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Evolution of R&D Capabilities: The Role of Knowledge Networks Within a Firm

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In this paper, we suggest that the characteristics of individual positions in an intraorganizational network of inventors or intrafirm knowledge network predict the likelihood with which knowledge created by an inventor is used in the firm's research and development (R&D) activities. Such choices lead to path dependence and subsequent specialization. We provide empirical evidence that a firm's R&D is concentrated in those areas where it chooses to recombine knowledge, offering support for the path-dependent evolution of capabilities. We test this theory by analyzing the R&D networks in DuPont, a highly regarded Fortune 500 chemical company. Cox Proportional Regression models of intrafirm citations on network characteristics offer strong empirical support for our theory.

Key words: R&D capabilities; knowledge networks; evolutionary; path dependence
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Introduction

R&D capabilities have been suggested as one of the primary characteristics that help to differentiate successful from unsuccessful firms (Bettis and Hitt 1995, Teece 1982). Hence, it is logical that an understanding of the evolution of capabilities is critical to understanding performance differentials among firms (Nelson 1991, Tsai 2001). The main function of R&D is to generate new knowledge by recombining existing knowledge (Fleming 2001, Henderson and Cockburn 1994, Kogut and Zander 1992). Such knowledge recombinations can be within, outside, or across organizational boundaries (Katila 2002, Rosenkopf and Nerkar 2001). Different choices of knowledge used in recombination can lead to different technological capabilities and, consequently, different performance (Arthur 1989, Stuart and Podolny 1996, Teece et al. 1997). Specifically, internal recombination allows firms to establish and retain competitive advantage arising from such recombination for a longer duration of time (Chesbrough and Teece 1996). However, not all knowledge held by a firm is used in its internal recombination process (Podolny and Stuart 1995). Understanding R&D capabilities of firms requires a deeper exploration of the process by which knowledge is chosen for recombination.

Research on R&D within the firm has examined a range of issues from different theoretical perspectives. Management researchers, for instance, have researched special boundary-spanning roles in the innovation process (Tushman 1977) and the relation between group longevity, communication, and performance (Katz 1982). This paper integrates and extends research done by organizational sociologists who have looked at the nature of conflict in R&D structures (White 1961). This stream of research at the intraorganizational level has led scholars to suggest sociometric or network models for understanding decision making in organizations in general (Gulati 1995, Pfeffer and Salancik 1978) and more specifically in the innovation and R&D context (Argyres and Silverman 2003, Tichy et al. 1979, Tsai and Ghoshal 1998, Tushman and Romanelli 1983). That said, the process by which firms make internal choices with respect to knowledge, especially when such choices can lead to different paths, remains unexplored. In this paper, we propose that inventors and their knowledge networks are used in the selection of recombined knowledge within firms (Oliver and Liebeskind 1998, Tsai 2001). Specifically, the structural characteristics of members in an intraorganizational network serve as indicators of quality and richness of knowledge generated by these inventors. We examine these indicators used in selecting knowledge for recombination. Thus, this paper contributes to the understanding of how inventors in intrafirm knowledge networks influence the evolution of R&D capability.

We test our theory on E.I. DuPont de Nemours, a chemical and pharmaceutical firm, over a period of 27 years (1972 to 1998). We consider patents as indicators of knowledge (Levin et al. 1987) and coinventing as a tie between inventors who file patents. Based on three-year moving windows, we construct inventor networks and measures associated with inventors in these networks. We observe that two characteristics of inventors' positions—centrality and spanning of structural holes—in the intraorganizational network influence the choice of knowledge in R&D. Furthermore, inventors who span structural holes and have high centrality are more likely to have their knowledge chosen by their peers. We also present evidence in support of specialization in R&D. We show that intrafirm citations (choices made within the firm) are highly concentrated in certain technological areas. This concentration of knowledge inputs is associated with a similar concentration pattern in patent output, offering support for our argument that choices with respect to use of knowledge lead to specialization or development of capabilities.

The paper is structured as follows: In the first section we develop a theoretical rationale for the use of networks for examining R&D activities. Based on this, we develop a set of testable hypotheses that link the network characteristics of individual researchers involved in R&D activities with the likelihood that knowledge created by them will be used by other researchers. Next, we present the evidence of specialization in a chemical firm. This is followed by research methods and results. We then present the discussion section, and finally we describe the limitations of this study and provide suggestions for future research.

Theory

Capabilities, Specialization, and Drivers of Choice in R&D

R&D has been suggested as one capability that differentiates successful from unsuccessful firms (Bettis and Hitt 1995, Teece 1982). Past empirical research has shown that some firms are persistently competent at generating knowledge in certain technological areas (Helfat 1994). We define a capability as the specialization or concentration of the activities of the firm within certain areas (Selznick 1957, Smith 1799). Such specialization or concentration represents the firm's ability to perform activities in those areas as opposed to other areas.[1] To explore the evolution of this specialization, we need to address how this specialization emerges in certain technological areas within the organization. R&D activities involve recombinant processes on the part of the inventors (Henderson and Clark 1990). By focusing on knowledge created within the boundaries of the firm, inventors can substantially reduce the costs of a search (Nelson and Winter 1982).

Different knowledge assets of a firm represent different alternatives available for the firm in the recombination process (Dosi 1982). Consequently, this choice of knowledge assets in the recombination process has an important bearing on the course of specialization of R&D and can lead to differences in firm capabilities over time. However, because of limited resources, firms cannot pursue all the possible alternative paths available to them while conducting R&D. The effects of limited resources, bounded rationality, and incomplete information lead firms to direct their R&D efforts toward some areas at the expense of others. Some solutions ("The winners") form the foundation for future knowledge development, while other solutions become dead ends (Podolny and Stuart 1995).

Searching for knowledge created within, as opposed to knowledge created outside organizational boundaries, is a habitual or routinized response of inventors. However, inventors still need to decide which of this internally produced knowledge should be recombined. Inventors recombining knowledge benefit from the use of knowledge of a certain quality (fitness for use) and richness (diversity of content). These two features of knowledge help to improve the outcomes of R&D efforts (March 1991).[2] Although inventors could use the technological characteristics of knowledge to assess quality and richness of knowledge, earlier research has shown that these technological characteristics alone are not sufficient to explain their selection (Arthur 1989, Katz and Shapiro 1985). Individuals within firms are bounded rational and lack complete information and recombine knowledge on the basis of different mechanisms that are developed based on their experiences and based on cues received from the environment (Pfeffer and Salancik 1978, Simon 1991, Walker 1985). We argue that one such mechanism on which inventors base their search and selection involves the signals of quality and richness based on positions of inventors in intrafirm knowledge networks.

