	0.84*	0.29*	0.15*	0,06	0.57*	0.49*	-0,02	0.80*	0.42*	0,09	-0.34*	1					
13	Centrality	0.48*	0.12*	0.39*	0,09	0.60*	0.56*	-0,05	0.24*	0.21*	-0.15*	-0.27*	*0.58	1				
14	Selfcites	0.13*	0,04	0.14*	0,05	0.22*	0.26*	-0,04	0.19*	0.31*	0.13*	-0.16*	0.24*	0.29*	1			
15	Fabless	-0.2*	0,02	0,05	-0,05	-0.37*	-0.12*	-0,01	-0.23*	-0.12*	-0.12*	0.13*	-0.21*	-0.23*	-0.16*	1		
16	Vertically Integrated	0.21*	0,06	0,08	0,07	0.52*	0,32	-0,03	0.31*	0.54*	0.24*	-0.56*	0.42*	0.41*	0.28*	-0.18*	1	
17	IDM	-0,09	-0,05	0,01	0,06	-0,18	0,00	0,04	-0,10	-0,08	0,00	0.17*	-0.15*	-0,02	-0,08	-0,51	-0,33	1
	Mean	334,86	1781,33	0,64	-0,02	23,22	7,22	0,75	81,88	0,51	0,23	0,77	1143,88	20,89	0,11	0,30	0,16	0,38
	S.D.	937,85	1962,00	0,20	0,41	21,50	2,54	11,14	201,86	0,35	0,21	0,42	3342,02	25,67	0,17	0,46	0,36	0,49
	Min	0	0	0	-8,23	0	0,48	0,00	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Max	7158	10138,5	1	0,66	109	12,90	278,53	1621,00	0,99	1,00	1,00	27525,34	130,00	1,00	1,00	1,00	1,00

* p <0.05

TABLE 2

Results of Negative Binomial Regression for Number of Citations (FE)

	Model 1	Model 2	Model 3	Model 4
Constant	-0.40*	-0.43*	-0.49**	-0.46*
	(0.19)	(0.18)	(0.19)	(0.18)
Contacts Inventive Performance		0.40**	0.39**	0.42**
		(0.06)	(0.06)	(0.06)
Structural Holes			0.42**	0.33**
			(0.10)	(0.11)
Prolific contacts X Structural Holes				-0.22*
				(0.09)
Centrality	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Performance	-0.07	-0.04	-0.05	-0.05
	(0.06)	(0.06)	(0.06)	(0.06)
Age	0.21*	0.25**	0.24**	0.24**
	(0.09)	(0.08)	(0.08)	(0.08)
R&D intensity	0.07*	0.07*	0.06*	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
Knowledge Base Size	0.25**	0.25**	0.26**	0.24**
	(0.04)	(0.03)	(0.03)	(0.03)
Knowledge Base Generality	0.47**	0.42**	0.42**	0.44**
	(0.07)	(0.07)	(0.07)	(0.07)
Knowledge Base Diversification	0.84**	0.77**	0.74**	0.75**
	(0.07)	(0.07)	(0.07)	(0.07)
Selfcites	0.11**	0.13**	0.11**	0.11**
	(0.04)	(0.04)	(0.04)	(0.04)
Technological Fertility	0.05†	0.05†	0.05†	0.05†
	(0.03)	(0.03)	(0.03)	(0.03)
Fabless	0.10	0.01	-0.04	-0.04
	(0.12)	(0.12)	(0.12)	(0.12)
VI	-0.20†	-0.21†	-0.27*	-0.25*
	(0.12)	(0.12)	(0.12)	(0.12)
IDM	-0.07	-0.15	-0.26*	-0.24*
	(0.12)	(0.12)	(0.12)	(0.12)
US	0.09	0.10	0.09	0.07
	(0.08)	(0.08)	(0.08)	(0.08)
Period dummies	included	included	included	included
Observations	631	631	631	631
Number of cusip2	132	132	132	132
Log likelihood	-2144.23	-2123.46	-2113.7	-2108.68
Increase in log likelihood		20.77**	9.76*	5.02*

Standard errors in parentheses

† significant at 10% * significant at 5% ** significant at 1%

Essay 3

THE IMPACT OF INTRAFIRM NETWORKS AND KNOWLEDGE BASE HETEROGENEITY ON FIRMS' INNOVATION

ABSTRACT

This paper explores how a firm's internal collaboration network affects its ability to integrate knowledge in the generation of new technologies. Building on the knowledge-based view of the firm, we contrast the relative efficacy of densely connected and brokered (i.e., cluster-and-bridge) structures, showing how the costs and benefits of both structures vary depending on the heterogeneity of a firms' knowledge base. To put our arguments to a test , we use a novel dataset describing the patent co-authorship networks of 121 semiconductor firms over the period 1992-1998. The results offer support to our predictions and they yield important implications for the design of organizations.

Key words: Knowledge integration, intra-organizational networks, innovation, knowledge based theory.

A central tenet of the knowledge-based perspective on organizations is that the ability to effectively integrate the specialized knowledge of individual organizational members is critical to a host of organizational capabilities (Kogut & Zander, 1992; Grant, 1996a; Grant 1996b; Brusoni, Prencipe & Pavitt, 2001). In particular, the question of how firms should organize their knowledge integration activities in order to favor technological innovation is at the core of the academic debate (e.g., Allen, 1977; Tushman, 1978; Kogut & Zander, 1996; Argyres & Silverman, 2004). Received research on this topic univocally indicates that firms' internal collaboration networks play a pivotal role in shaping both processes and outcomes of knowledge integration (Hansen, 1999a; Tsai, 2001; Reagans & Zuckerman, 2001; Reagans & McEvily, 2003). However, opinions concerning which collaborative structure is most conducive to innovation diverge widely. In this paper, we address perhaps the most fundamental of such outstanding academic controversies: Is innovation favored by densely connected, team-like collaboration networks or, conversely, by brokered, cluster-and-bridge ones?

Densely connected collaboration structures (Figure 1a) are argued to boost knowledge integration and innovative productivity by reducing the risks of knowledge sharing, by providing richer information channels, and by facilitating the diffusion of tacit coordination practices among organizational members (Coleman, 1988; Clark & Fujimoto, 1991; Iansiti, 1995). By contrast, brokered collaboration structures (Figure 1b) are argued to enhance innovation because they feature both dense clusters, wherein the abovementioned advantages apply, and bridges, which economize on redundant information channels (Allen, 1986; Burt, 2004; Fleming *et al.* 2007). To date, much empirical evidence has been found supporting both arguments, and the controversy remains largely unresolved. One important reason for this stalemate may be that extant studies have primarily focused on unveiling the distinctive advantages of each network structure. Our goal, by contrast, is to explain under which conditions dense and brokered collaborative structures facilitate innovation. This goal poses two requisites. First, we need a theory that specifies how both the costs and benefits of dense and brokered structures vary as a function of specific contingent conditions. Second, to empirically test the predictions of such theory, we need data on the internal collaboration network of a large number of firms (and, of course, on their innovative productivity).

Insert Figure 1 about here

In this paper, we build on the knowledge based perspective on organizations to argue that the relative costs and benefits of knowledge integration in closed and brokered collaboration networks depend on the heterogeneity of a firm's knowledge base (Hansen, 1999a; Birkinshaw, Nobel & Ridderstrale, 2002; Nickerson & Zenger, 2004; Rodan & Galunic, 2004). To test our conjectures, we use a novel, longitudinal dataset describing the evolution of the intra-organizational collaboration networks of 121 technologically active firms in the worldwide semiconductor industry between 1992 and 1998. We use patent-based indicators to measure firms' knowledge output and co-patenting as an indicator of collaborative ties among inventors (Nerkar & Paruchuri, 2005; Fleming, Mingo & Chen, 2007). Further, we use "whole network" measures to characterize densely connected and brokered structures (Hansen, 1999a; Reagans & Zuckerman, 2001; Reagans & McEvily, 2003; Nerkar & Paruchuri, 2005).

Our analyses provide several insights on the relative efficacy of dense and brokered structures in fostering the creation of new technological knowledge. As we argue and show, on average brokered structures tend to enhance firms' innovation output, while dense networks tend to depress it. Thus, having a cluster-and-bridge collaboration network positively affects firms' innovation relative to having a more homogeneous tie distribution.

