NEW PRODUCT SEARCH OVER TIME:
PAST IDEAS IN THEIR PRIME?

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Abstract

This paper investigates how the age of the knowledge that firms search affects how innovative they are. Two seemingly contradictory propositions are examined: (1) old knowledge hurts by making innovation activities obsolete, and, (2) old knowledge helps because it is more reliable and legitimate, thereby promoting innovation. Results based on longitudinal data on 131 robotics firms reconcile the contradictory propositions: while old intra-industry knowledge hurts, old extra-industry knowledge promotes innovation.

Key words: product innovation, organizational search, time, knowledge.

This study examines how firms search for new innovations over time. I study how firms, at the present time, search for and access knowledge that was created at different points in the past, in order to create new products. Two contradictory accounts in the literature make the question of how old knowledge influences the search for new knowledge interesting. A number of researchers have argued that firms should build on the most recent technological foundations to enhance innovation. As knowledge ages, it becomes obsolete, and no longer matches the demands of the current environment (e.g., Eisenhardt, 1989; Thompson, 1967). Yet, in contrast, other researchers have shown that older and established knowledge is more reliable and valuable, and that firms might be able to learn not only from recent, but also from distant times (March, Sproull, & Tamuz, 1991). Many modern technologies are in fact a fusion, or novel combinations, of ideas discovered at different points in time (Fleming, 2001). For example, 3M's recent introduction of microflex circuits is based on a technology the firm nearly abandoned in the early 1980s (Tatge, 2000), and the technologies underlying robotics were developed during five decades prior to the introduction of the first industrial robots in the 1960s (Brossia, 1983).

Nevertheless, surprisingly little theoretical or empirical work has examined in detail how age of knowledge affects innovation (see Rosenkopf & Nerkar, 2001 and Sørensen & Stuart, 2000 for studies that have started to examine this issue). In this paper I address this question more comprehensively by investigating how the average age and the age diversity of the searched knowledge affects innovativeness. The characteristics of searched knowledge are measured through the firms' patenting behavior, and innovativeness through new product introductions. The study is longitudinal and focuses on industrial robotics firms.

Several theoretical mechanisms support both the use of recent and the use of old knowledge. First, organization-environment fit, capability-building in emerging areas, and reduced search costs explain why recent knowledge enhances innovation. Organization ecologists and learning researchers argue that organizations should build on recent knowledge to constantly maintain a fit between an organization and its environment (Hannan & Freeman, 1984; Thompson, 1967). "Learning and adjusting structure enhances survival chances only if the speed of response is commensurate with the temporal patterns of relevant environments" (Hannan & Freeman, 1984: 151). One mechanism that firms use to adapt to changing environments is new product innovation (Schoonhoven, Eisenhardt, & Lyman, 1990). Thus, to successfully adapt and to maintain the organization-environment fit, firms should build on recent knowledge in their new product search. For example, Sørensen and Stuart (2000: 81) argue that "Difficulties of keeping pace with incessant external developments cause firms' innovative output to become obsolete relative to the most current environmental demands." Recent knowledge can also enhance the firm's ability to expand to new technological areas. Firms that build on recent knowledge frequently are better able to predict the nature of future technological advances – lack of investment in an area early on may foreclose the firm from the future developments in that area (Cohen & Levinthal, 1989; McGrath, 1999). The third mechanism that explains why recent knowledge benefits innovation is reduced search costs. Searching recently created knowledge conserves cognitive capabilities, and is more likely to lead to rewards (Cyert & March, 1963).

Second, the literature provides three theoretical arguments – increased reliability, decreased risk of retaliation, and uniqueness – to explain why recent knowledge hurts, and old knowledge, in fact, enhances innovation. In general, innovation is uncertain, and most new ideas turn out not to be as beneficial as people had hoped. Knowledge that has been around for a longer period of time is usually considered more legitimate, reliable (March, 1991), elegant, and robust (Hutchins, 1983), increasing the chances of its successful recombination and successful innovation. Older knowledge can also be more beneficial due to the decreased threat of retaliation (Smith, Grimm, Gannon, & Chen, 1991). Building on recent knowledge is likely to be seen as a direct attack against the creators of that knowledge, and is likely to initiate a retaliatory response. In contrast, a retaliatory response to building on older knowledge is much less likely, since firms tend to weight the most recent events and ideas more heavily, i.e., exhibit recency bias (Levinthal & March, 1993). The third argument that supports the use of old knowledge is uniqueness. As mentioned above, organizations tend to focus on recently created knowledge. While recent knowledge is relatively easily available for many firms, older knowledge is often more difficult to access and build on (Argote, 1999; March et al., 1991). Organizations may be able to create unique resources through search of older knowledge (Barney, 1991).

In this paper I analyze these two seemingly contradictory propositions on search age – that building on old technological foundations hurts innovation, and, that old knowledge may in fact be a source of valuable ideas that enhance innovation – and show that these propositions are not contradictory, but apply to different kinds of knowledge. Building on and extending prior work (such as Ahuja & Katila, 1999; Baum, Li, & Usher 2000; Rosenkopf & Nerkar, 2001), I make a distinction between three areas of the firm's search space: the search of its own knowledge-base, the search of its competitors' knowledge, and the search of external (outside-industry) knowledge, and find that both propositions about time hold, but under different types of search. Whether age hurts or promotes innovation depends on where firms search.

The contributions of the study are two-fold. The paper increases our knowledge of organizational search; we learn that firms differ in how they search old and new knowledge, and that these differences affect innovation. Second, the study examines the simultaneous effects of search space and time (see also Baum et al., 2000), and shows that the search of older knowledge does not always hurt innovativeness, unlike prior work often assumes, but in fact promotes innovation if the searched knowledge is outside the firm's own industry.

CONCEPTUAL DEVELOPMENT

New product introductions

New product introduction is an important measure of innovativeness, because it indicates the potential commercial significance of the firm's innovation activities. Most innovations cannot influence firm performance until the idea has been put into use and introduced to the market. Although Barnett and Freeman (2001) showed that product introductions can become "too much of a good thing" if too many products are introduced simultaneously and Sorenson (2000) warned that product introductions become less valuable as the total number of products in the industry increases, prior research generally finds that new products enhance market share, market value (Chaney & Devinney, 1992), performance (Roberts, 1999) and survival of firms (Banbury & Mitchell, 1995). Yet, few studies examine the characteristics of search that lead to new products – most search studies focus on the effects on more intermediate outputs such as patent citations.