Knowledge required for recombination does not reside in one particular individual in an organization, nor is it distributed uniformly throughout the organization. It resides in the group of individuals and

[1] Whether such specialization leads to superior performance depends on the selection environment in which the firm operates (Nelson and Winter 1982) and is beyond the scope of this paper.

[2] Quality knowledge is that knowledge which is fit to use and leads to improvements in the mean of the performance distribution of R&D efforts, whereas richness of knowledge suggests diversity of content and helps to increase the variability of the performance distribution. See March (1991) for a detailed exposition of these issues.

the routines that connect these individuals (Nelson and Winter 1982). Individuals following these routines need not necessarily be aware of these routines (Polanyi 1966). Such networks, when formed at different levels, perform different functions in the evolution of knowledge. Past research in the area of biotechnology has identified interpersonal networks of inventors as the primary mechanism through which exchanges of new scientific knowledge took place, whereas interorganizational ties were used mainly to commercialize the knowledge developed (Liebeskind et al. 1996, Oliver and Liebeskind 1998, Zucker et al. 1996). Thus, knowledge resides in a network of people, and this network has an effect on knowledge-creation activities.

The flow of knowledge that takes place across actors of an organizational network influences the creation of new knowledge (Allen and Cohen 1969, Tushman and Romanelli 1983, Walker 1985, White 1961). We examine the network of inventors created within a firm. A tie between inventors could be any of the multiple relations, such as membership in the same division, friendship, collaboration, and so on. We specifically examine the effect of interpersonal ties of copatenting between inventors on the processes of knowledge creation. Each node in this network represents an inventor, and each tie between two nodes represents copatenting by the two inventors. If a pair of inventors copatents multiple times, this is represented as the strength of that tie. We consider two characteristics of networks that influence the likelihood of information flow across knowledge networks: (1) centrality and (2) spanning of structural holes (Burt 1997, Podolny 1994, Rice and Aydin 1991, Sorenson and Stuart 2001).

Hypotheses

Centrality and Choice of Knowledge

Making decisions under uncertainty and with incomplete information requires decision makers to draw inferences about future events (Schwenk 1984). Researchers studying such phenomena have highlighted the importance of heuristics and other signaling mechanisms used by decision makers (Tversky and Kahneman 1989). Such heuristics can help to reduce the uncertainty surrounding the choice. Heuristics used for decision making under uncertainty range from simple rules such as "highest price as good quality" to more complex interconnected set of rules. In the context of strategic decision making, managers typically look for indicators that are convergent with their underlying expectation of future events. One of the most important indicators or heuristics used by individuals in general and by managers in particular is the centrality of the actors involved. Researchers have used the concept of centrality to indicate the status of the actor (Podolny 1993), power wielded by the actor (Brass and Burkhardt 1993), and the social capital captured by the location of an actor in a network (Ahuja 2000b). For instance, Ibarra (1993) shows that centrality is important for participating in innovative roles in an organization. Other research has examined the effect of centrality on individual behavior in organizations (Brass and Burkhardt 1993) and on individual performance (Ahuja et al. 2003, Mehra et al. 2001).

In the context of knowledge creation, bounded rational inventors search across the internal knowledge network on the basis of incomplete information about which knowledge should be recombined. Inventors working inside organizations look for indicators of quality absent any information about actual future impact (Merton 1968). Technological indicators that are embedded in existing knowledge may be insufficient because they help to reduce the number of alternatives but do not necessarily lead to an unambiguous choice. For example, Podolny and Stuart (1995) show that the status of firms influences the decision of other firms to enter technological niches. Inventors searching knowledge networks within organizations are similarly influenced by the centrality of the inventors in the network in two ways.

First, centrality can be perceived as a signal of quality (Sorenson and Stuart 2001), especially when the centrality of an inventor derives from the inventors with whom the focal inventor is associated. If an inventor is connected to other inventors of high centrality, then the focal inventor also has high centrality (Bonacich 1987). Because of this association of the focal inventor with other inventors of high centrality, the knowledge associated with the focal inventor is perceived to be of high quality. For example, past research showed that an individual's propensity to adopt an innovation is influenced by the extent to which persons of centrality in his or her network have adopted that innovation (Burt 1987, Coleman et al. 1957). The presence of a highly central inventor (inventors) in a knowledge network is likely to lead other inventors in the network to recombine knowledge created by these central inventors with the expectation that such recombination would lead to greater impact. Hence, the centrality of inventors associated with knowledge creates an attraction for that knowledge to be selected by other inventors in their recombination activities.

Second, centrality leads to greater reach to other parts of the network, because inventors become globally central because of their connections to other inventors of high centrality. The centrality of these other inventors is derived from the pattern of overall connections among inventors. Globally central inventors can reach any inventor in the network much faster than other inventors. By the same token, other inventors can access the globally central actor much faster than another inventor with low global centrality. Also, because the inventor with high global centrality may also have status and power that are perceived as signals of quality, information disseminated by this inventor carries more weight than similar information given out by another inventor of low centrality. This combined effect of greater reach and esteem brings the knowledge created by the central inventors into the active consideration of other inventors. This active consideration by other inventors of the knowledge created by central inventors increases the likelihood of that knowledge being more often selected. Hence,

Hypothesis 1. *Centrality of an inventor in an intraorganization knowledge network will be positively associated with the likelihood of his knowledge being selected by other inventors.*

Structural Holes, Boundary Spanning, and Choice of Knowledge

Past research shows that individuals who perform "boundary spanning" (boundaries include group, functional, network, or expertise) roles are considered influential, or gatekeepers, by their peers (Tushman 1977, Tushman and Scanlan 1981). The concept of structural holes helps to explain how certain inventors who span boundaries can play a key role in recombinant activity. In an intrafirm network where everyone is connected to everyone else, there are no structural holes (Burt 1992). However, intrafirm networks are rarely completely connected, leading to structural holes. The structural hole approach focuses on the individual ego, and posits that individuals who span structural holes are better off; that is, inventors situated between other inventors who are not directly linked enjoy efficiency and control benefits (Burt 1992). The presence of structural holes in a network presents an opportunity for knowledge brokers or boundary spanners to bring together different knowledge streams, leading to richer content (Hargadon and Sutton 1997). An inventor who spans a structural hole benefits by brokering and controlling flow of information between the unconnected inventors. This inventor spanning structural holes influences the selection of knowledge in two ways.