Conversely, firms with dense collaborative structures are on average less innovative than firms whose inventors operate more autonomously from one another. However, these relationships are altogether reversed for firms whose knowledge base is heterogeneous and, hence, complex. As a consequence, the higher the heterogeneity of the knowledge base to be integrated in the process of technological production, the more dense collaboration structures turn out to boost innovation. Furthermore, as knowledge exchange requirements increase with knowledge heterogeneity, bridges are easily overloaded, making brokered structures particularly inefficacious.

This article aims to make a threefold contribution. First, it extends recent studies in the knowledge based view of the firm (Nickerson & Zenger, 2004) by advancing a theoretical framework that explains the relative efficiency of alternative organizational forms in the creation of new knowledge. Most studies using a knowledge based perspective have explained the choice of hierarchies versus market-based modes by articulating the efficiency of vertically integrated organizations in economizing on knowledge exchange (Demsetz, 1988; Conner, 1991; Prahalad & Conner, 1996) or in facilitating knowledge transfer (Kogut & Zander, 1996; Grant, 1996a; Kogut & Zander, 1996). Our study extends this line of research arguing that the same logic may well apply to illuminate choices regarding the internal organization of a firm's knowledge generation activities. Second, our approach makes it possible to gain new insights on the role of cohesive and brokered collaborative structures in the generation of new knowledge. Apart from few cases (Hansen, 1999a; Rodan & Galunic, 2004) extant models of firms' intra-organizational structures focused either on structural features or on knowledge characteristics to explain the process of knowledge generation. By contrast, this paper shows that choices regarding collaborative structure that support the process of integration and the heterogeneity of a firm's knowledge base are inherently intertwined and much can be learned by more carefully exploring the main and relative effect of these mechanisms. Third, the paper concurrently answers the quest for empirical work in the knowledge based perspective (Foss, 1996) and a recent call for empirical studies at the network level that investigate the effect of whole network properties on collective outcomes (Provan, Fish & Sydow, 2007: 465).

The paper is structured as follows. In the first section, we advance a view of the firm as a knowledge integrating institution, and develop a theoretical rationale for a framework that encompasses both collaborative forms and knowledge base characteristics. On these premises, we develop a set of testable hypotheses that relate the development of new corporate knowledge to structural properties of the organization and to the heterogeneity of a firm knowledge base. Next, we present our dataset, which describe the evolution of intra-firm collaborative activity of 121 semiconductor players between 1992 and 1998. We then present and discuss the results of our empirical analyses. In the last section, we elaborate on the limitations and implications of our study and suggest the next steps that need to be undertaken to improve this line of research.

THEORETICAL FRAMEWORK

Firms as knowledge integrating systems

A central insight of the knowledge based perspectives on organizations is that the role of firms is to integrate and apply "existing knowledge to the production of goods and services" (Grant, 1996a: 112). Building unique combinations (Schumpeter, 1939; Nelson & Winter, 1982) or synthesis (Henderson & Clark, 1990) of distinct and rapidly evolving domains of knowledge, firms produce goods and services, which strengthen their competitive position (Kogut & Zander, 1992; Grant, 1996b).

Two main arguments have been advanced to support the efficiency of firms in knowledge exchange relative to markets. The first argument posits that hierarchies exist essentially to avoid, or economize on, knowledge exchange and transfer (Demsetz, 1988; Conner, 1991; Conner & Prahalad, 1996), emphasizing the firm's capacity to exercise authority in directing members' actions. The other view claims that hierarchies exist instead to facilitate knowledge transfer (Arrow, 1974; Kogut & Zander, 1992; 1996; Nonaka, 1994; Nahapiet & Goshal, 1998), emphasizing the firm's capacity to support the creation of shared language and identity. As Hakanson (2006: 19) notes: "firms themselves may form epistemic communities of their own right, conferring on their members the means by which knowledge can be effectively combined and integrated".

The difference between economizing and facilitating knowledge transfer in the knowledge integration process is rigorously discussed in Nickerson and Zenger (2004). In their original work, the authors articulate the knowledge based advantages of markets, authority based and consensus based, and predicts that a match would occur between these alternatives and the complexity of knowledge needed to solve the problem, based on the associated *benefits* and *costs* in governing the knowledge integration process. Similarly, other studies suggest that fit between governance choices and specific problem characteristics significantly improves problem solving performance (Marengo, Dosi, Legrenzi & Pasquali, 2000; Macher, 2006).

If the match between knowledge type and boundary choices may be usefully applied to explain a firms' ability to generate knowledge and capabilities (Nickerson & Zenger, 2004; Macher, 2006), this logic may well apply to illuminate choices regarding the internal organization of a firm's knowledge generation activities. Technological innovation represents a prototypical example of problem solving that requires the integration of different knowledge trajectories and the generation of new knowledge (Fleming, 2001). Following our reasoning, the relative effect of different intra-organizational choices on a firms' ability to develop new technologies is likely to vary as a function of specific contingent conditions. Yet, before investigating how the fit between internal organizational structure and knowledge type impacts innovative productivity, it is critical to define what knowledge attribute is fundamental to discriminate the cost and benefits of different collaborative forms in technology development. We take up this issue in the following section.

Knowledge base heterogeneity

The production of increasingly complex technological goods requires the integration of highly heterogeneous and divergent technological trajectories (Dosi, 1982; Tushman & Rosenkopf, 1992) and the heterogeneity[1] of combinatorial inputs (Hargadon & Sutton, 1997) is strategically pivotal in the development of technological innovations (Fleming, 2001; Fleming & Sorenson, 2004). In principle, the set of potential inputs and, a fortiori, the set of combination of those inputs, is infinite. Individual cognitive limitations, though, limit the maximum amount of heterogeneity that individual inventors can handle simultaneously in technological search (Fleming, 2001). As a result, individuals and groups tend to research locally and specialize within specific domains.

While maintaining a balance between the depth of knowledge acquired by specialization and the breadth of insights emerging from heterogeneous disciplines is extremely hard for individual inventors, it becomes much easier when inventors can draw on others' knowledge and experience in addition to their own (Yayavaram & Ahuja, 2008). Inventors do certainly learn from peers in many ways, and interacting with colleagues within

[1] In general terms, a firm's knowledge base heterogeneity refers to the breadth of knowledge applied by the firm as it carries out its production tasks. Applying this definition to the task of technological innovation, a firm is characterized by low knowledge base heterogeneity when its search for recombinant inputs is confined within a restricted number of technology domains. On the contrary, the knowledge base of firms that customarily recombines knowledge inputs across many distinct technology domains is high. In the NK jargon, knowledge heterogeneity refers to the N distinct technological components searched. Hence, increasing heterogeneity implies increasing complexity.

firms' laboratories and research units is certainly a fundamental source of ideas (Brown & Duguid, 1991). To favor knowledge exchange between inventors', firms devise formal and informal collaborative structures (Allen, 1986; Argyres & Silverman, 2004). The benefits and costs of different collaborative structures in the generation of new technological knowledge are likely to vary depending on the type of search needed to integrate increasingly heterogeneous bodies of knowledge.

Matching knowledge base heterogeneity and collaborative structures

Literature has extensively debated how firms should organize their innovative activities to favor the integration of heterogeneous knowledge (e.g., Allen, 1977; Tushman, 1978; Brown & Duguid, 1998; Kogut & Zander, 1996; Argyres & Silverman, 2004; Schmickl & Kieser, 2008). Received research on this topic univocally indicates that firms' internal collaboration networks play a pivotal role in shaping both processes and outcomes of knowledge integration (Hansen, 1999a; Tsai, 2001; Reagans & Zuckerman, 2001; Reagans & McEvily, 2003). However, opinions concerning which collaborative structure is most conducive to innovation diverge widely. Research emphasized that two different designs are generally adopted.

On one side, firms may favor the emergence of densely connected, team-like collaboration networks (Figure 1 A), where dense formal and informal ties connect individuals belonging to diverse specialties and functions (Clark & Fujimoto, 1991; Iansiti, 1995; Hansen, 1999a). The distribution of collaborative ties is homogeneous (Figure 1A), so that all members in the organization have approximately a similar number of connections. Cohesive structures generate new knowledge by maximizing the amount of transpecialist understanding through trust and integrating practices (Postrel, 2002). On the contrary, firms may adopt brokered, cluster-and-bridge[2] collaborative structures (Figure 1 B), characterized by separate teams and units connected by boundary spanning roles (Tushman, 1978; Allen, 1986; Burt, 2004; Fleming *et al.* 2007). While in the case of cohesive networks the distribution of collaborative ties is homogeneous, in this case the number of connections of the individuals is highly skewed, with few individuals, called brokers or gatekeepers, accounting for the majority of the connections and knowledge exchanges in the network. Brokered networks preserve a high level of specialist knowledge and rely on boundary spanning roles to connect specialized island of mutual ignorance (Postrel, 2002). A variety of results has been found supporting the positive effect of either form on firms' ability to develop new knowledge, and the controversy remains theoretically and empirically open.