Innovation search

Innovation search is one of organizations' problem-solving activities (Nelson & Winter, 1982). In innovation search, firms solve problems through combining knowledge elements with the goal of creating new products. Essentially, innovation search is one type of organizational learning process (Huber, 1991): through search, organizations improve upon their current technology (Nelson & Winter, 1982), learn and develop new skills (Makadok & Walker, 1996), and adapt to environmental changes (Cyert & March, 1963).

Innovation search across space and time

How do firms search for new products? One theory has been that firms search *over a knowledge space*, i.e., they search and combine knowledge across a set of knowledge elements in their environments (e.g., Katila, 2000; Nelson & Winter, 1982). This search space can be divided in internal and external search: whether firms search knowledge created within their own organization, or knowledge created by others (see for example Grant, 1996; Mansfield, 1988; Rosenkopf & Nerkar, 2001). In other words, firms may be more innovative because they are productive in translating their internal knowledge into new products, or because they are good at capturing knowledge spillovers from other firms or from academia. External search space can be further divided in two: search of knowledge created within the industry vs. outside it. Because industries differ in the types of knowledge that they use, firms develop industry-specific knowledge-spaces. This prior industry-specific knowledge helps firms more easily absorb new knowledge that is inside the industry than outside it (Cohen & Levinthal, 1990). The firm's search space is therefore divided into internal, competitor (intra-industry), and external (extra-industry) space.

In this study I add another, less-researched dimension, time, to further refine the analysis of how firms search for new products. How firms search *over time*, i.e., whether firms use relatively recent or more distant knowledge, can critically affect the firm's ability to innovate. In the next section the mechanisms that introduce the pros and cons of searching knowledge of various ages are used to form specific hypotheses about how search age affects innovation.

HYPOTHESES

In the following hypotheses I propose that the age of searched knowledge has different effects on product innovation depending on the search area. *New product introduction* is defined as the number of new products introduced by each firm yearly. *Internal search* is defined as the firm's search of its own, previously created knowledge, *competitor search* as the search of knowledge created by the firm's competitors, and *external search* as the search of extra-industry knowledge. Hypotheses 1-3 focus on *average search age*, defined as the mean of the age of knowledge used in the firm's yearly innovation search; Hypothesis 4 on *search quantity*, i.e., the number of external knowledge elements searched each year; and Hypotheses 5-7 on *diversity in search age*, defined as the variance in the age of knowledge used in the firm's yearly innovation search.

Average search age

Average internal search age. Older internal knowledge enhances innovation in two main ways. First, old internal knowledge is more reliable. Organizations that created the knowledge elements in the past have had time to thoroughly learn and understand their consequences, and to compare the effects under various environmental conditions. Older internal knowledge is usually also better tested and established than more recent or external knowledge, decreasing the chances of costly errors, and increasing the productivity of search (Cooper & Kleinschmidt, 1986; Levinthal & March, 1993).

Second, searching knowledge from the more distant past of the organization's life can make the innovation seem more legitimate. Dougherty and Heller (1994) argue that, by definition, innovation is illegitimate in established organizations. However, scientists can link the present innovation to knowledge created in the organization's past, and thus "instill their innovation with a sense of legitimacy that otherwise would be lost" (Kantrow, 1987). In other words, older internal knowledge can be used to fight the "not invented here" syndrome. Consequently, the chances for commercializing the idea increase.

However, beyond some threshold, problems with knowledge depreciation start reducing these positive effects. For example, forgetting, lost records, and turnover in R&D personnel (Argote, 1999) cause the reliability and legitimacy benefits to diminish over time. The individual tendency to mold the historical data to support the organizational beliefs may also stimulate multiple or incomplete interpretations of the original knowledge (March et al., 1991). Thus, in situations where interpretations of events, knowledge, and ideas are called forth a long time after their original creation, the original knowledge can get obscured. These memory problems increasingly lead to a need to resolve conflicting interpretations and to close gaps in memory, and, consequently, increase the costs of using the old knowledge effectively. Eventually, due to these problems, the costs of old age will exceed the benefits.

Competency traps may also explain why the effects of old knowledge become negative over time. A firm that to a large extent builds on its past knowledge-base often passes on a chance to build experience with more recent, and potentially more rewarding knowledge. For example, Sørensen and Stuart (2000) found that semiconductor firms who built on their own old knowledge extensively received fewer subsequent citations from other firms. Eventually, as time passes and the new knowledge starts to show its value, the firm can get caught in a competency trap if its experience with this more recent, superior knowledge is inadequate to make it rewarding to use (Levitt & March, 1988). If the firms' competitors already use the new knowledge, the firm may find it increasingly difficult to introduce products based on the old knowledge. Based on the above observations, I suggest:

Hypothesis 1. *The mean age of internal knowledge searched by a firm will be curvilinearly related (inverted U-shape) with the number of new products introduced by the firm.*

Average competitor search age. Spillover effects, i.e., the ability to benefit from the R&D activities of others in the industry, are well documented (Cohen & Levin, 1989). For example, search of recent competitor knowledge helps firms build early-mover advantages, and keep up with the changes in the industry. In fact, population ecologists measure an organization's fitness as relative to that of the other organizations in its environment (Hannan & Freeman, 1984; Stuart & Podolny, 1996). As the competitor search age increases, however, firms may end up searching obsolete or non-unique information that rapidly starts hurting innovativeness. For example, Hannan and Freeman (1984: 151) state that "organizations should learn about their environments and change strategies and structure as quickly as environments change."

First, building on recent competitor knowledge helps firms avoid obsolescence. Although population ecologists assume that, in general, there are limitations on the ability of individual organizations to change, they acknowledge that change can be successful if its timing is right, i.e., if the firm and its competitors change simultaneously (Hannan & Freeman, 1984: 151). On the other hand, firms that lag behind their competitors may not be prompted to start changing on time, and may face increasingly high product performance standards and increasingly lower product output as the performance limits of the old knowledge are reached, and the competitors have switched to newer bases of knowledge with higher performance potential (Foster, 1986). For example in robotics, a US robotics pioneer Unimation ignored its competitors' change from hydraulic to electric technology and lost its leading position in the industry. "The Unimate was a good robot at the time, but Unimation neglected to change in an environment that was very dynamic." The company did introduce an electric robot eventually, but all this came too late when other companies had already moved to next generations of electric robots (Naj, 1990).