First, R&D as knowledge creation is a recombinant activity. Hence, one important aspect of this knowledge creation is gathering information about knowledge to be recombined. An inventor with greater access to such information is perceived as an important resource in knowledge-creation activities. The presence of structural holes means inventors are not aware of the knowledge in different parts of the network. One way for inventors to search knowledge in other parts of the network is to rely on the cues generated by their collaborative networks. An inventor who spans a structural hole exchanges unique information from different people rather than obtaining redundant information from these people (Allen et al. 1979, Burt 1992). Such an inventor not only economizes on the number of ties in gathering information, but also possesses greater information that is rich in content. Consequently, the knowledge generated by such an inventor is also perceived to be rich. This perception of richness attracts other inventors to seek out the knowledge for recombination in their activities, consequently leading to increased likelihood of use in recombination.

Second, an inventor spanning structural holes is in a position of control—she is the only one connected to the other actors in an efficient way that economizes on the number of ties. This efficiency in connections means that inventors who value speed in their search for knowledge have to rely on the focal inventor. The reach in connections leads to inventors who value richness in their search for knowledge having to channel their search efforts through the focal inventor (Burt 1997). Assuming that each inventor wants her knowledge to have a high impact, an inventor spanning structural holes is more likely to disseminate information about her own knowledge than any other knowledge.[3] This information dissemination, along with the perception of richness of content, brings her knowledge to the radar screen of other inventors. Hence, we propose the following:

Hypothesis 2. *The extent of structural holes spanned by an inventor in an intraorganizational knowledge network will be positively associated with the likelihood of their knowledge being selected by other inventors.*

Centrality, Structural Holes, and Choice of Knowledge

The earlier discussion of centrality and structural holes hypothesizes that these network characteristics of inventors in knowledge networks have an independent positive effect in the selection of recombined knowledge. Although centrality serves as an indicator of quality, the spanning of structural holes serves as an indicator of richness. In this section, we explore the relations between these constructs and their impact on future use within the network. Recent research has examined the simultaneous effects of structural holes and centrality on the formation of market segments whereby the bridging of structural holes in a network

[3] The brokerage explanation of structural holes suggests that the inventor spanning the structural hole would broker the knowledge of a third party. However, inventors spanning structural holes also have the control to disseminate their own knowledge more than brokerage knowledge of a third party. See Burt (2004) for more on the role of brokers in the development of good ideas. We thank the reviewer for pointing out this difference.

performs the role of a pipe, whereas the centrality of actors provides a prism on the quality of information being sought in the market (Podolny 2001). This is consistent with the framework put forward by Rowley (1997), whereby highly central actors in dense networks are compromisers, whereas in sparse networks they are commanders. In intraorganizational networks a similar pattern can be expected. Inventors seeking knowledge for recombination expect to gain the most from using knowledge created by inventors who span structural holes. However, the signal of quality of the knowledge of this inventor is not certain.

The centrality of inventors who span structural holes can help to amplify the signal of the underlying quality of the knowledge. For example, Rowley et al. (2000) find that the positive relationship between strong ties (facilitating exchange of rich information) and firm performance was greater in sparse ego networks than in dense networks in the context of interorganizational networks in the steel and semiconductor industry. Similarly, knowledge created by an inventor who spans structural holes and is highly central is perceived to have both characteristics—quality and richness. Because these signals reinforce and amplify each other's effect, this combined perception of high quality and richness leads to higher likelihood of this knowledge being selected. Hence an inventor who spans structural holes and is highly central is able to disseminate her knowledge to many more inventors in an efficient way. Additionally, other inventors would hold the focal inventor in higher esteem because of her reach. Because of this high esteem and increased dissemination, this inventor is more successful in bringing her knowledge into active consideration of other inventors. Hence, considering the joint effects of signaling and dissemination we posit that

Hypothesis 3. *The relationship between the centrality of an inventor in an intraorganizational knowledge network and the likelihood of her knowledge being used by other inventors is positively moderated by the extent to which this inventor spans structural holes in the network.*

Methods

Research Site and Sample

To test the hypotheses, we compiled a data set of all the patents that were issued to DuPont over the period of 1972–1998 from the U.S. Patent and Trademark Office (USPTO) online database of patents. We follow other researchers who have considered patents as excellent indicators of technological competence (Ahuja 2000b, Jaffe et al. 1993, Narin et al. 1987, Silverman 1999) and patent citations of knowledge flows across firms and individuals (Song et al. 2003). E.I. DuPont de Nemours, a chemical and pharmaceutical firm, was chosen for two reasons. First, prior research clearly indicates that patenting activity is an important source of technological advantage in the chemicals industry (Levin et al. 1987). Patents in the chemicals and pharmaceutical sector can provide a substantial revenue stream until they expire. Hence, there is a tendency to patent all the knowledge that can be patented (Grabowski and Vernon 1992, Mansfield 1986, Scott Morton 2000). Second, given our research question—evolution of R&D specialization—we needed a firm that is sufficiently old and large to document the evolution of specialization in its R&D activities.

Each patent contains extensive information about inventors who created that knowledge, the company to which it is assigned, the number of claims or contributions that it makes, and the technological classes under which it falls. Each patent of a firm provides objective archival evidence of a piece of knowledge held by that firm. We collected all the patents that were successfully granted and the intrafirm citations that were made in them in the period between 1972 and 1998. There were a total of 10,908 patents. Furthermore, these 10,908 patents were cited 13,729 times by these 10,908 patents. Of this set of 13,729 citations, 7,571 are nonself-citations and the rest are self-citations by the inventors. Before proceeding further, we explored the evolution of specialization of R&D within DuPont.

Specialization in R&D

We considered a subset of the larger set of patents, patents filed in the period 1972 to 1992[4] to carry out this analysis. In the period 1972 to 1992, DuPont filed 8,882 successful patent applications. These 8,882 patents cited 14,572 DuPont patents, of which 9,098 were citations to the 8,882 patents and the rest were to DuPont patents filed prior to 1972. We examined all the 14,752 citations of 8,882 patents to examine the patterns of sourcing and patenting in various technological classes. We found that whereas 330 technological classes were cited in these patents, 5,934 of these (40% of 14,572) intrafirm citations fell predominantly into five technological classes. The cumulative rankings of the top five classes, along with their technical and business descriptions, are shown in Table 1. We also examined the annual intrafirm citation data to

[4] We were restricted by the information that is available about the classes for DuPont patents prior to 1972. We have collected information about all the patents that were cited in patents till 1992 and hence we present the analysis on a limited data. However, given the earlier research findings by Helfat (1994) and Patel and Pavitt (1997), we think that the concentration patterns would be similar when data till 1998 are included.