Extant results may be reconciled through our matching perspective (Nickerson & Zenger, 2004). The benefits and costs of different network structures is likely to be contingent on the way these structures deal with knowledge formation hazards at increasing levels of input heterogeneity. To put it simply, to favor the development of new technological solutions, network structures need to be matched in a discriminating way to the heterogeneity of the knowledge that is continuously integrated and produced, based on their associated *costs* and *benefits* in the process of knowledge integration (Nickerson & Zenger, 2004; Rodan & Galunic, 2004).

With this picture in mind, we can develop a set of testable hypotheses that relate the collaborative structure of organizations to firms' ability to integrate knowledge into novel solutions. In addition, we can make conjectures regarding the efficiency of different structures when organizational members build on increasingly heterogeneous knowledge inputs. Our contention is that, by deepening our understanding of the matching between the heterogeneity

[2] Literature (Watts & Strogartz, 1999; Watts, 1999; Fleming *et al*., 2007) refers to these structures as small world. We define them "brokered" or "cluster-and-bridge" to relax the stringent requirement of small world networks, and to extend this characterization even to small networks, or to network that are partially disconnected. A similar approach is adopted by Schilling and Phelps (2007).

of the knowledge base and the collaborative structure that supports technological problem solving, on the other side, we can advance a more encompassing framework that explains under which conditions densely connected or brokered collaborative structures facilitate innovation.

HYPOTHESES

We described cohesive collaborative networks as characterized by dense formal and informal ties connecting individuals belonging to diverse specialties and groups. Knowledge integration through a dense network of collaboration surely entails costs, which should be taken into account when evaluating the efficiency of a collaborative network. In particular, maintaining a dense knowledge exchange structure among organizational members implies that a great amount of time and energy be committed to preserving existing collaboration ties and the relational knowledge they entail (Hansen, 1999b). Such costs increase with the number of relationships. In addition, dense collaboration networks imply collective, lengthy knowledge integrating procedures and decision cycles (Cross, Erlich, Dawson, & Erferilich, 2008) which reduce the amount of time for creative activities and increase the likelihood of engaging in redundant knowledge transfer (Tsai, 2001). Finally, cohesive networks also entail higher social costs in innovative activities, as maintaining overly closed relationships stifles experimentation (Uzzi & Spiro, 2005), reduce the ability to react to errors (Hoopes & Postrel, 1999) and encourage groupthink, so that people will generate fewer ideas (Hunt, Ogden & Neale, 2003).

These arguments suggest that, in absolute terms, building and maintaining cohesive networks is necessary only when innovation requires the transfer of complex knowledge across technological domains (Hansen, 1999a). Thus, controlling for the degree of knowledge heterogeneity of problem solving inputs, the relative efficiency of a sparse network in the innovative process will be superior to the efficiency of overly connected collaborative structures:

Hypothesis 1: Ceteris paribus, the greater the density of a firm collaborative structure, the lower the firm's innovative output.

The prior hypothesis suggest that, holding constant the heterogeneity of a firm's knowledge base, economizing on tie formation and maintenance cost is positively related to firms' knowledge generating performance. Yet, once the number of ties within an organization is fixed, how should these relationships be distributed? Prior research on small world networks (Watts & Strogartz, 1998; Watts, 1999; Cowan & Jonard, 2003; Uzzi & Spiro, 2005; Fleming, Juda & King, 2007) emphasized the benefits of structures of collaborative structures, characterized by localized pockets of dense connectivity bridged by a few boundary spanning individuals (Figure 1B), *vis à vis* structures where ties are homogeneously distributed.

From the perspective presented in this paper, brokered structures – i.e. cluster and bridge networks -, present two fundamental efficiency advantages in the integration of knowledge into new technologies. On the one hand, separate clusters tend to increase efficiency by favoring transfer of specialized, embedded knowledge within each cluster. Individuals embedded within different clusters search locally on a delimited area of the problem solving space and specialize in a specific area (Schilling & Phelps, 2007). In each cluster, the development of shared understanding of problems and solutions greatly facilitates communication and further learning (Brown & Duguid, 1991). Similarly, the creation of common practices eases solution search and evaluation (Hansen, 1999; Uzzi & Spiro, 2005; Schelling & Phelps 2007; Fleming *et al.*, 2007). At the same time, the presence of external bridges across clusters make it possible to economize on knowledge transfer (Schilling & Phelps, 2007; Watts, 1999) and reach out to a number of network members, while preserving knowledge integrity and speed of transmission. This results in an efficient division of innovative labor (Arora & Gambardella, 1994), whereby specialization is efficiently managed by specialized individuals in separate clusters, and transfer and integration is guaranteed by brokers (Burt, 1992), also called gatekeepers (Tushman, 1978) or system integrators (Brusoni *et al.*, 2001; Brusoni & Prencipe, 2006). Based on these arguments, we predict that, holding constant the heterogeneity of a firm knowledge base, cluster-and-bridge structures, in absolute terms, will favor the process of knowledge integration into new technologies:

Hypothesis 2: Ceteris paribus, the more a firm collaborative structure combines high clustering and high reach, the greater the firm's innovative output.

When an organization builds upon highly heterogeneous disciplines, the challenges of knowledge integration become increasingly severe (Postrel, 2002), as extensive specialization results in a situation where each individual is largely ignorant of the activities of his fellows. Thus, the associated costs and benefits of the abovementioned structures are likely to vary depending on the heterogeneity of a firm knowledge base.

Let us start with cohesive collaborative networks. We argued that, holding constant the degree of variety in a knowledge network, densely connected structures bear heavy maintenance and social costs that reduce the efficiency of the innovative process. Yet, in collaborative structures leverage increasingly heterogeneous competencies, maintenance costs are increasingly offset by the knowledge transfer benefits that cohesive structures guarantee (Postrel, 2002).

On the one hand, heterogeneity increases the benefits of knowledge transfer through dense relationships. Cohesive structures create shared norms and practices that speed knowledge transfer (Nonaka, 1994) and facilitate the transfer of increasingly heterogeneous and complex knowledge. As Hansen (1999a; 1999b) suggests, when knowledge is increasingly complex and difficult, strong and redundant ties are fundamental to maintain speed and integrity of knowledge search and transfer. On the other hand, increased heterogeneity reduces the social costs of cohesive structures. The coexistence of heterogeneous learning heuristics and diverse knowledge can counteract the staleness of closed collaborative structures, which tend to recycle information (Simonton, 1999). As Fleming and colleagues suggest (2007: 448), “the non redundant information that heterogeneous agents possess and that would naturally bring to the collaboration will be of less value unless their social isolation is ameliorated by the collaboration within a locally cohesive structure”. If this is the case, variety of knowledge in problem solving would reduce, in principle, the likelihood of redundant conversation an feedback processes, and thus reduce the relative duplication and maintenance costs of denser structures.

Accordingly, we expect that, in organizations whose innovative activity requires the integration of highly heterogeneous domains, the integration and coordination benefits resulting from cohesive network will compensate the social and maintenance costs:

Hypothesis 3: Ceteris paribus, knowledge base heterogeneity will positively moderate the relationship between the density of a firm collaborative structure and the firm’s innovative output.

Hypothesis 2 states that, holding constant the level of knowledge input heterogeneity, brokered collaborative structures favor innovation as they concurrently enhance knowledge transfer within clusters and economize on knowledge transfer through dedicated boundary spanning roles. Both advantages offered by “cluster-and-bridge” structures need to be discussed when the problem solving activity demands the integration of increasingly heterogeneous knowledge.