Second, the pace of innovation reduces nonlinearly as competitor knowledge age increases. Firms that build on knowledge created in the industry's past are increasingly more likely, as the knowledge ages, to deplete and eventually exhaust the pool of knowledge combinations that would lead to products that are new to the industry. At the same time, the new combinations that include the old knowledge element are likely to be increasingly complex and expensive since the "easy" variations have already been exploited previously (Ahuja & Katila, 1999; Fleming, 2001). Consequently, search of old competitor knowledge starts rapidly hurting innovation. A following nonlinear relationship is proposed:

Hypothesis 2. *The mean age of competitor knowledge searched by a firm will have a faster than linearly decreasing relationship with the number of new products introduced by the firm.*

Average external search age. As described previously, external search is defined as the search of knowledge created by companies outside the firm's own industry, by the government, by independent innovators, and by researchers in the academia. Increasing the age of externally searched knowledge provides time to (1) codify the new knowledge, and (2) to build the competencies to absorb that knowledge.

First, accessing external knowledge soon after its creation is often expensive since new knowledge is tacit (that is, difficult to articulate for transfer). Although firms who have common or similar experiences may, to some degree, share tacit knowledge, tacitness makes it problematic for firms outside the industry to understand and to use the knowledge effectively (Polanyi, 1967). In fact, new technological knowledge often takes a long time to diffuse across industries. Thus, recent external knowledge is less likely to promote innovation than older knowledge.

Second, firms may not be able to build upon distant knowledge until they develop capabilities in that area. Such capability-building takes time (Cohen & Levinthal, 1990). Also Dosi (1988: 1131) notes that "information about what other firms are doing spreads quickly, however, the ability to produce or replicate innovative results is much more sticky." Consequently, firms may not be able to use very recent external knowledge effectively in their innovation efforts. Based on the above arguments, a following hypothesis is proposed:

Hypothesis 3. *The mean age of external knowledge searched by a firm will be positively related with the number of new products introduced by the firm.*

Average external search age and search quantity. In the previous three hypotheses the average age of internal, competitor, and external search were examined. While the search of recent internal knowledge and contemporary competitor knowledge promote innovation, in external search, firms benefit most if they search old knowledge. This third proposition is especially interesting because it suggests that recent knowledge foundations may not always be optimal, unlike previous research on innovation has assumed. However, one potential problem is that it costs more to search old external knowledge than the other types of knowledge. In Hypothesis 4 I propose in more detail how firms can enhance their chances of succeeding in old external knowledge search.

Hypothesis 4 suggests that old external knowledge and number of searched knowledge elements leverage each other in new product search. Evolutionary theorists point out that the more alternatives there are to select from, the greater the contribution of the alternative that is selected (Campbell, 1960; Nelson & Winter, 1982). In innovation search firms can increase the amount of choices simply by increasing the amount of different knowledge elements the firm searches. Having a low number of alternatives is especially risky when the focal firm's familiarity with the knowledge elements is low, i.e., knowledge is external (Heiner, 1986). Thus, I hypothesize that the combination of old external knowledge and high external search quantity enhances new product innovation:

Hypothesis 4. *An interaction of the firm's external search age and external search quantity will be positively related with the number of new products introduced by the firm.*

Diversity in search age

Hypotheses 1-4 focused on the average age of knowledge the firms search. However, these hypotheses did not specify whether it is better to search a range of ages or tightly around the average. In other words, we do not know how diversity in search age affects innovation. Theoretically, more diverse ages can expose the firm to more diverse knowledge, and thereby benefit innovation. On the other hand, searching diverse knowledge ages can make the search costly, and thus hurt innovativeness. Diversity of search age is defined as the degree of temporal heterogeneity in search; i.e., the extent to which firms search a narrow or a broad range of knowledge of various ages. Hypotheses 5-7 relate the diversity in internal, competitor, and external search age to the number of new product introductions.

Diversity in internal search age. The positive effect of temporally diverse internal search is based on the argument that firms can create new innovations through bringing together their existing ideas into new, previously unconnected combinations (Schumpeter, 1934). A firm's historical knowledge-base – a set of information inputs, knowledge, and capabilities created over time – provides a source for inventors to draw on when looking for new innovative combinations. Intrafirm knowledge combinations of this kind are also potentially valuable since they are based on the firm's own well-established underlying knowledge-base developed over time, in contrast to the ones grounded in less familiar, externally developed bodies of knowledge (Cohen & Levinthal, 1989). Therefore, diverse knowledge age in internal search is proposed to promote innovation.

Alternatively, it is possible that internal knowledge is not diverse enough for recombination. Evolutionary researchers such as Nelson and Winter (1982) suggest that firms tend to produce new knowledge that is closely related to the old, that is, a firm's R&D activities are path-dependent. Empirical evidence supports this argument. Helfat (1994) found that the firms' R&D allocations on different technological areas change relatively little over time, and Wade (1996) and Martin and Mitchell (1998) discovered that firms tend to introduce new product designs that are similar to their existing designs. These empirical findings also support the population ecology arguments that firms' search activities are bounded and subject to pressures of inertia (Hannan & Freeman, 1984). Consequently, these arguments suggest that increasing temporal diversity in internal search is not likely to create enough variety to produce new recombinations and to promote innovation, but still entails higher search costs since the organization has to search back in time. According to this argument, diversity in internal search age is more likely to hurt than enhance innovation. Thus, two alternative hypotheses are proposed:

Hypothesis 5a. *The age variance of internal knowledge searched by a firm will be positively related with the number of new products introduced by the firm.*

Hypothesis 5b. *The age variance of internal knowledge searched by a firm will be negatively related with the number of new products introduced by the firm.*

Diversity in competitor search age. In any single industry, different technological communities (Wade, 1996) and technological paradigms dominate at different times: each paradigm focuses the innovation search in a particular direction, narrowing the set of objectives to be pursued, and hence narrowing the range of technological alternatives, problems, and answers. Unlike a single firm's R&D activities that tend to be path-dependent and local, the R&D activities of firms, or cohorts of firms in an industry can follow widely different search paths (Jaffe, 1989). Thus, searching ideas across various paradigms brings variety, and increases the number of elements available for novel combinations (Schumpeter, 1934). Searching old competitor knowledge also provides information on the technological directions that were not taken, or were used only for a short time in the industry's past. These abandoned directions contain valuable lessons of why these approaches did not work – and possibly include knowledge elements that could be re-evaluated and re-used in today's changed circumstances. Therefore, searching across cohorts of competitor knowledge should enhance innovation.