Table 1 **DuPont's Areas of Technological Capabilities (1972–1992)**

Class	Rank based on cumulative intrafirm citations at the end of year 1992*	Rank based on cumulative patents at the end of year 1992*	Technical description	Business description
428	2	1	Stock material or miscellaneous articles	Fibers
525	1	2	Mixed synthetic resins, block or graft copolymers	Polymer science
524	4	3	Resins with nonreactive additives	Coatings
430	5	5	Radiation imagery chemistry: Process, composition, or product thereof	Imaging
71	3	10	Chemistry: Fertilizers	Plant science

Source. USPTO and DuPont company website. The only key capability that is not represented from the top five areas is that of "Class 544: Natural resins having six-membered ring with more than one hetero nitrogen," which is predominantly related to the business areas of biotechnology and plant science, respectively.

examine the persistence of these patterns. We specifically focused on the top five classes of cumulative intrafirm citations. Figure 1 shows a graph of the occurrence of any of these five classes in the top five rankings in each year. We find that these five classes consistently appear in the top five classes in most years.[5] This suggests that DuPont has been consistently recombining knowledge from the same technological classes and also shows that this pattern is persistent over time.

We then examined the concentration of output or the outcomes of these knowledge recombinations. DuPont's 8,882 patents fell under 340 technological classes. However, the top five classes, four of which (fibers, coatings, polymer science, and imaging) are the same as the sourcing top five classes, account for more than 50% of all patents granted to DuPont in this period, and the top 10 technological classes account for more than 85% of the patent output. The only technological class that does not feature in the top five output classes is plant science, but even this technological class is ranked within the top 10 output classes.

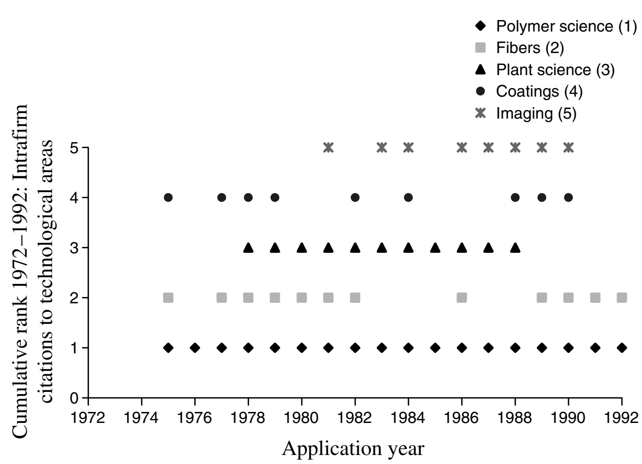
The rank ordering of the top five intrafirm citation classes with respect to the output classes are also presented in Table 1. There are differences in the ranks of the intrafirm citation classes and the output classes. However, the Spearman rank order correlation coefficient between all the 330 intrafirm citation technological classes and all the 340 output technological classes was 0.6 and statistically significant. This evidence sheds light on the process of specialization by showing that classes from which knowledge is recombined are also the classes in which knowledge is generated.

Finally we examined the distribution of the annual output in the top intrafirm citation classes. We graphically depict the top five intrafirm citation technological classes rather than top five patent output classes because it gives a clear evidence of the match between sourcing and outputs. Figure 2 shows a graph of the occurrence of any of these five classes in the annual output top five rankings. Again, we see the consistent appearance of these citation classes in the annual top five output rankings. This suggests that DuPont's specialization in the classes of fibers, coatings, imaging, polymer science, and plant science has been persistent over time. Figure 2 read in conjunction with Figure 1, along with evidence presented in Table 1, offers strong support, consistent with past research, on path dependence and capability evolution (Helfat 1994, Patel and Pavitt 1997). Given this evidence of specialization, we now turn to the construction of variables for testing the hypotheses stated earlier.

Dependent Variable and Analytical Technique

Although patent citations have been considered an excellent measure of technological impact and performance (Ahuja 2000b, Albert et al. 1991, Podolny and Stuart 1995), they are also an excellent indicator of knowledge flows (Jaffe et al. 1993). We con-

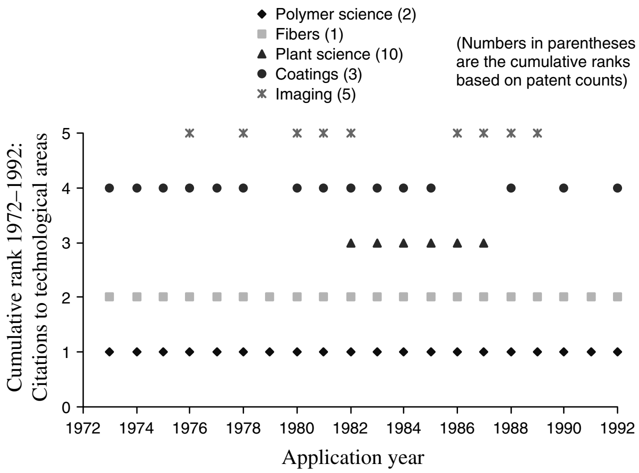
Figure 1 **Top Five Technological Classes: Intrafirm Citation Counts**



Note. Each data point above represents an appearance in the top 5 ranks of patents in that year.

[5] We arbitrarily chose the top five ranks as a cutoff. We experimented with other cutoffs up to 10, but our results did not change. Beyond 10 it was difficult to pictorially represent the evolution.

Figure 2 Top Five Technological Classes (Capability): Patent Counts



Note. Each data point represents an appearance in the top 5 ranks of patents in that year.

sider a patent citation as a choice made by the firm to build on knowledge contained in the patent. Citations to other patents in a patent are determined by the patent examiner as compared to academic citations, which are decided by the author (authors) of the academic work. Intrafirm citations are less likely to be added or retained unless they are relevant to the research covered by the patent. The dependent variable is the rate of intrafirm citation to a patent by inventors other than those who are involved in its creation. We eliminate self-citations by inventors while constructing this dependent variable by excluding such citations from our sample, thus reducing our set of events from 13,729 to 7,571. Following Podolny and Stuart (1995) and Podolny et al. (1996), we use a repeated event hazard rate analysis to model citation patterns. Hazard rate models are used because they incorporate information on both censored and uncensored cases, i.e., whether or not a patent is cited. If T is the duration since the patent was first granted[6] or since it was last cited, then the instantaneous (hazard) rate of a patent being cited again at time t is defined as

$$r(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T < t + \Delta t)}{\Delta t}.$$

We modeled the hazard rate using semiparametric Cox models (Allison 1995, Cox 1972, Kalbfleisch and Prentice 1980). The equation that we estimate takes the following specification:

$$r(t) = h(t) \exp\{XB + Y(t)S\},$$

where $r(t)$ is the transition rate or hazard rate of a patent being cited within the network by other inventors, $h(t)$ is an unspecified baseline rate for the transition, X is a matrix of time-constant covariates, $Y(t)$ is a matrix of time-varying covariates, and B and S are vectors of unknown regression parameters. In this case, X consists of the set of controls, whereas $Y(t)$ is the set of independent variables. Unobserved heterogeneity can be a substantial problem in a research design such as the one proposed above. By including a variable, prior citations, that measures the number of times the dependent variable has previously occurred for each patent, we control for unobserved heterogeneity (Heckman and Borjas 1980). As Podolny and Stuart (1995) indicate, by including such variables we can control for the time-constant effects of unobserved factors that produce variance in an individual's abilities or dispositions to cite patents.