On one side, insulating tendencies will emerge when increased heterogeneity will result in densely connected clusters of homogeneous knowledge bridged by a few individuals. Clusters will push specialists to pursue the challenges of their specific fields rather than the common objective of knowledge generation (Allen, 1986). Stronger integrating practices will be required to overcome these tendencies, at additional costs. The effectiveness of knowledge transfer within clusters will be offset by a stronger demand of integration across clusters. Thus, the benefits of knowledge transfer will be diminished. In addition, knowledge heterogeneity can decrease the advantages of coordination via boundary spanning roles. Brokers are fundamental to preserve the connectivity of the organizational structure and to allow access to diverse bodies of knowledge residing in different subgroups (Burt, 1992). Yet, as the heterogeneity of knowledge increases, brokers face a number of challenges. In highly diverse knowledge environments, brokers not only guarantee the translation and transfer of knowledge across groups, but truly participate to both communities' innovative activity (Brown & Duguid, 1998) and develop technological competencies at the interface between different areas (Brusoni & Prencipe, 2006). As a consequence, they become cognitively and relationally overloaded by the amount and variety of information that they need to transmit (Fleming *et al.*, 2007). In addition, extreme variety in the network increases the hazard of brokers' opportunism, as very few individuals in the structure can develop similar integrating skills (Nickerson & Zenger, 2004). For example, brokers may have the incentive either to assimilate knowledge from different groups and profit individually from that knowledge or to strategically shape the heuristics that guide search to their interest. Finally, as in diverse environments brokers develop stronger integrating and translation capabilities and embody unique combinations of knowledge profiles, it becomes increasingly difficult for firms to retain them. All these reasons diminish the fidelity of knowledge translation and reduce the relative efficiency of coordination through dedicated bridges.

For this reason, we argue that, at increasing levels of knowledge heterogeneity, brokered, cluster-and-bridge network will display higher costs than organizations where ties are homogeneously distributed. Such cost would result in a negative impact on firms'innovative performance. This leads to our last hypothesis,

Hypothesis 4: Ceteris paribus, collaborative structures that combine high clustering and high reach will exhibit higher innovative output at low levels of knowledge base heterogeneity; conversely at high levels of technological heterogeneity, the more a corporate inventors' network combines high clustering and reach, the lower the firm subsequent innovative output.

METHODS

Sample and data collection

To test our predictions, we focused on the intraorganizational networks of inventors of 132 firms in the worldwide semiconductor industry. Research and development units are the locus of technological innovation, and the design of appropriate collaborative structure is fundamental to facilitate the process of knowledge integration into new solutions (Hansen, 1999a; Reagans & Zuckerman, 2001; Argyres & Silverman, 2004; Nerkar & Paruchuri, 2005).

We decided choose the semiconductor industry as the setting for this study for a number of reasons. First, it is a setting characterized by continuous technological change, and firms' ability to continuously and speedily generate new knowledge is absolutely crucial to command a competitive advantage (Langlois & Steinmueller, 1999). Second, semiconductor device producers vary greatly with respect to the collaborative structure of their innovative activities (West, 2002): organizational forms range from fully centralized to extremely dispersed structures with divisional and factory scientific and engineering labs, and the use of *ad hoc* roles to guarantee communication and feedback at various juncture and intersection points in the R&D process (Okimoto & Nishi, 1994: 190). Thus, the issue of how to choose between alternative forms of collaboration is critical to firms' ability to generate new knowledge. Third, the increasing miniaturization of semiconductor devices paved the way to the emergence of new downstream markets knowledge (Di Biaggio, 2007), so that the effective integration of specialist knowledge related to different application fields into new solutions is absolutely crucial to keep up with the technological frontier. Fourth, patenting is extensively carried out in the semiconductor industry, and all relevant players patent their invention at the USPTO (Hall & Ziedonis, 2002), thus making it easier to reconstruct the pattern of intrafirm collaboration and to monitor firms' problem solving activity.

We focus on the semiconductor industry in the period between 1992 and 1998. To select our sample, we used the following procedure. We first identified a list of semiconductor device designers and producers through authoritative specialized market data providers[3]. We then used the Directory of Corporate Affiliation to detect the subsidiaries of each firm in the sample. Financial and economic data about these firms and their subsidiaries were retrieved from three data sets: COMPUSTAT Global, COMPUSTAT North America, and Osiris. Further, we consulted business directories (*Hoovers Premium*, Who owns Whom US, UK and Asia), industry sources (ICE annual volumes) and prior research (Hall & Ziedonis, 2001) to identify each firm's founding date, and to establish whether a firm should be categorized as "integrated device manufacturer", "fabless", or "vertically integrated producer". All

[3] We relied on the annual *Profiles of IC Manufacturers and Suppliers* published by Integrated Circuit Engineering Corporation (ICE), a semiconductor industry market research firm, on the online reports published by Gartner Research, by *Electronic Business* and through data Semiconductor Industry Association.

remaining organizational types (i.e., foundries, components producers, and service providers other than fabless), were categorized as "others".

To collect patent data on this sample of firms, we used two independent data sets: the NBER Patent and Patent Citations Data Set (Hall, Jaffe & Trajtenberg, 2001), and the National University of Singapore's NUS Patent Data Set (Lim, 2004). The updated NBER data set comprises information on all the patents granted by the US Patent and Trademark Office (USPTO) between 1975 and 2002. The information codified in the NUS data set is largely overlapping with that in the NBER data set, and its coverage period extends to 2004. Concurrently using the NBER and NUS data sets made it possible to cross validate our data in many ways. First, we retrieved detailed patent information for all our semiconductors companies between January 1, 1990 and December 31, 2001 and we traced forward citations to these patents up to the end of 2004. Second, using both NBER and NUS data makes it possible to corroborate inventors' information, thus making it possible to refine our matching technique. Third, while most studies employ only the first classification listed on firms' patents to characterize technological location, we were able to retrieve information regarding all technological class assignments, which offers a higher-quality description of the firm technological position (Benner & Waldfogel, 2008).
We follow Yayavaram & Ahuja (2008) to identify semiconductor related classes[4] (table 1).

Insert Table 1 about here

We look at the classes that were assigned to all the patents of the firms in our sample. We ranked the classes by the number of firms that had patents assigned to that class and then considered the top 30 to be semiconductor classes. These top 30 classes accounted for about

[4] Our patent class list is slightly different from the one presented in Yayavaram and Ahuja (2008), as they sampled patents between 1984 and 1994, while we used patents filed between 1990 and 2001. Differences between the two lists reflect recent technological trends in the semiconductor industry: the increasing relevance of software interfaces and virtual design and verification tools and the emergence of nanotechnologies and semiconductor lasers.

63% of all the patents that belonged to the firms in the sample. This method generated a wider set of classes as compared to previous studies that were based on the semiconductor industry such as Macher (2006)[5]. We believe that using a wider set of classes provides a better criteria to identify inventors in semiconductor related R&D activities as that would include classes that are not typically classified as semiconductor classes but are nevertheless combined with semiconductor classes to create semiconductor related patents. This approach allows us to cast a wider net with the end to make sure that we build a representative picture of the organization collaborative structure.

Prior research on the link between firms' collaborative structure and organizational ability to generate new knowledge span several levels of analysis, including to R&D unit (Birkinshaw *et al.*, 2002), team (Hansen, 1999a; Hansen, 1999b; Tsai, 2001) and firm (Argyres, 1996; Argyres & Silverman, 2004; Nerkar & Paruchuri, 2005). Given the aim of our study, we focus on the firm as level of analysis, taking into account all assignee codes mapping to the same organization[6].

Building inventors' networks

We describe a firm's collaborative structure based on co-patenting data within each organization. Previous work (Singh, 2005; Fleming *et al.*, 2007) reports significant knowledge flows and interaction between co-authors. Thus, co-patenting ties are informative of the pattern of collaboration in knowledge related activities.

For each firm, a network of inventors was constructed by using all the patents that were filed in the three year period before the focal year. Because inventors are not uniquely

[5] Specifically, patents identified according to Macher (2006) criteria represent a subsample which represents 80.89% of the patents considered for this study.
[6] Our field interviews at a large European semiconductor company reveal that firms largely vary with respect to the number and use of assignee code. Some companies decide to patent all invention, even those developed by their subsidiaries, using the parent company assignee (generally through a centralized function). Others adopt a decentralized approach. Thus, using the assignee as unit of analysis and focusing on the collaborative structure of each subsidiary may engender a truncation bias in the definition of the collaborative structure.

identified (patents by the same person often appear under different combinations of initials and names, and there can be multiple inventors with the same name), we applied an inventor-matching algorithm to determine each inventor's patents and other inventors with whom the focal inventor had coauthored. We used inventor name, surname, middle name initial[7], inventor's state, assignee, patent technology as matching criteria. The inventors associated with each of these patents were considered an affiliation network. Each patent could have multiple inventors, and each inventor could be on multiple patents. This affiliation network, which is a two-mode network of patent to inventor, was transformed into a one-mode network of inventor to inventor, using UCINET VI (Borgatti, Everett & Freeman, 2002). This leads to a network of inventors with copatenting as non-directional tie (Singh, 2005; Nerkar & Paruchuri, 2005; Fleming *et al.*, 2007); a tie connects two inventors if the firm was awarded a patent on which they are copatentees. As developing technological knowledge requires close collaboration and joint problem solving between these inventors, copatenting is considered a strong tie (Hansen, 1999a). For each firm in each time window, we use these one-mode networks of inventors to construct our independent variables.