Excessively diverse temporal search of competitor knowledge will, however, eventually harm innovation. First, the positive effects of new knowledge combinations across paradigms will increase at a decreasing rate as the "easy" combinations get formed first, and the remaining ones are increasingly complex and expensive sources of new innovations (e.g., Ahuja & Katila, 1999). Second, integrating knowledge from different paradigms to the firm's knowledge-base is costly: each new knowledge element needs to be integrated to the firm's existing knowledge base, and common interfaces need to be established among knowledge elements (Barley, 1986). The wider the scope of knowledge being integrated, the increasingly more complex are the problems of creating and managing the integration (Grant, 1996: 377); not only do the new knowledge elements need to be absorbed, but also increasing number of relationships between these elements need to be managed. Therefore, firms that are trying to adapt to a number of different cohorts of knowledge face increasingly higher costs (Barnett & Hansen, 1996). These mechanisms will exceed the benefits of diversity at some point, and make the relationship between competitor search age variance and innovation curvilinear (inverted U):

Hypothesis 6. *The age variance of competitor knowledge searched by a firm will be curvilinearly (inverted U-shape) related with the number of new products introduced by the firm.*

Diversity in external search age. As was discussed in Hypothesis 3, old external knowledge promotes innovation. However, age diversity in search, i.e., searching also more recently created external knowledge, may play an important role in the ability of firms to successfully absorb and utilize such old knowledge. It might be the very act of scanning recent knowledge that makes the firm aware of new developments and induces capability-building that might allow firms to capitalize on the external knowledge later in time (e.g., Cohen & Levinthal, 1990). This scanning activity is especially important for external knowledge, since firms are much less likely to follow and be aware of developments outside their own industry unless they make a conscious effort to do so. Sometimes scanning of external knowledge may also reveal new developments in complementary technological areas that could, in turn, trigger development of old concepts that have been shelved in the industry for a long time, because the complementary knowledge had not been ripe.

However, eventually the firm's ability to build on increasingly diverse knowledge will cease. As the temporal diversity increases, more and more recent knowledge elements will be included in recombinations. As discussed before, integrating this knowledge is costly due to its tacitness. The previously described knowledge integration costs also increase as diverse knowledge elements need to be integrated to the firm's existing knowledge base. Since the firm is searching in areas where the knowledge is extremely unfamiliar to the organization, these negative effects are likely to be increasingly stronger as the diversity increases. Consequently, I propose that the number of new products will first increase with diversity in external knowledge age, but beyond a point, additional diversity will cause a fall in product output:

Hypothesis 7. *The age variance of external knowledge searched by a firm will be curvilinearly (inverted U-shape) related with the number of new products introduced by the firm.*

RESEARCH METHODS

Research setting and sample

The research sample consisted of 131 public industrial robotics companies that originate in Europe, Japan, and USA. The data for these companies extends from 1985 to 1997. Industrial robotics companies develop robots that can be programmed to move materials, parts, tools or specialized devices to perform a variety of industrial tasks (Robotics Industry Association, 1979).

Studying the robotics industry is especially topical now since "after decades of promises, hopes and disappointments, the long-awaited 'robot revolution' may at last be starting to get underway. Quasi-autonomous devices have become increasingly common on factory floors, hospitals and farm fields. Physicians use robotics to aid in bone and brain surgery" (Suplee, 2000: A14). And even personal robots are slowly starting to enter our lives (Lewis, 1998). These developments, and the high R&D intensity and complex search problems that the robotics firms solve, make industrial robotics an appropriate and exciting setting for the study.

A list of companies in the industrial robotics industry was obtained through an extensive search of robotics trade magazines and databases, and through discussions with industry experts.

All companies on the list were then examined to distinguish those companies that develop or were planning to develop industrial robots, excluding, for example, part suppliers and companies that manufacture or market through a license. This comprehensive sample selection method assured that the study would not be sampling on the dependent variable: all relevant companies for which the control variable data were available were included independently of their product performance. The final sample included 131 public firms, and covered 1255 firm-years. The firms were included in the sample for the time period they participated in the industry. Industry entry and exit data for each company were collected from *Predicasts* and industry reports.

Data sources

Two primary sources of data were used: new product introduction announcements and patents. I used the "literature-based innovation output indicator" method to assemble data on new products (Coombs, Narandren, & Richards, 1996). This method generates a comprehensive set of new robot introductions from editorially-controlled new product announcement sections of technical and trade journals as well as relevant product catalogs. These data are highly reliable since multiple sources are used to confirm the announcements.

The main source for the patent data collection was the *United States Patent and Trademark Office* database. *Who owns whom* directories were used to create the patent portfolios for each firm. Given the large amount of patents to be analyzed, computer programs in C language were written to clean, compile, and analyze the data. These programs made it possible to comprehensive analyze the data over a period of twelve years for 131 companies, instead of analyzing only a cross-sectional set of patents for a subset of companies, as has been done in several previous studies. The data for the control variables were collected from annual reports, databases, *Predicasts*, and industry studies.

Dependent variable

Number of new product introductions. To operationalize the dependent variable, ***Number of new products***$_{it}$, I used Martin and Mitchell's (1998) definition of a new product as change in the product's design characteristics. A robot is defined to be new if there is a change in one or more of its design characteristics in comparison with the firm's previous robots. Robots' design characteristics include load capacity, number of axes, power source, repeatability, sensors, speed, weight, and application areas. According to this definition, introducing an existing product design in a new geographical area, for example, does not qualify as a new product.

Independent variables

Citations in patents are used to construct the independent variables. Patent citations record the previous scientific and technical information, or knowledge, upon which the patent idea is based (Walker, 1995: 3). The technological domain of the patent starts only from the point where the prior art (i.e., citations) ends, discouraging generous or inaccurate citing. Patent laws are also designed to ensure that firms do not cite too few patents: "Applicants for a patent have the duty to disclose at the time of application any pertinent prior art. Not to do so can result in a charge of fraud, can cause the resulting patent to be voided and other penalties" (Walker, 1995: 85). Several authors such as Trajtenberg (1990) and Albert et al. (1991) have shown that this system works; patents that are highly cited are also economically and technically important. Thus, possibly unlike other types of citations, patent citations are not accidental, but represent a relatively accurate picture of the search activities of firms.

Several factors motivate the use of patent citation data to measure the age of searched knowledge. Since patents, by definition, include a description of a technical problem and a solution to that problem (Walker, 1995), patent data gives us a detailed and consistent chronology of how firms solve problems, i.e., search. Patent citations show what knowledge was combined, and what the age of the combined knowledge was. Such data are usually not public, or, even if available, often extremely resource-consuming to collect across long time periods (Cohen, 1995: 205). Several authors have in fact used patent data as an indicator of innovative activity in parallel with, or in lieu of R&D expenditure data. For example Jaffe (1989) used patent technology classes to describe technological positions of firms, and Stuart and Podolny (1996) and Rosenkopf and Nerkar (2001) used patent citations to operationalize innovation search. The use of patents to measure search is also appropriate in robotics since patents correlate highly with other indices of robotics R&D efforts (Grupp, Schwitalla, Schmoch, & Granberg, 1990: 125), and patents have been shown to be an important appropriability mechanism in robotics (Kumaresan & Miyazaki, 1999), as they are in the industrial machinery industry in general (Arundel & Kabla, 1998; Cockburn & Griliches, 1987).