The distribution of citations on patents is presented in Table 2. There were 7,948 patents with zero citations and two patents with 46 citations. Following earlier research (Podolny and Stuart 1995), spells of up to one year are created for each patent. For each patent, the first spell begins on the date of issue of that patent and either ends on the close of the same year if it is

Table 2 Frequency of Events per Patent

Citations	Patents	Total citations = citations ∗ patents
0	7,948	0
1	1,495	1,495
2	592	1,184
3	310	930
4	183	732
5	116	580
6	56	336
7	62	434
8	29	232
9	17	153
10	23	230
11	21	231
12	7	84
13	14	182
14	6	84
15	6	90
16	4	64
17	2	34
18	1	18
19	1	19
20	3	60
21	1	21
26	1	26
27	1	27
28	1	28
31	2	62
33	2	66
34	1	34
43	1	43
46	2	92
Total	10,908	7,571

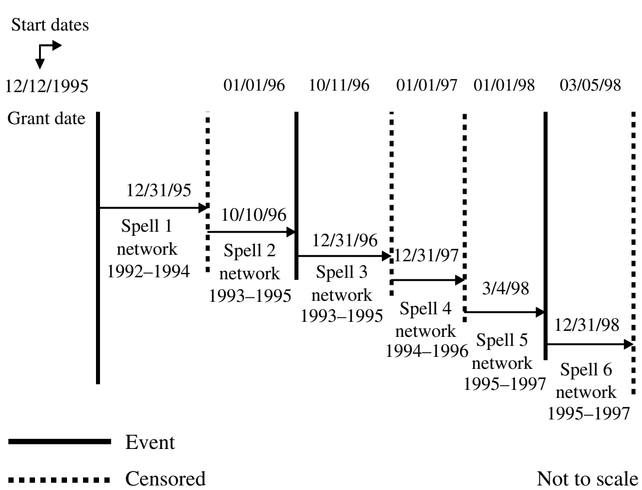
[6] We use the grant date instead of the application date because a patent is at risk of being cited only after its grant, following Podolny and Stuart (1995). A patent unless granted cannot be cited because the inventors do not have a number to cite in the prior art. We control for the time to grant by including a variable that measures the number of years a patent application was under review.

not cited in that year and is marked as censored or ends when it is cited and is marked as cited. The next spell begins with the beginning of the next year in the event that it is not cited or on the date of the latest citation if it is cited. Therefore, a spell begins at the start of the year if the earlier spell ended in a censor or begins at the time of citation if the earlier spell ended in a citation; all spells end either at the end of the year and are marked censored if they are not cited, or at the time of citation and are marked as cited.

Figure 3 shows an example of a patent that was granted on December 12, 1995, and has two citations on October 10, 1996, and March 4, 1998, respectively. For this patent we created the following spells: The first spell begins from the date of issue of that patent (December 12, 1995) and finishes at the end of that year (December 31, 1995) and is marked censored. The network variables, centrality and structural holes, are computed on the basis of the network three years prior to 1995, that is, based on a network of inventors patenting within DuPont between 1992 and 1994 (both years included). The second spell begins on January 1, 1996, and ends on October 10, 1996, and is marked cited. For this spell the network of inventors is based on patenting between 1993 and 1995. The remaining spells are constructed in a similar manner. The last spell begins on March 5, 1998, and ends on December 31, 1998, and is marked as censored. For all patents the last spell is automatically censored because we stop observation of citation records on December 31, 1998.

As mentioned above, the time-varying covariates, centrality and structural holes, are computed for inventors in each year based on the network of inventors in the prior three calendar years. We chose a three-year window because past research suggests that researchers are productive (have successful patents) for a period of three to five years (Rappa and Garud 1992). Our data corroborate this number. A three-year window allows us to capture changes (if any) in the network variables over time. Similarly, control variables that are time varying are also recomputed whenever a spell begins. The above coding of the data led to a total of 153,347 spells, of which 7,571 led to citations or events; the remainder were censored. Finally, because there are multiple observations for each patent, we use robust standard errors clustered on patent in estimation.

Figure 3 Spell Construction



Construction of Measures: Independent Variables

We measured the independent variables, centrality and spanning of structural holes, by constructing a network of inventors in moving three-year windows.

A network of inventors was constructed by using all the patents that were filed in the three-year period prior to the year in which the spell started. 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 an inventor network, which is one-mode network of inventor to inventor, using UCINET VI (Borgatti et al. 2002). This leads to a network of inventors with copatenting as a nondirectional tie. A tie connects two inventors if the firm was awarded a patent on which they are copatentees. Because the creation of knowledge is an activity that requires intensive interaction between these inventors, copatenting is a strong tie (Hansen 1999). We use the one-mode continuous network of inventors to construct our independent variables (Marsden and Campbell 1984).

Centrality as Bonacich Power. The Bonacich power measure would suggest that an inventor is central to the extent that he or she copatents with other central inventors. The centrality of other inventors arises from the pattern of relations among all the inventors. This has been used as a measure of centrality in earlier research (Sorenson and Stuart 2001). Using the matrix of the one-mode network of inventors that has been created, we calculated the Bonacich power measure for each of the inventors using the following formula (Bonacich 1987):

$$\mathbf{c}(\alpha,\beta)=\alpha\sum_{K=1}^{\infty}\beta^{k}R^{k+1}\mathbf{1}_{i},$$

where $\mathbf{c}(\alpha,\beta)$ is a vector of centrality scores for the inventors, α is an arbitrary scaling factor, β is a weight, and $\mathbf{1}$ denotes a column-vector of ones. The magnitude and sign of the variable β determine the extent to which the centrality of inventors connected to inventors on the focal patent figures into their centrality. In order for $\mathbf{c}(\alpha, \beta)$ to be well defined, β must be less in absolute value that the largest eigenvalue of X.) When β is set to zero, the measure effectively collapses to a degree centrality scaled by α. With $\beta > 0$, inventors that are linked to influential inventors are themselves more influential by virtue of that linkage. The case of $\beta < 0$ corresponds to that in which being affiliated with central partners reduces one's own power (Bonacich 1987). Interpretively, the Bonacich power measure corresponds to the notion that the centrality of a vertex is recursively defined by the sum of the power of its alters. The nature of the recursion involved is then controlled by the power exponent, i.e., positive values of β imply that vertices become more powerful as their alters become more central and powerful (as occurs in cooperative relations), whereas negative values of β imply that vertices become more central and powerful only as their alters become weaker (as occurs in competitive or antagonistic relations). We set β equal to three fourths of the reciprocal of the largest eigenvalue of X, as is the norm in the social networks literature (Bonacich 1987, Podolny 1993). This measure is calculated for all the active inventors in the three-year window using UCINET VI (Borgatti et al. 2002). We hypothesize that the maximum centrality of the inventors on a patent will be positively associated with the number of times that knowledge is picked up, i.e., cited in the future. To obtain this independent variable, we calculated the maximum of the Bonacich power measure of the associated inventors for each patent.