To make our network representation meaningful, we considered only those firms with at least five inventors. This leaves us with 152 firms and seven three years windows in the period 1992-1998, where each network at time t is based on the inventions filed by a firm in the three prior years (i.e. 1990-1992, 1991-1993, …, 1996-1998).

Measures

Dependent variables. Following a well established tradition (Griliches, 1990; Gittelman & Kogut, 2003), we use patent data to measure our dependent variable, *firms'*

[7]We wrote a text algorithm that performs a simplified coding of inventors' names, middle names and surnames to correct for phonetic misspellings. Robustness checks using SOUNDEX (Trajtenberg, 2005) are currently being performed.

innovative output. Patents are strongly correlated with new products (Comanor & Scherer, 1969), literature-based invention counts (Basberg, 1982), and nonpatentable innovations (Patel & Pavitt, 1997). Knowledge based theories focus on firms' ability to develop knowledge that has an economic value (Grant, 1996: 112) – i.e. can be turned into the production of goods and services. Of course, simple patent counts do not accurately capture the value of underlying innovations (Griliches, 1990). To address this heterogeneity in patent value, a widely used and validated indicator of technological inventiveness consists of counting the number of patents granted to a firm, weighed by the number of citations they received within a given time interval (Sampson, 2007; Yayavaram & Ahuja, 2008). Citation-weighed patent counts were found to be very highly correlated to both the economic and the social value of inventions (Trajtenberg, 1990; Harhoff, Narin, Scherer, & Vopel, 1999). Furthermore, citation-weighed patent counts were directly validated as measures of innovativeness by two studies in which surveys were administered to inventors and technical experts (Albert *et al*, 1991; Jaffe *et al.*, 2000). In our study, we measure *firms' ability to develop new knowledge* via a count of citation-weighted firm patents in the year that follows each time window. For example, if we use the patents filed by a firm between t-2 and t to compute the network variables, we observe the number of forward cites received by the patents filed by firm *i* in year t+1.

Independent variables. The overall *density* of the network for each firm in a given time window was computed as follows:

$$Density = \frac{2 \times L}{n(n-1)}$$

where L is the number of existing links in the network and n is the number of inventors' in a firm inventors' network. Since collaboration ties are symmetrical and undirected, this variable measures the ratio of existing links in the network to the number of possible pair wise combinations of inventors. Density may range from 0 to 1, with larger values indicating increasing density.

Brokered, cluster-and-bridge networks are characterized as networks with high clustering and high reach (Schilling & Phelps, 2007). To measure the clustering of each network for each time period, we used the weighted overall *clustering coefficient* measure (Borgatti *et al.* 2002, Newman *et al.* 2002):

$$Clustering_w = \frac{3 \times (\text{Number of triangles in the graph})}{(\text{Number of connected triples})}$$

where a triangle is a set of three nodes (e.g., *i, j, k*), each of which is connected to both of the others, and a connected triple is a set of three nodes in which at least one is connected to both the others (e.g., *i* is connected to *j* and *k*, but *j* and *k* need not be connected). This measure indicates the proportion of triples for which transitivity holds (i.e., if *i* is connected to *j* and *k*, then by transitivity, j and k are connected). The factor of three ensures that the measure lies strictly in the range of 0 and 1. For each inventor, the clustering coefficient tells us the proportion of partners that are themselves linked to each other. This variable can range from 0 to 1, with larger values indicating increasing clustering. While network density captures the density of the entire network, the clustering coefficient captures the degree to which the overall network contains localized pockets of dense connectivity. A network can be globally sparse and still have a high clustering coefficient.

To capture the *reach* of each network for each time period, we use a measure of average distance-weighted reach (Borgatti *et al.*, 2002). This is a compound measure that takes into account both the number of individuals that can be reached by any path from a given inventor, and the path length it takes to reach them. This measure is calculated as follows:

$$Average\ distance\text{-}weighted\ reach = \left[\sum_{n} \sum_{j} 1/d_{ij} \right] \Big/ n$$

where n is the number of nodes in the network, and d_{ij} is defined as the minimum geodesic distance d, from a focal node i to partner j, where $i \neq j$. Average distance-weighted reach can range from 0–n, with larger values indicating higher reach.

The interaction term was mean centered to avoid collinearity problems (Aiken, West & Reno, 1991). As said, previous studies used other measures, such as the small world coefficient (Watts & Strogatz, 1998; Fleming *et al.*, 2007) to describe brokered networks. We use this approach for two reasons. First, distance weighted reach provides a meaningful measure of the overall size and connectivity of a network, even when that network has multiple components, and/or component structure is changing over time (Schilling & Phelps, 2007). Second, it avoids the typical infinite path length problem typically associated with disconnected networks by measuring only the path length between connected pairs of nodes, and it provides a more meaningful measure than the simple average path length between connected pairs by factoring in the size of connected components (Borgatti *et al.*, 2002; Schilling & Phelps, 2007)

To gauge the extent to which firm integrate diverse technological trajectories, we measure *knowledge base heterogeneity* as follows:

$Heterogeneity_i = 1 - \sum_j s_{ij}^2$, where s_{ij} denotes the share of patents by firm i in the technology class j in a given window.

Controls. We include *network size* and a *fragmentation* measure to account for heterogeneity in size and fragmentation levels (Schilling & Phelps, 2007). A firm's *size* may affect both the scope and the scale of its knowledge-related activities (Henderson & Cockburn, 1994). Thus, we control for firm size, measured as the natural logarithm of the number of corporate assets. *R&D intensity* has been often been used as a measure of input in the process of technological generation (Ahuja, 2000; Katila & Ahuja, 2002). We followed the literature in computing R&D intensity as the ratio between a firm's R&D expenditure and its net sales. Previous studies have hypothesized that the economic performance of a firm may have both positive (Katila & Ahuja, 2002) and negative (Cyert & March, 1963) effects on its innovative capability. We measure a firm's economic *performance* by its ROA (Return on Assets). Some firms are likely to be cited simply because they produce more innovation. This variable is measured as the *number of patents* granted to the firm in the time window (Yayavaram & Ahuja, 2008). Controlling for network size and number of patents would also control for the fact that networks based on co-authorship have clustering properties by definition (Fleming *et al.*, 2008). In addition, variance in citation frequency may vary across classes reflecting field specific factors such as patenting propensity and technological opportunity. For that reason, a firm that patents mainly in classes that have high citation rates can get spuriously high citation rates for its inventions. To control for these effects we use *technology class* dummies. Finally, we introduce *time dummies* to account for time varying effects.

Statistical model

Since the dependent variable is a count variable that has high variance relative to mean, we used a negative binomial regression analysis (Cameron & Trivedi, 1986). Negative binomial models are preferred because our data demonstrate overdispersion (rejection of the Poisson model at $p<0.0001$). Though it sacrifices efficiency, a fixed effect model is preferred because it considers within-firm variation only, i.e. it controls for time invariant, firm idiosyncratic factors (a Hausman test rejects a random effects specification at $p<0.0001$). We used STATA 10.0 to estimate all equations.

RESULTS

Table 2 provides descriptive statistics and correlation for the key variables. To assess potential problems of multi-collinearity, we calculated variance inflation factors (VIF) based on the pooled data. Mean VIF is 4.59. Conventionally, VIF scores are regarded as indicative of multicollinearity problems when their value is greater than 10; in our case, three VIF values (density, size, fragmentation) were above this limit. To reduce collinearity issues between these variables, we follow a well established practice and orthogonalize the three network variables with highest VIF scores (Golub & Von Loen, 1996). These variables will be used also in our regression models.

Insert Table 2 about here
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53 firm-period observations reported missing values for some of the control variables; since these the criteria for data imputation were not met, we dropped those observations. Moreover, for 18 firms we had data regarding only one time window. Since we adopt a fixed effect specification, those observations were dropped. This leaves us with an unbalanced panel of 121 firms and seven time windows (1990-1992, 1991-1993, … , 1996-1998).

Insert Figure 2 about here

As figure 2 details, average network size ranges from 156 to approximately 180 collaborating inventors; the average size of the giant component is between 54% and 59%.

As said, in this paper, we contrast the relative efficacy of densely connected and brokered (i.e., cluster-and-bridge) collaborative structures. Let us offer a few visual examples from our dataset in order to clarify these structures.