Search age variables are measured through the age of those patents that are cited in a given firm's yearly patents (see also Bierly & Chakrabarti, 1996; Rosenkopf & Nerkar, 2001). In this study a firm's yearly patents are defined as patents that the firm applied for that year. The age of a citation is determined as the time elapsed between the time when the cited patent was originally issued, and the time when it was cited by the focal firm. In general, firms that cite new patents are elaborating on the state-of-the-art knowledge, whereas firms that cite older patents search more established knowledge. The details of the search age measures are given below.

Average internal search age. This variable represents the average age of the knowledge a firm uses in its internal search. Internal search age is signified by citations to the firm's own patents, and measured as the average age of such self-citations in the firm's patents each year.

Average competitor search age. This variable captures the average age of competitor knowledge the firm uses in its search. A patent is defined to be competitor knowledge if it was originally created by any of the other 130 robotics companies in the sample. Average competitor search age is then measured as the average age of citations to competitor patents each year.

Average external search age. This variable represents the average age of the external knowledge foundations used in search. External search age is measured as the average age of those citations in the firm's patents each year that were not self- or competitor-citations.

External search quantity. This variable describes the intensity of the firm's yearly external search efforts. As described previously, each patent includes a unique solution to a technical problem (Walker, 1995). Thus, I use the sum of external patents the firm cites each year to measure the quantity of its external problem-solving (search) efforts. Each patent, although possibly cited multiple times by the firm during a year, is counted only once.

Diversity of internal search age. This variable represents the diversity in the ages of internal knowledge elements the firm searches. It is measured as the variance (c.f. Sørensen, 2000) in internal search age for each firm yearly.

Diversity of competitor search age. This variable stands for the diversity in the ages of competitor knowledge the firm uses in its search. Again, it is measured as the variance in the firm's competitor search age yearly.

Diversity of external search age. This variable captures the diversity in the ages of the external knowledge used in search, and it is measured as the variance in the firm's yearly external search age.

Control variables

Firm size. Size influences innovativeness in several ways. Theoretically, learning, scale, and scope effects enhance innovation in large organizations (Cohen & Levin, 1989; Henderson & Cockburn, 1996). Increasing firm size can also hinder innovation: evaluation of R&D projects in large organizations is difficult, lowering incentives and reducing the productivity of individual scientists (Cohen, 1995). Empirical results on the effects of size on product innovation have been mixed, possibly reflecting these multiple underlying mechanisms. While most studies have reported a positive effect (e.g., Chaney & Devinney, 1992), some studies have found a negative effect (Mansfield, 1968), or no effect at all (Clark, Chew, & Fujimoto, 1987). Size is measured as the number of corporate employees.

Firm performance. A firm performance measure, return on assets, is included to control for the possibility that financial performance affects innovation. Prior research suggests two possible effects: organizational search theorists argue that increase in slack resources encourages search for new innovations (Levinthal & March, 1981); prospect theorists, on the other hand, predict the opposite: when organizational performance is good, managers are less likely to explore new alternatives (Cyert & March, 1963).

R&D expenditure. I used the firm's yearly R&D expenditure (M$) as a proxy for the firm's total R&D inputs to the innovation process. These data also control for the total amount of the firm's innovation search activities (Cohen, 1995).

Collaborations. Organizational researchers argue that businesses often cannot develop all innovations in-house (e.g., Mitchell & Singh, 1996). Since this concern is especially strong for complex, multi-technology robotics innovation, the number of sample firms' factory automation collaborations is included as a control for collaborative activity.

Technological diversification. Since firms usually search best locally, i.e., close to their existing knowledge-bases (e.g., Nelson & Winter, 1982), I control for the technological diversification of the firms' search activities. To operationalize this variable, I measure the proportion of the patent technology sub-classes the firm enters each year that are new to it (e.g., Fleming, 2001). Patent classes are assigned by the patent office to characterize the underlying technological foundations of each patent. Since knowledge depreciates and firms forget, the variable is constructed by comparing this year's classes with previous five years' classes in the firm's patent portfolio.

Product diversification. Product diversification can have both positive and negative effects on innovation. Since diversified firms have more opportunities to use new knowledge, diversification can enhance innovative output through an economies of scope effect (Kamien & Schwartz, 1982). On the other hand, Hoskisson and Hitt (1988) have shown that as firms become more diversified, corporate management understands the firm's R&D activities less, decreasing commitment to long-term innovation. A diversification dummy variable, which takes a value 1 if a firm has other businesses besides factory automation, is used.

Nationality. Since the sample firms are from different geographical areas, I include a dummy variable to control for the country-specific effects of research productivity and patenting propensity (e.g., Arundel & Kabla, 1998). Region dummies (Japan, Europe, US) are included to indicate the origin of the robotics firm. Japanese firms are the omitted category.

Calendar time. Time effects were controlled through year dummies (1985-1996). Year 1996 was the omitted category.

Statistical method

Since the dependent variable of the study, ***Number of new products$_{it}$***, includes counts of new products with a large number of zero values (no product introductions in a given year), negative binomial regression is used (Cameron & Trivedi, 1998). Additionally, longitudinal data with repeated yearly observations for each subject can introduce bias since observations for the same subject can be correlated. Within-subject correlation usually reduces the variance of the parameters and overestimates the significance of the covariate effects. To correct for potential bias caused by such correlations, I used the generalized estimating equations method (Liang & Zeger, 1986; see also Haveman & Nonnemaker, 2000). I report the results with robust standard errors (White, 1980) that relax the assumption that the choice of the correlation structure follows exactly the hypothesized one.

Data analysis

Descriptive statistics and correlations for all variables are shown in Table 1. All independent and control variables are lagged by one year, based on qualitative evidence that there is a 1-2 year lag in introducing robotics products to market (Grupp et al., 1990). My interviews with industry experts and participants confirmed this short development cycle in the industry.

--- Insert Table 1 about here ---

A panel regression approach is used for testing the hypotheses. Regression analysis pertains to years 1985-1996. The independent variables are centered on their means before creating the interaction terms (Cronbach, 1987). I used the statistical package Stata to estimate all models.