Structural Holes. There are two different approaches, constraint based and redundancy based, to measuring structural holes based on the ties between inventors. We present results with both these measures of structural holes. We computed the efficiency measure from Burt (1992) that uses the ratio of nonredundant contacts to total contacts for a focal inventor as

$$\left[\sum_j \left(1 - \sum_q p_{iq} m_{jq}\right)\right] \Big/ C_j,$$

where p_{iq} is the proportion of inventor i's ties invested in connection with contact q, m_{jq} is the marginal strength of the relationship between contact j and contact q, and C_j is the total number of contacts for inventor i. Higher values on this index reflect inventors whose ego networks are rich in structural holes. If all the coinventors of a scientist are unconnected to one another, the index takes a value of one, indicating that none of the inventor's contacts is redundant. The greater the number of ties between a scientist's coinventors, the greater is the redundancy and the fewer the structural holes. For inventors without any coinventors, the index was set to 0.1 (Ahuja 2000a). The constraint measure of structural hole (Burt 1992) is computed as

$$\left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2, \quad q \neq i, j,$$

where p_{ij} is the proportional strength of i's relationship with j, p_{iq} is the proportional strength of i's relationship with q, and p_{qj} is the proportional strength of q's relationship with j. UCINET VI was used to calculate these measures (Borgatti et al. 2002). To calculate the independent variable, we used the maximum value of the structural holes spanned by any of the inventors associated with a focal patent.

Construction of Measures: Control Variables

We include two variables that accelerate the baseline rate of citations (Podolny and Stuart 1995):

Calendar Age. This variable keeps a count in our data set of the time elapsed in years since the first patent was granted to DuPont. With improvements in search techniques as well as databases, the passage of time has led to an increase in citations in patents.

Patent Age. Assuming that patents that have been around longer are more likely to be cited than newer patents, we include a variable that measures the time elapsed in years since the focal patent was granted. A squared term was also included to account for the fact that with time the importance of the patent may decrease.

Because technical attributes of the knowledge could explain choice of selection on the part of individuals in the firm, we need to control for the variables representing technical attributes. We use a range of variables to control for the technical attributes, along with other explanations that may account for citation of the patent.

Scope of a Patent. The USPTO uses a technology-classification system whereby each patent is classified into one or many relevant classes. For instance, inventions related to pharmaceutical applications are typically classified in the category of drugs and bioaffecting compositions (Class 514). The current classification system has more than 400 such classes. Various researchers have used the number of classes into which a patent is classified to represent the breadth of the patent. This is shown to have some effect on the impact of that patent in various contexts (Lanjouw and Schankerman 2001, Lerner 1995). Hence, we use the count of the classes to which a patent is assigned as a control.

Claims. The number of claims that a patent makes is considered as the value of the patent by various researchers (Tong and Frame 1994). Lanjouw and Schankerman (2001) interpret the claims as the product "spaces" that are occupied or protected by a patent.

Hence, we include the count of the number of claims made by a patent as a control variable in the analysis.

Age of Prior Art. We also include a variable that measures the age of the prior art in the focal patent because research indicates that patents that build on old knowledge have different citation patterns than patents that build on new knowledge (Nerkar 2003). This is measured as the median of the difference between the grant year of the focal patent and that of the references cited in the focal patent.

Self-Citation. Local search at the individual level leads many inventors to cite themselves (Rosenkopf and Nerkar 2001). Information of a patent that has been self-cited may flow more easily than patents that have not been easily cited because inventors may be biased to such patents. Also, self-citations indicate the confidence of the focal inventors in their patent. This might influence other inventors to select this patent. We control for this by including a variable that indicates if a patent has been self-cited by any of the inventors before the beginning of the spell.

Number of Patent References. Patents represent knowledge-creation efforts. Some efforts cite more patents than others. Patents that cite more prior art may be in technologically crowded classes and have differential influence compared with other patents (Fleming 2001). To control for this effect, we include a variable that measures the total number of patents cited in the prior art of the focal patent.

Academic References. The use of academic or theoretical knowledge represents the fundamental nature of innovations. Inventors might perceive a patent as a fundamental innovation when it builds on more academic knowledge. This leads to more citations to the focal patent. We control for this by including a variable that measures the number of publications cited by the focal patent.

Team Size. We measured our primary network variables by considering the maximum of each of the individual measures of inventors associated with the focal patent. However, heterogeneity in team member skills can lead to differences in team performance (Reagans and Zuckerman 2001). To account for the effect of other inventors on the patent, we control for the team size by counting the number of inventors on the focal patent.

International Presence. Past research indicates that knowledge flows across international borders are substantially different from domestic knowledge flows (Almeida 1996). To control for this effect, we include a variable that takes a value of one if an inventor on a patent was located outside the United States and zero otherwise.

Time to Grant. After an application for a patent is filed in the USPTO, it takes time for a patent to be granted to that invention. This time varies for different patents. A patent granted immediately could be uncontroversial and simple, whereas a patent that is granted after a very long time could be controversial and complex. For instance, the first patent in the field of biotechnology was granted in 1981 after being under review for more than six years. Patents that are more complex and that take longer to be granted could be cited within the firm more than other patents. To take into consideration such a possibility, we control for the duration between the application and the grant of a patent. This is calculated as the difference between the grant date and the application date, both of which are available from the patent database.

Year Effects. Finally, we included fixed-year effects that control for differences in years when each spell begins.

Technological Controls. To control for differences in patenting across technological classes, we include dummy variables that capture the top 20 classes where DuPont patented over the 25-year period. This includes the five technological classes presented in the earlier section where we show stylized evidence of path dependence in the emergence of specialization within DuPont.

Results

The descriptive statistics along with the correlations among variables are presented in Table 3. All correlations with values above 0.05 are significant at $p < 0.05$. All correlations except those between centrality and structural holes measured as constraint and efficiency are quite low, and hence do not pose any multicollinearity problems.