Insert Figure 3 about here

Figure 3 represents the structure of the inventors' network of two semiconductor firms, Rambus Inc. and Integrated Device Technology Corp., in 1998. The firms have similar size and employ roughly the same number of patenting inventors (58 versus 62 inventors in this time window). Yet, Rambus Inc. collaborative network is characterized by high density, while Integrated Device Technology Corp. is a sparse network.

Insert Figure 4 about here

Similarly, in figure 3 compares the structure of collaboration between inventor in two small firms, Actel Corp. and Kopin Inc., in 1995. Kopin Inc. represents a prototypical example of brokered, cluster-and-bridge network, with dense clusters isolated clusters and high reach, while ties are distributed in a more uniform fashion in Actel Corp. Both pictures were drawn with Netdraw (Borgatti *et al.*, 2002) and used a Spring Embedding multidimensional scaling algorithm.

These examples from our dataset help us to make two important points. First, despite these firms operate in the same technological environment and face similar competitive challenges, networks of inventors are highly heterogeneous with respect to their structural properties. Second, the measures we chose to describe collaborative structures well apply not only to large networks of collaboration, such as those of key players such as AMD, Intel, Texas Instruments Inc. or STMicroelectronics, but also to smaller firms, such as those described in the examples. Thus, it is meaningful to use a network approach to describe firms' collaborative structure.

In table 3, we report the results of our analyses[8].

[8] We report standard coefficients of robust fixed effect negative binomial regression.

Insert Table 3 about here

Model 1 is a baseline model including a set of covariates that, according to prior studies, may affect the impact of firms' technological inventions. Among firm level controls, patents, number of assignees, number of R&D units and firms' size do indeed have a positive effect on firms' innovative output. In addition, among the network variables, network reach has a strong, positive effect on problem solving performance. It is important to point to the negative effect of knowledge base heterogeneity on firm level ability to generate new knowledge (β=-0.055, $p<0.10$). Thus, a firm that uses heterogeneous knowledge inputs in its problem solving activity pays higher costs of knowledge integration and this is detrimental to its ability to develop new technologies.

In order to ensure that our estimates are robust, model 2 and 3 introduce separately the main effects of network density and the interaction between clustering and reach, while model 4 includes both structure-related covariates. Similarly, model 5 and 6 introduce the interaction terms between heterogeneity and structural parameters separately, while model 7 include both interaction effects. Since models based on three-way interactions should include controls of al the second order interactions (Aiken, West & Reno, 1991) we focus on model 7 to discuss the results of our analyses.

In line with our expectations, our prediction concerning the negative impact of network density on firms' subsequent knowledge output (H1) is supported (β= -0.255, $p<0.001$). The size of the effect is large: a one standard deviation increase in density corresponds to a 22% decrease in innovative performance. Hence, controlling for knowledge base heterogeneity, overly cohesive structures imply higher coordination costs, which hamper the firms' innovativeness. In addition, in line with hypothesis 2 (H2), brokered collaborative structures balance the benefits of autonomous clusters and the efficiency of knowledge transfers through boundary spanning roles, which favor the integration of knowledge into new technologies. Hypothesis 2 is strongly supported ($\beta=0.048$, $p<0.001$).

Also our predictions concerning the relative efficacy of different collaborative structures at increasing levels of knowledge heterogeneity are supported. Hypothesis 3 predicted that the negative effect of density would decline with the extent to which firms' need to integrate increasingly heterogeneous bodies of knowledge to develop new technologies. In line with this prediction, the coefficient for the interaction term is positive and significant ($\beta=0.149$, $p<0.001$). Similarly, our framework suggested that collaborative structures that combine high clustering and high reach will exhibit higher innovative performance at low levels of knowledge base heterogeneity; conversely at high levels of technological heterogeneity, the more a corporate inventors' network combines high clustering and reach, the lower the firm subsequent ability to develop new knowledge (H4). Our empirical results support this contention ($\beta=-0.076$, $p<0.05$).

Sensitivity analyses

We assessed the robustness of our results in multiple ways. First, we address the concern of unobserved heterogeneity, which may affect our results. Blundell, Griffith and Van Reenen (1995) argued that because the main source of unobserved heterogeneity in models of innovation lies in the different knowledge stocks with which firms enter a sample, a variable that approximates the build-up of firm knowledge at the time of entering the sample is a particularly good control for unobserved heterogeneity. For this reason, we estimated "pre sample" firm fixed effect estimators for our main equations. Results hold. Also, another limitation is that the model we present treats network structure as exogenous, but they may be an outcome of other variables, such as individuals or group demographic or experience variables. This possibility raises the issue of whether any omitted variables create a spurious association between the main structure variables and firms' ability to generate new knowledge. While the time lag employed in constructing explanatory and control variables and the estimation of pre-sample fixed estimators mitigates such concerns to some extent, it does not completely eliminate them. To check for this possibility: i) I ran other models where I included additional controls, such as average inventor experience (and standard deviation for experience) or inventors knowledge overlap (and standard deviation for overlap) ii) I estimated "pre sample" fixed effects estimator with an endogenous specification for our key predictors. The inclusion of additional variables did not alter the results. To reduce multicollinearity issues, these controls were excluded. To assess the robustness of our empirical models to alternative operationalizations of the dependent variable, we used patent counts to measure firms' ability to generate new knowledge. Both the direction and significance of the coefficients for the variables of interest are consistent with those presented in table 3. As suggested by recent research (Yayavaram & Ahuja, 2008), we included decomposability and decomposability squared as additional controls. Regression coefficients signs and significance for these terms was in line with received theory, and our main results were robust to the inclusion of these variables.

DISCUSSION AND CONCLUSIONS

It is by now widely recognized that firms' ability to develop new products and services depends crucially on the integration of heterogeneous and rapidly evolving disciplines and practices (Grant, 1996a; Brusoni *et al.*, 2001). Also, most scholars agree that the extent to which a firm is able to integrate specialized knowledge into new technological solutions depends crucially on the structure (Hansen, 1999a; Hansen, 1999b; Reagans & Zuckerman, 2001; Tsai, 2001). Building on the knowledge based theory of the firm, the present article offers a reconciliation of the controversy over the benefits of densely connected and brokered collaborative structures. Our findings suggest that organizational structures have to be matched in a discriminating way to the heterogeneity of a firm knowledge base, based on the associated costs and benefits in the problem solving process (Nickerson & Zenger, 2004; Rodan & Galunic, 2004). Namely, brokered, cluster-and-bridge networks provide the highest relative net effect when the knowledge is relatively homogeneous and easy to transfer through boundary spanning roles. By contrast, when the knowledge is highly heterogeneous, dense and homogeneously connected collaborative structures are positively related to firms' innovative performance.

By concurrently looking at the structure of a firm's internal collaboration network and at the heterogeneity of a firm knowledge base, this study contributes a number of theoretical and empirical insights.

First, we extend recent studies in the knowledge based tradition (Nickerson & Zenger, 2004; Macher, 2006) by advancing a theoretical framework that explains the relative efficiency of alternative collaborative structures in the formation of new knowledge. Research in the knowledge based tradition argued that firms exist either to economize on knowledge exchange (Demsetz, 1988; Conner, 1991; Prahalad & Conner, 1996) or to facilitate knowledge transfer (Kogut & Zander, 1996; Grant, 1996a; Kogut & Zander, 1996). Our study extends this line of research arguing that contrasting the costs and benefits of alternative governance modes is a promising logic to illuminate not only why firms exists, but when they exist and what intra-organizational structure would better support their knowledge formation activity.

Second, this approach makes it possible to gain new insights on the role of cohesive and brokered collaborative structures in the generation of new knowledge. As said, the role of collaborative structures in the development of new knowledge has been largely debated and a controversy has emerged over the relative benefits of densely connected and “cluster-and-bridge” networks. In most empirical works, the relationship between structure and problem solving performance is tested and the dynamics that characterize the organizational knowledge base are treated as underlying mechanism (Tsai, 2001; Reagans & Zuckerman, 2001). Our matching perspective shows that choices regarding collaborative structures and the heterogeneity of a firm’s knowledge base are inherently intertwined but distinct. Testing the relative efficiency of both structures at different degrees of heterogeneity allows reconciling previously divergent findings.