In total, 1125 new robotics introductions were included in the analysis. On average, the sample companies introduced approximately one new robotics product each year. Some companies had no new product introductions in a given year, while others introduced over 20 new robots. The average age of internal knowledge that was searched was 2.3 years, while the searched competitor knowledge was almost twice that old (4.1 years). The average age of the external knowledge the firms searched was 11.5 years. These age differences broadly support the argument that intrafirm learning processes are faster than external.

RESULTS

Hypothesis testing

Table 2 reports the results of the regression analysis on the effects of search age on product innovation. In sum, four of the seven hypotheses were supported (H1-H4) and Hypothesis 7 received partial support. Citing relatively young internal knowledge is beneficial, leading to a nonmonotonic (inverted U) relationship. Building on older competitor knowledge harms product innovation, whereas, the older the external knowledge is, the more new products the firm introduces. Search quantity leverages this effect. I also find that the diversity in neither internal nor competitor search age strongly affects innovation, and that the increasing diversity in external search age rapidly starts hurting product innovation.

--- Insert Table 2 about here ---

In Table 2, ***Number of new products***$_{it}$ is the dependent variable as described above. The first model reports the baseline where ***Firm size***$_{it-1}$, ***Return on assets***$_{it-1}$, ***R&D expenditure***$_{it-1}$, ***Collaboration frequency***$_{it-1}$, ***Technological diversification***$_{it-1}$, ***Product diversification***$_{i}$, and nationality and year dummies are included as control variables. Model 2 introduces ***Internal search age***$_{it-1}$ and ***Internal search age***$_{it-1}^{2}$, ***Competitor search age***$_{it-1}$ and ***Competitor search age***$_{it-1}^{2}$, and the ***External search age***$_{it-1}$ variables. Model 3 contains the interaction effect of ***External search age***$_{it-1}$ with ***External search quantity***$_{it-1}$, and in Model 4 ***Diversity in internal search age***$_{it-1}$,

Diversity in competitor search age$_{it-1}$, and ***Diversity in external search age$_{it-1}$*** variables are added. Below, I discuss the results based on the full model (Model 5 in Table 2).

In Hypothesis 1 I proposed that internal search age has a curvilinear (inverted U) relationship with new product innovation. In Model 5 the coefficient for the internal search age variable is positive, while the coefficient for the squared term of internal age is negative and significant, supporting the hypothesis. Hypothesis 2 proposed a nonlinearly decreasing relationship between competitor search age and new products. Since search age is always positive, the negative and significant square term (and a nonsignificant linear term) confirms the hypothesis. Hypothesis 3 proposed a positive relationship between external search age and new products. Consistent with the expectation, the linear coefficient for external search age in Model 5 is positive and significant, thus supporting Hypothesis 3. I also included a square term of external age in a separate model, but this term was not significant. Hypothesis 4 predicted that age and quantity in external search leverage each other, resulting in a combined positive effect on product innovation. The estimated positive interaction between external search age and external search quantity in Model 5 provides support for this hypothesis.

Among the variance effects of search age, Hypotheses 5a and 5b proposed that the diversity in internal search age can either promote or hurt product innovation. Although the coefficient for diversity in internal search age is negative in Model 5, it does not improve the model fit when added to the model separately. One possibility is that the non-significant coefficient reflects both the positive and negative mechanisms that work simultaneously. In Hypothesis 6 I proposed a curvilinear relationship between the variance in competitor search age and innovation. Although the linear and square terms for this variable have correct signs in Model 5, they do not reach significance. I will consider possible explanations for this result in the discussion section.

Finally, a curvilinear relationship between diversity in external search age and innovation was proposed in Hypothesis 7. The square term is indeed negative and significant, but the linear term does not reach significance in Model 4. Diversity in external search age therefore has a nonlinearly decreasing relationship with new products. Since the linear term for diversity in external search age did not improve the model fit in Model 4, only the square term was retained in the full model. In all, adding each of the hypothesized search age variables (except the diversity in internal and competitor age) significantly improved the model fit.

Of the control variables, corporate diversification (***Product diversification$_i$***) has consistently negative effects in Table 2. The result that corporate diversification hurts innovation supports Hoskisson and Hitt's findings (1988). The negative sign of the ***Technological diversification$_{it-1}$*** variable shows that firms search best locally (Nelson & Winter, 1982). It is also interesting to note in Table 2 that ***Japanese*** robotics firms innovate more than their competitors in Europe and in the US. This result supports prior findings by other researchers (e.g. Mansfield, 1988).

Sensitivity analyses

First, I tested the robustness of the results to alternative controls that help partial out unobservable differences across firms. In addition to the generalized estimating equations model, I ran the models with a lagged dependent variable (Heckman & Borjas, 1980; Helfat, 1994) and a random effects estimation. In both cases the pattern of the original results was supported. The lagged dependent variable results are reported in Model 6 in Table 2.

Second, I ran a generalization of the two-step Heckman sample selection correction method discussed by Lee (1983) to account for possible bias due to companies leaving the industry before the observation period ended. The results exhibited the same pattern as the original findings. I also used a multiple imputation procedure to test the sensitivity of the results to observations missing due to lack of control variable data (Rubin, 1976). Again, the imputation results strongly supported the original findings. These results are available from the author.

Third, I included alternative measures of the key variables to make sure the results were not affected by particular operationalizations. As a first alternative measure, instead of using all corporate patents to measure search, I included each sample firm's robotics patents only. To identify robotics patents, I used a comprehensive approach including both word and technology class searches (Grupp et al., 1990). Using all corporate patents in the analysis assumes that the search for new robots benefits from the other search activities in the company (Henderson & Cockburn, 1996), whereas restricting the definition of search to robotics patent only is in line with the assumption that knowledge is "sticky" and transfers relatively poorly across divisions (Szulanski, 1996). However, the latter approach also assumes that we can accurately isolate the search efforts that contribute to new robotics products. The robotics patent results broadly exhibit the same pattern as the original results, and are reported in Model 7 in Table 2. Finally, in Hypothesis 1 I proposed that the negative effect of high internal search age on product innovation is caused by a competency trap effect. To more comprehensively test the competency trap argument, I include an *Experience* variable to control for the repeated use of knowledge by the firm (Model 8 in Table 2). *Experience* is measured through the firm's frequency of using the same patent technology sub-classes, and including the variable does not affect the original results.

DISCUSSION

The study provides evidence that knowledge age in innovation search has several different effects. The older the competitor knowledge the firm is searching, the more its innovativeness suffers, whereas the opposite was true for external search: searching old external knowledge boosted product innovation. The quantity of external search further intensified this positive effect. I also found that increasing internal knowledge age first promotes then harms innovation, and that the diversity in the ages of searched knowledge in general does not affect innovativeness, with the exception of diversity in external search age. These results have implications for theory and research, as discussed below.