Table 4 presents Cox Proportional hazard regression models. Model 1 consists of all the control variables. All control variables (except use of academic knowledge) are significant. The hazard rate of citation increases with an increase in calendar year, prior citations, self-citation, patent references, scope, claims, and team size, and decreases with an increase in international presence and academic references. Furthermore, the hazard rate of citation has an inverted-U shape relation with the patent age.

Model 2 adds centrality along with all the control variables in Model 1. All control variables (except use of academic knowledge) are significant, similar to Model 1 estimation. The coefficient for centrality is positive and significant ($\beta = 0.1374$; $p < 0.01$). This supports Hypothesis 1, which posits that the hazard rate of citation increases with the increase in the centrality of the inventors associated with that patent.

Table 3 Correlation Matrix

Variable description	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Centrality	0.370	0.665	1.000												
(2) Structural holes$_{constraint}$	0.298	0.427	0.561	1.000											
(3) Structural holes$_{efficiency}$	0.293	0.414	0.531	0.879	1.000										
(4) International presence	0.061	0.240	−0.031	−0.010	−0.028	1.000									
(5) Prior performance	0.486	1.734	0.017	−0.031	−0.028	−0.018	1.000								
(6) Self citations	0.010	0.076	0.034	0.037	0.046	−0.014	0.119	1.000							
(7) Number of patent references	1.782	0.644	0.027	0.008	0.008	−0.033	0.039	−0.008	1.000						
(8) Scope of patent	2.080	1.182	0.013	0.008	0.000	−0.040	−0.021	−0.021	0.099	1.000					
(9) Claims	2.114	0.846	0.051	0.032	0.044	−0.079	0.072	0.025	0.070	0.052	1.000				
(10) Team size	1.512	0.822	0.386	0.247	0.196	0.077	0.028	0.017	0.050	0.034	0.025	1.000			
(11) Academic knowledge	1.460	4.264	0.027	0.011	0.018	−0.039	0.017	−0.005	−0.005	0.095	0.098	0.049	1.000		
(12) Time to grant	1.815	0.961	0.002	−0.007	−0.010	−0.028	−0.001	−0.015	0.063	0.056	0.043	0.041	0.077	1.000	
(13) Median age of prior art	2.163	0.604	−0.023	−0.031	−0.032	−0.024	−0.034	−0.059	0.095	−0.016	−0.078	−0.019	−0.032	0.101	1.000

Note. All coefficients above 0.05 are significant at $p < 0.04$.

Model 3 adds structural holes$_{constraint}$ to the control variables in Model 1. The coefficient of this variable is positive and highly significant ($\beta = 0.1923$; $p < 0.01$). Model 4 is similar to Model 3, but includes the structural holes$_{efficiency}$ measure. The coefficient of this variable is positive and highly significant ($\beta = 0.2184$; $p < 0.01$). Results from Models 2 and 3 offer support for Hypothesis 2, which posits that the hazard rate of citation increases with the increase in the structural holes spanned by the inventors associated with that patent.

Models 5 and 6 consist of independent variables—centrality and structural holes$_{constraint}$ and centrality and structural holes$_{efficiency}$—along with all the control variables. All control variables (except the use of academic knowledge) are significant and in the same direction as in Model 1. The coefficients for the independent variables, centrality, structural holes$_{constraint}$, and structural holes$_{efficiency}$, are significant and in the expected direction.

Models 7 and 8 consist of the interaction term between centrality and the two measures of structural holes, along with the variables of Model 6. The interaction of the efficiency measure of structural holes with centrality is significant and in the hypothesized direction ($\beta = 0.1242$; $p < 0.05$), but the same is not true for the interaction effect of the constraint measure of structural holes with centrality. This term is not significant but is in the expected direction ($\beta = 0.0220$). Thus, Hypothesis 3 is partially supported.

Discussion

We have hypothesized that the inventors of a firm would have an effect on the processes of recombination and hence also on the evolution of R&D capabilities. We tested the hypotheses that the selection of knowledge depends on the structural characteristics of the inventors in the network of inventors within the firm. The ties between inventors that are considered are copatenting ties, which are strong (Hansen 1999).

Our evidence, by examining patents of DuPont, indicates support for the hypotheses that centrality of inventors and spanning of structural holes by inventors have a positive impact on the use of knowledge created by them. Our analysis and results offer strong support for the argument that network characteristics of inventors involved in knowledge creation influence selection of technological paths. The data and evidence that we present are based on the information that we obtained from the patent records of DuPont.

Some of the results described above need further discussion. Comparing the independent direct effects of each of the network variables from Models 2, 3, and 4, respectively, shows some interesting patterns. A one-standard deviation increase in each of the network variables centrality structural holes$_{constraint}$ and structural holes$_{efficiency}$ spanned leads to a corresponding 9.56% ($\exp(0.1374 \times 0.665) = 1.0956$), 8.55% ($\exp(0.1923 \times 0.427) = 1.0855$), and 9.46% ($\exp(0.2184 \times 0.414) = 1.0946$) increase in the hazard of citation, respectively. This suggests that of the two network variables, centrality and structural holes spanned, centrality accounts for the higher increase in the hazard of citation. The interaction effect between centrality and structural holes$_{constraint}$ is not in the direction hypothesized but is not significant. However, the interaction effect between centrality and structural holes$_{efficiency}$ is in the hypothesized direction and significant. This suggests that inventors of high centrality who span structural holes draw benefits from minimizing redundancy in their networks, leading to an information-rich knowledge network. In contrast, internal knowledge networks of high-centrality inventors seem less likely to support the assumption that information is more likely to diffuse over exclusive ties.