Finally, we enlarge the empirical content of the received theoretical perspectives. Extant models of organizational collaborative structure (Tushman, 1978; Allen, 1986; Hansen, 1999a; Hansen, 1999a; Reagans & Zuckerman, 2001; Tsai, 2001; Reagans & McEvily, 2003; Argyres & Silverman, 2004), relied heavily on cross sectional, survey and field data to infer collaborative patterns and organizational form. By contrast, we offer a simple network-based operationalization of cohesive and organizational forms and provide evidence of the performance implications of these alternatives based on archival, longitudinal data on collaborative inventors in a large sample of organizations. By these means, we concurrently answer the quest for empirical work in the knowledge based perspective (Foss, 1996; 2007) and recent call for empirical studies at the network level that investigate the effect of whole network properties on collective outcomes (Provan, Fish & Sydow, 2007: 465)

Our study has also some noteworthy implications for the design of organizations. It is nowadays common for firms to produce technologies that can potentially serve a variety of downstream markets. As the scope of potential applications for a general purpose technology increases, firms need to leverage and integrate heterogeneous, market specific knowledge to develop new technological solutions. This issue, for example, is pervasive in the semiconductor industry, where the increasing miniaturization of semiconductor devices paved the way to emergence of new downstream markets, which impose greater specialization of technological knowledge (Di Biaggio, 2007). Our results offer managers some insights on how increasing degrees of knowledge specialization in heterogeneous fields can be managed and how collaborative may be designed to guarantee trans-specialist coordination. Managers should align internal design choices by evaluating the relative benefits and costs of alternative designs, and devise procedures to assess the fir between structure and knowledge base characteristics.

There are some limitations to this study that provide avenues for future research. Though this paper uses a unique dataset of patents and studies the networks of inventors over a period of ten years to identify the intra-organizational collaborative structure, the networks that are considered are only of a single type of ties, that of co-patenting. There could be other possible types of ties among these inventors, such as their membership in trade associations, their being members of the same department, and so on. If we had included these differences, findings would have been more comprehensive (Haveman, 2000). Also, our approach focuses on structure as depicted by the patterns of collaboration between inventors, and abstracts away from formal characteristics of the organization of corporate research activities, such as centralization, autonomy and hierarchy. Indeed formal design choices, such as these ones, have an impact on the integration of heterogeneous knowledge. Studying the relationship and interaction of formal and informal attributes of organizations of research within established firms represents a promising extension of this research. Finally, we only focused on innovation as an example of firms' knowledge generating activities. Further research could explore the effect of the division and coordination of knowledge within organization on other dimensions of technological performance, such as publications, products and radical technologies.

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FIGURE 1

Cohesive vs. Brokered Structures

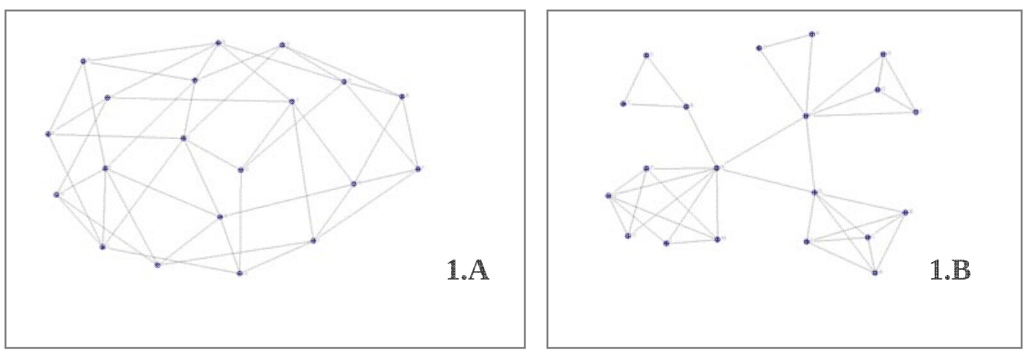

FIGURE 2

Average inventors' network size and size of the largest component between 1992 and 1998

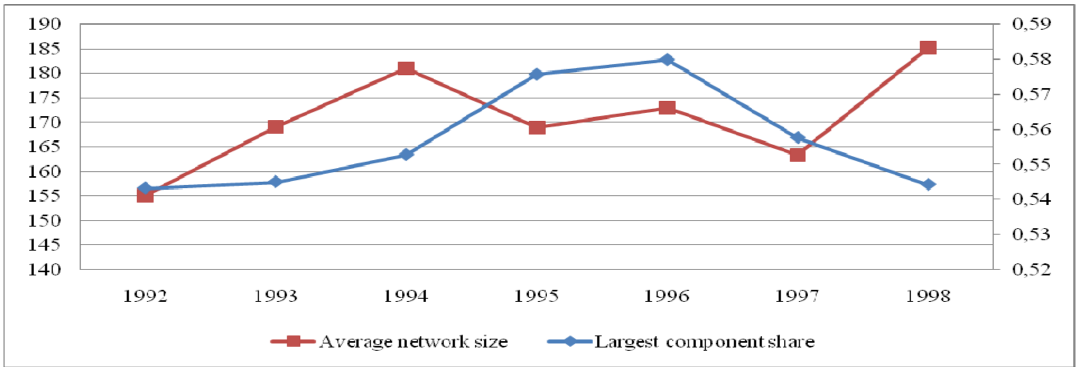

FIGURE 3

Inventor's network structure:

Rambus Inc. vs. Integrated Device Technology Corp. in 1998

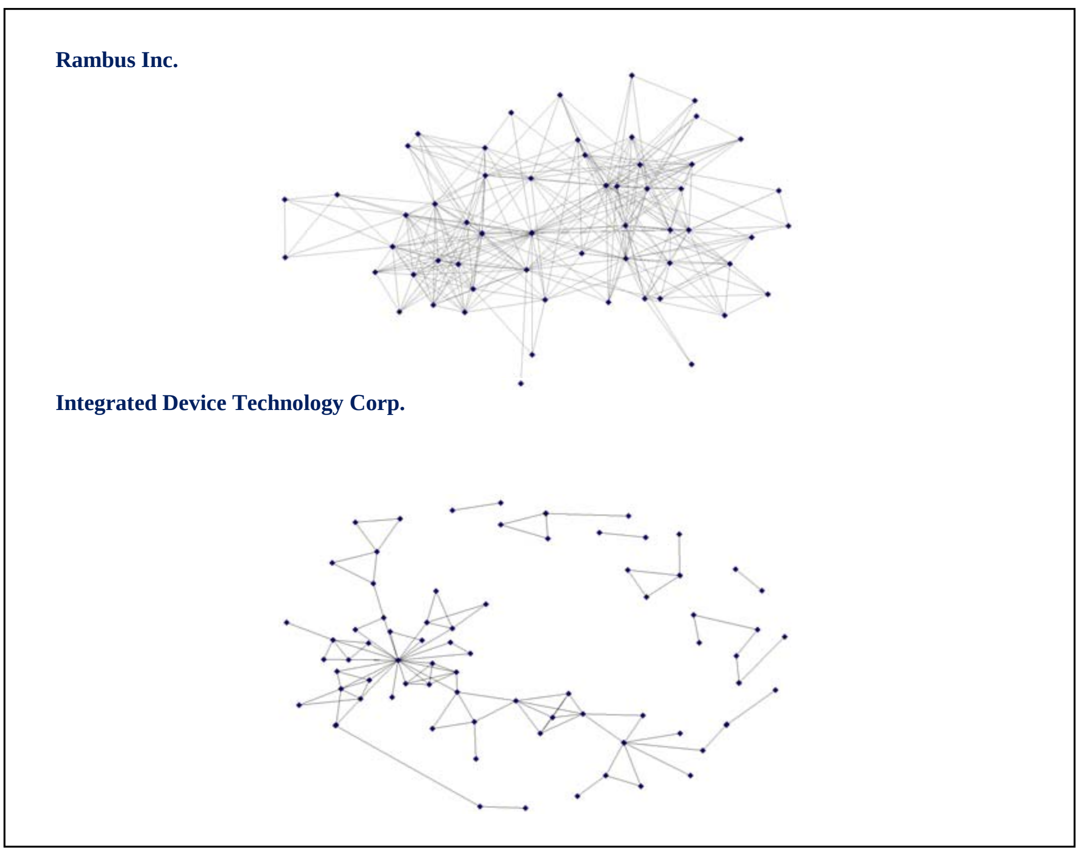

FIGURE 4

Inventor's network structure: Kopin Inc. vs. Actel Corp. in 1995

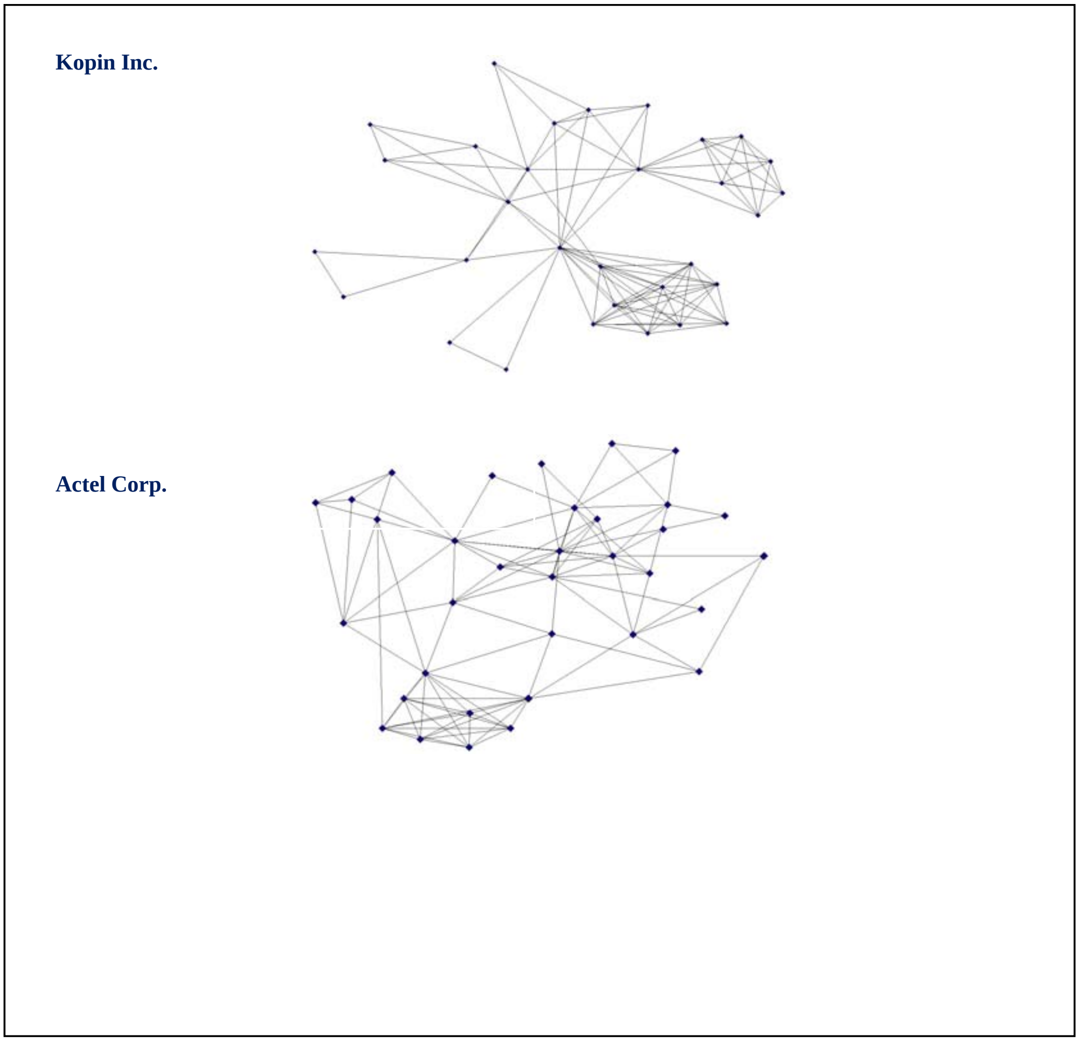

TABLE 1

Semiconductor related classes

Class Number	Title
257	Active solid-state devices (e.g. transistors, solid state diodes)
324	Electricity: measuring and testing
326	Electronic digital & logic circuitry
327	Miscellaneous active electrical nonlinear devices, circuits & systems
330	Amplifiers
341	Coded data generation or conversion
345	Computer graphics processing and selective visual display systems
347	Incremental printing of symbolic information
348	Television
359	Optic systems (communication) including elements
360	Dynamic magnetic information storage and retrieval
361	Electricity: electrical systems and devices
365	Static information storage and retrieval
369	Dynamic information storage and retrieval
370	Multiplex communications
375	Pulse or digital communication
382	Image analysis
395	Information processing system organization
430	Radiation imagery chemistry: process, composition or product thereof
438	Semiconductor device manufacturing: process
455	Telecommunications
707	Data processing
708	Electrical computer: arithmetic processing and calculating
709	Electrical computers and digital processing systems: multiple computers and process coordination
710	Electrical computers and digital data processing systems: input/output
711	Electrical computers and digital processing systems: memory
712	Electrical computers and digital processing systems: processing architectures and instruction processing
713	Electrical computers and digital processing systems: support
714	Error detection/correction and fault detection/recovery

TABLE 2

Descriptive statistics and correlation between the main variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Impact of invention	1												
2. Density	-0.12	1											
3. Reach	-0.16*	0.00	1										
4. Clustering coefficient	-0.02	.21*	-0.03	1									
5. Network size	0.56*	0.00	-0.00	-0.05	1								
6. Fragmentation	-0.19*	0.51*	0.14*	0.07*	-0.47*	1							
7. Knowledge base heterogeneity	-0.29*	-0.08*	-0.10*	0.05	0.03	0.36	1						
8. Patents	0.53*	0.14*	0.02	0.01	0.52*	-0.21*	0.05	1					
9. RD intensity	0.07*	-0.01	0.00	0.05	0.03	-0.00	0.07*	0.04	1				
10. Size	0.32*	-0.36*	-0.10*	0.04	0.24*	-0.49*	0.16*	0.37*	-0.18*	1			
11. ROA	0.08*	-0.23*	-0.01	-0.05	0.05*	-0.22*	0.04	0.07*	0.09	0.16	1		
12. Number of RD units	0.23*	-0.19*	-0.06	0.03	0.14*	-0.29*	0.03	0.30	-0.00	-0.36*	0.06*	1	
13. US	-0.09*	0.11	0.04	-0.14*	0.07*	0.18	-0.15	-0.17*	-0.01	-0.47*	-0,07*	-0.5*	1
Mean	2031.93	0.25	10.22	0.63	171.58	0.58	0.71	295.14	0	5.82	-0.04	1.45	0.67
S.D.	5841.14	0.27	31.92	0.30	705.54	0.30	0.21	814.80	8.55	2.89	0.38	1.18	0.42
Min	1	0	0	0	5	0	0	0	0	0	-6.16	1	0
Max	14451	1	564.88	1	8620	1	1	8170	157.83	15.62	0.35	13.00	1

TABLE 3

Results of negative binomial panel regression for innovative output

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	1.034**	1.126**	1.035**	1.151**	1.081**	1.293**	1.249**
US	0.074	0.093	0.095	0.128	0.126	0.157	0.156
ROA	-0.015	-0.018	-0.018	-0.022	-0.014	-0.016	-0.005
RDintensity	0.181**	0.202**	0.172**	0.191**	0.225**	0.188**	0.227**
LOGassets	0.170**	0.178**	0.169**	0.176**	0.182**	0.177**	0.186**
Heterogeneity	-0.055†	-0.095†	-0.047†	-0.091†	-0.296†	-0.076*	-0.322*
Number of parents	0.086**	0.091**	0.072**	0.081**	0.085**	0.093**	0.095**
Number of assignee	0.071**	0.076**	0.077**	0.086**	0.083**	0.090**	0.088**
Fragmentatiom	-0.009	-0.068	-0.016	-0.015	-0.035	-0.022	-0.046
Network size	0.021†	0.031†	0.053*	0.072*	0.080*	0.089†	0.094†
CC	-0.046†	-0.032†	-0.034†	-0.027†	-0.027†	-0.051†	-0038†
Reach	0.032**	0.043**	0.068**	0.085**	0.097**	0.495**	0.515**
CC x Heterogeneity						0.024	-0.002
Reach x Heterogeneity						-0.350**	-0.362**
Density		-0.213**		-0.240**	-0.183**	-0.331**	-0.255**
CC x Reach			0.048**	0.060**	0.065**	0.117**	0.107**
Density x Heterogeneity					0.127**		0.149**
CC x Reach x Heterogeneity						-0.095*	-0.076*
Time dummies included	included	included	included	included	included	included	included
Class dummies included	included	included	included	included	included	included	included
Firm type dummies	included	included	included	included	included	included	included
Log likelihood	-3034.10	-3023.79	-3029.53	-3016.19	-3002.87	-3002.55	-2984.42
Observations	655	655	655	655	655	655	655
Number of firms	121	121	121	121	121	121	121

Standard errors in brackets

† significant at 10%; * significant at 5%; ** significant at 1%