Table 4

Variable description	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality		0.1374***			0.1044***	0.0977***	0.0929**	0.0272
		(0.0224)			(0.0255)	(0.0253)	(0.0471)	(0.0544)
Structural holes$_{constraint}$			0.1923***		0.1174***		0.1091**	
			(0.0321)		(0.0366)		(0.0459)	
Structural holes$_{efficiency}$				0.2184***		0.1474***		0.1119**
				(0.0336)		(0.0378)		(0.0448)
Struc. holes$_{constraint}$ × centrality							0.0220	
							(0.0738)	
Struc. holes$_{efficiency}$ × centrality								0.1242**
								(0.0626)
Age of patent	0.1073**	0.1137**	0.1175**	0.1181**	0.1183**	0.1191**	0.1183**	0.1187**
	(0.0505)	(0.0504)	(0.0504)	(0.0504)	(0.0504)	(0.0504)	(0.0504)	(0.0504)
Age of patent × age of patent	−0.0041***	−0.0041***	−0.0043***	−0.0043***	−0.0043***	−0.0043***	−0.0043***	−0.0043***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar age	−0.0700*	−0.0753*	−0.0719*	−0.0719*	−0.0752*	−0.0750*	−0.0752*	−0.0751**
	(0.0497)	(0.0497)	(0.0496)	(0.0496)	(0.0497)	(0.0496)	(0.0497)	(0.0496)
Prior performance	0.1126***	0.1128***	0.1130***	0.1132***	0.1130***	0.1131***	0.1130***	0.1131***
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
International presence	−0.2193***	−0.2076***	−0.2100***	−0.2062***	−0.2049***	−0.2022***	−0.2053***	−0.2022***
	(0.0555)	(0.0555)	(0.0555)	(0.0557)	(0.0555)	(0.0556)	(0.0556)	(0.0557)
Self citations	5.5352***	5.5207***	5.5278***	5.5243***	5.5200***	5.5177***	5.5199***	5.5154***
	(0.0606)	(0.0609)	(0.0605)	(0.0606)	(0.0607)	(0.0608)	(0.0607)	(0.0607)
Number of patent references	0.3477***	0.3489***	0.3463***	0.3449***	0.3478***	0.3467***	0.3478***	0.3459***
	(0.0235)	(0.0237)	(0.0235)	(0.0236)	(0.0236)	(0.0236)	(0.0236)	(0.0236)
Scope of patent	−0.0742***	−0.0748***	−0.0726***	−0.0712***	−0.0737***	−0.0726***	−0.0737***	−0.0720***
	(0.0156)	(0.0157)	(0.0156)	(0.0155)	(0.0157)	(0.0156)	(0.0157)	(0.0156)
Claims	0.1164***	0.1075***	0.1119***	0.1103***	0.1071***	0.1060***	0.1072***	0.1052***
	(0.0167)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0166)
Team size	0.1155***	0.0667***	0.0911***	0.0939***	0.0638***	0.0666***	0.0627***	0.0637***
	(0.0152)	(0.0174)	(0.0160)	(0.0158)	(0.0174)	(0.0173)	(0.0177)	(0.0175)
Median age of prior art	0.2237***	0.2189***	0.2275***	0.2290***	0.2224***	0.2238***	0.2222***	0.2226***
	(0.0237)	(0.0239)	(0.0238)	(0.0238)	(0.0239)	(0.0238)	(0.0239)	(0.0238)
Time to grant	0.0153	0.0172	0.0184	0.0190	0.0186	0.0191	0.0187	0.0195*
	(0.0139)	(0.0143)	(0.0138)	(0.0139)	(0.0141)	(0.0142)	(0.0141)	(0.0142)
Academic knowledge	0.0030	0.0030	0.0029	0.0026	0.0030	0.0027	0.0030	0.0026
	(0.0029)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0031)
Year effects	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.
Technology effects	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.
−2 Log-likelihood	164,163	164,107	164,119	164,110	164,094	164,089	164,094	164,085
Improvement in LL		55.47	43.46	52.48	68.25	73.53	0.11	3.86
Comparison		(1)	(1)	(1)	(1)	(1)	(5)	(6)
Spells	153,347	153,347	153,347	153,347	153,347	153,347	153,347	153,347
Events	7,571	7,571	7,571	7,571	7,571	7,571	7,571	7,571
Censored	145,776	145,776	145,776	145,776	145,776	145,776	145,776	145,776

Notes. Values in parentheses are robust standard errors clustered on patents.
LL = Log-likelihood.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Our findings are corroborated by information that we gathered from company documents available publicly and from field visits. The inventors we identify as occupying strategic positions in the knowledge networks within DuPont also feature in the list of inventors honored by the company as persons who contributed to the technological development within DuPont. Also, such recognition is based on a multitude of factors that include successful patent applications, academic publications, and commercial products developed. This qualitative evidence helps to alleviate our concerns about the internal validity of our findings. These results, along with the earlier patterns of evolution of specialization, suggest that the network of inventors in a firm influence the way the R&D capability of a firm evolves.

Conclusions

This paper explores the processes underlying the evolution of R&D capabilities. We focused on the knowledge of a firm measured as the stock of patents and studied the processes that mold the evolution of specialization or competence in particular R&D areas.

In particular, we identified the mechanisms through which knowledge is selected for recombination. The paper shows empirically that network-based mechanisms are used to overcome problems of bounded rationality, uncertainty, and incomplete information. Furthermore, this paper finds that the inventors shape the way in which the capabilities of a firm evolve by using these routines. This paper makes a contribution by increasing our understanding of the evolution of R&D capabilities through identification of the routines that underlie the selection of knowledge assets for recombination. These selection processes, based on signaling and control, form an important part of the organizational routines among inventors in the firm (Nelson and Winter 1982).

There are some limitations to this study that provide avenues for future research. Though this paper uses a unique data set of patents and studies the networks of inventors over a period of 27 years to identify the processes underlying R&D capabilities within a firm, the networks that are considered are only of a single type of ties, that of copatenting. 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 different ties, the findings would be more comprehensive (Haveman 2000).

A second avenue for future research would be to include individual level controls. Past research shows the importance of individual and team demographics on performance (Reagans and Zuckerman 2001). We also find from our field data that our measures have external validity. However, future research could incorporate individual level variables that would shed light on their impact in the network context. Future studies could collect primary data through surveys (Ibarra 1993, Tsai and Ghoshal 1998) to find out the actual positions within the hierarchy and the different ties that exist between inventors in an organization to bring a holistic approach to this analysis.

We are among the first to use the sociological concept of networks to explore the evolution of R&D capabilities within a firm. This paper uses network concepts to identify factors involved in the process of selection (Podolny 1994, Salancik 1995, Uzzi 1999). Network concepts are used to propose that the inventors in strategic positions within a network of inventors influence the processes of selection in their favor. Thus, this paper brings socioeconomic explanations to the evolution of R&D capabilities of a firm. Another contribution of this paper is in its detailed tracking of the evolution of R&D capabilities within DuPont, thus lending support to the argument of evolutionary development of such capabilities. These findings have both theoretical and practical implications. Theoretically, this paper advances a way of incorporating the sociological explanations into the burgeoning stream of strategy research exploring the capabilities view, which is mostly economics oriented (Eisenhardt and Martin 2000). The findings in this paper suggest that inventors use routines that emphasize network positions that shape the capabilities of a firm. Managers should pay particular attention to these routines, because the development of capabilities is path dependent (Teece et al. 1997). Taking this paper as a cue, we hope future research will incorporate sociological concepts, as distinct from economic concepts, into the study of evolution of capabilities.

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