Implications for theory

By combining the effects of search space and search age, this study addressed the tension between the common assumption in the innovation literature that firms should build on recent knowledge foundations, and the opposite prediction that older knowledge enhances new product innovation. To my knowledge, the present study is the first to directly test this relationship in a longitudinal study. I reviewed the theoretical mechanisms through which search age can affect innovation performance, and showed that the firm's choice of how to search over time cannot be studied in isolation from its choice of how to search over space. Whether age hurts or promotes innovation depends on where firms search.

The study also contributes to the search literature by examining a relatively little-researched relationship between industry-external search back in time and innovation. While we know a lot about the firms' ability to search internally over time (e.g. Garud & Nayyar, 1994; Szulanski, 1996), and, on the other hand, about the ability of firms to search contemporary external knowledge (e.g., Cohen & Levinthal, 1990), little is known on whether and when firms should absorb old external knowledge. This gap was addressed in this study, discovering the interesting result that older external knowledge can be a source of new innovations.

The results also confirm and extend a number of previous findings in the organizational learning literature. Consistent with Baum and Ingram's (1998) result that the firm's experience has an inverted U relationship with survival, I found that the firm's internal search age first has a positive effect on innovation performance, but, in excess, decreases it. Also, past studies of interorganizational learning have generally found that firms tend to learn only from related organizations (Argote, 1999). The present study also found evidence that robotics firms learn from their competitors (in the global robotics industry the large, public companies analyzed in the study tend to be related through the same customers and suppliers, for example), but also introduced an important qualifier to this relationship. The speed of learning matters: organizations that learn slowly from competing organizations may actually find their innovation performance rapidly deteriorating. In fact, it was surprising how fast the competitors' knowledge lost its value. Interestingly, Rosenkopf and Nerkar (2001) find a similar effect in the R&D activities of optical disc firms: firms that cite older knowledge are less likely to have an impact on the subsequent research activities of their competitors. These findings have interesting implications for understanding the resource-based perspective as well (Barney, 1991). Firms that are fast in responding and building on their competitors' actions introduce more products, thus encouraging imitation rather than uniqueness.

In slight contrast with several prior studies (c.f., Darr, Argote, & Epple, 1995), I also found interesting evidence that unrelated experience does make a difference, at least in the empirical setting of this study. Old external knowledge increased the innovation performance of robotics firms. One possible reason why the previous studies did not see this effect is that the knowledge base required for robotics innovation is broader than the knowledge bases used in many other industries. It is also possible that the long time lag that exists between when the external knowledge is born and when it becomes useful (the average external citation age in this study was 11.5 years) has prevented examination of this effect. The methodology and longitudinal data used in this study made it possible to observe the effect despite such lags.

Implications for research

The lack of support for Hypothesis 6 on diversity in competitor search age deserves more analysis. I hypothesized that searching temporally moderately diverse competitor knowledge would enhance innovation, but did not find a significant such effect. One reason could be that building on knowledge from competing paradigms within the industry is not easy. In fact, Stuart and Podolny (1996) found that among the largest firms in the semiconductor industry, only one firm was able to move significantly across the technological groupings in the industry. Alternatively, it is possible that in the empirical setting of this study the competitors' search efforts are relatively homogeneous across time; few firms experiment, and thus the variety that would enhance innovation does not exist. To test for this possibility, I ran an additional analysis by dividing the study period in two phases based on prior work on the industry life-cycle stages of the robotics industry. Years 1984-1989 have been named a period of shakeout, and the period after 1990 a time for regrowth in robotics (Dahlin, 1993). We would expect that during the earlier, shakeout period companies would be more likely to experiment with different technological approaches. Indeed, in the empirical analysis, I found that the diversity in competitor search age had a curvilinear, inverted U-shaped relationship with innovation during the earlier period, but the effect disappeared in the later period.

Finding a rapidly decreasing rather than a hypothesized inverted U-shaped relationship between diversity in external knowledge age and innovation (Hypothesis 7) also needs further thought. One possibility is that my measures do not capture the positive monitoring effect proposed in the hypothesis. Since monitoring new external knowledge does not necessarily result in its use to solve problems, monitoring may not be captured in the patent citation measures.

The study also has limitations. Previous studies have shown that the propensity for patenting varies considerably across industries (see for example Cockburn & Griliches, 1987). Such variability is not a problem in this study because I focus on one industry, industrial robotics. However, the patent measures do not necessarily generalize to all other industries. Patents also focus on the firm's technological search, and often do not, for example, capture search across the science-base (see for example Ahuja & Katila, 1999) or across the customer-base (Sorenson, 2000).

This study also leads to several exciting questions for future search research. For example, how do firms build capabilities for searching recent competitor knowledge, and older external knowledge? Whether certain firms are better in some types of search should also be investigated. In future work other versions of the dependent variable could be examined as well. Instead of looking at only the quantity of new products, the quality of innovation could be measured. For example, Fleming's (2001) work on technology space suggested that firms that have greater variation in their technological efforts come up with fewer, but more radical innovations. Future work should test whether firms that build on temporally diverse foundations also innovate less frequently, but bring more radical, and possibly also more successful, products to the market. Another interesting area for future work is to study how the age of knowledge affects the speed of the new product development process, and whether this effect differs across industries (e.g., Clark et al., 1987; Eisenhardt & Tabrizi, 1995).

Conclusion

This study examined how firms search to introduce new products. The study drew attention to the multiple meanings of time in the innovation process, and especially to the different benefits of recent and distant knowledge in search. The study discovered that the firm's choice of how to search over time cannot be studied in isolation from its choice of how to search over space. The innovation performance differences between firms were shown to be based on the different capabilities in deploying internal, related, and external knowledge over time. This way, the study helped us open up the "black box" of innovation search and understand how firms create new knowledge.

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TABLE 1
Descriptive statistics and correlations[a].

		Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Number of new products$_{it}$	0.90	2.32															
2	Internal search age (avg)$_{it-1}$	2.32	2.49	0.01														
				0.65														
3	Competitor search age (avg)$_{it-1}$	4.14	3.16	-0.01	0.29													
				0.80	<.0001													
4	External search age (avg)$_{it-1}$	11.54	7.29	0.02	0.29	0.32												
				0.46	<.0001	<.0001												
5	External search quantity$_{it-1}$ /100	4.21	8.85	0.13	0.14	0.06	-0.10											
				<.0001	<.0001	0.03	<.001											
6	Internal search age (div)$_{it-1}$	8.30	14.75	0.02	0.55	0.20	0.17	0.20										
				0.47	<.0001	<.0001	<.0001	<.0001										
7	Competitor search age (div)$_{it-1}$	17.63	41.61	0.03	0.12	0.28	0.11	0.06	0.10									
				0.27	<.0001	<.0001	<.001	0.04	<.001									
8	External search age (div)$_{it-1}$	196.9	187.9	0.05	0.25	0.24	0.82	-0.07	0.21	0.12								
				0.08	<.0001	<.0001	<.0001	0.02	<.0001	<.0001								
9	Firm size$_{it-1}$	38.64	98.07	-0.03	0.17	0.10	0.07	0.43	0.21	0.06	0.07							
				0.30	<.0001	<.001	0.01	<.0001	<.0001	0.03	0.01							
10	ROA$_{it-1}$	0.02	0.05	-0.004	0.06	0.06	0.03	0.08	0.07	0.03	0.04	0.06						
				0.88	0.03	0.04	0.28	0.01	0.02	0.23	0.16	0.05						
11	R&D expenditure$_{it-1}$	0.33	0.78	0.07	0.15	0.07	-0.03	0.67	0.19	0.05	-0.02	0.84	0.03					
				0.01	0.14	0.01	0.35	<.0001	<.0001	0.06	0.44	<.0001	0.23					
12	Collaboration freq$_{it-1}$	0.16	0.50	0.31	0.06	0.01	0.05	0.14	0.08	0.01	0.06	0.06	0.04	0.08				
				0.31	0.05	0.65	0.06	<.0001	0.01	0.85	0.02	0.02	0.16	<.001				
13	Technological diversification$_{it-1}$	0.26	0.25	-0.04	-0.05	0.09	0.30	-0.25	-0.12	-0.001	0.14	-0.17	-0.05	-0.22	-0.02			
				0.12	0.06	0.003	<.0001	<.0001	<.0001	0.96	<.0001	<.0001	0.06	<.0001	<.0001			
14	Product diversification$_{i}$	0.93	0.25	-0.10	0.16	0.13	0.17	0.12	0.13	0.06	0.14	0.10	-0.01	0.11	-0.13	0.02		
				<.001	<.0001	<.0001	<.0001	<.0001	<.0001	0.03	<.0001	<.0001	0.79	<.0001	<.0001	0.52		
15	European firm$_{i}$	0.15	0.36	-0.06	0.05	0.04	0.05	0.04	-0.01	0.01	0.04	0.28	0.03	0.18	-0.01	-0.02	0.01	
				0.04	0.10	0.19	0.08	0.14	0.71	0.60	0.11	<.0001	0.23	<.0001	0.69	0.47	<.0001	
16	American firm$_{i}$	0.21	0.41	-0.15	0.15	0.06	0.15	-0.02	0.09	-0.02	0.09	0.17	0.03	0.05	0.01	-0.04	0.06	-0.22
				<.0001	<.0001	0.02	<.0001	0.47	0.001	0.47	0.001	<.0001	0.32	0.08	0.67	0.15	0.04	<.0001

[a] N=1255.

TABLE 2

Negative binomial GEE regression predicting *Number of new products* $_{it}$ [a,b]

Variable	1	2	3	4	5	6 *Lagged DV*	7 *Robotics*	8 *Experience*
Intercept	0.01	0.64	0.81	1.00 †	0.99 †	0.90	0.83 †	0.83
	0.55	0.54	0.53	0.53	0.55	0.55	0.44	0.56
Internal search age(avg)$_{it-1}$		0.10 *	0.10 *	0.09 *	0.10 *	0.10 *	0.06 †	0.09 *
		0.05	0.05	0.05	0.05	0.05	0.04	0.05
Internal search age(avg)$^2_{it-1}$		-0.01 ***	-0.01 ***	-0.01 **	-0.01 **	-0.01 **	-0.01 †	-0.01 **
		0.005	0.005	0.005	0.005	0.005	0.01	0.005
Competitor search age(avg)$_{it-1}$		0.06 †	0.05 †	0.03	0.03	0.03	-0.01	0.03
		0.04	0.04	0.04	0.04	0.04	0.03	0.03
Competitor search age(avg)$^2_{it-1}$		-0.01 *	-0.01 *	-0.01 *	-0.01 *	-0.01 *	-0.01 *	-0.01 *
		0.005	0.01	0.004	0.005	0.005	0.005	0.005
External search age(avg)$_{it-1}$		0.02 **	0.05 **	0.05 *	0.06 **	0.06 **	0.09 **	0.06 **
		0.01	0.02	0.03	0.02	0.02	0.04	0.02
External search quantity$_{it-1}$			0.03 *	0.03 *	0.04 *	0.01 †	0.02 **	0.01 *
			0.02	0.02	0.02	0.005	0.01	0.005
External search age(avg)$_{it-1}$*External search quantity$_{it-1}$			0.01 *	0.01 †	0.01 *	0.03 *	0.11 *	0.04 *
			0.005	0.005	0.005	0.02	0.05	0.02
Internal search age(div)$_{it-1}$				-0.004 †	-0.004 †	-0.004	-0.001	-0.004 †
				0.003	0.003	0.003	0.004	0.003
Competitor search age(div)$_{it-1}$				0.01	0.01	0.01	0.01	0.005
				0.01	0.01	0.01	0.01	0.005
Competitor search age(div)$^2_{it-1}$				-4.6E-06	-4.6E-06	-4.6E-06	2.5E-07	-4.1E-06
				4.1E-06	4.1E-06	4.4E-06	4.1E-05	3.7E-06
External search age(div)$_{it-1}$				8.6E-04				
				1.1E-03				
External search age(div)$^2_{it-1}$				-3.0E-06 **	-1.8E-06 *	-1.7E-06 *	1.3E-07	-1.6E-06 *
				1.2E-06	9.5E-07	9.6E-07	3.2E-07	7.9E-07
Firm size$_{it-1}$	0.001	-0.0005	-0.004 †	-0.004 †	-0.004 †	-0.004 *	-0.003	-0.005 *
	0.001	0.001	0.002	0.002	0.002	0.002	0.002	0.002
ROA$_{it-1}$	-0.42	-1.00	-1.26	-1.34	-1.35	-1.30	-0.85	-1.13
	0.93	1.24	1.18	1.30	1.29	1.35	0.95	1.23
R&D expenditure$_{it-1}$	0.17	0.25	0.45	0.45	0.44	0.42	0.37 †	0.46
	0.27	0.23	0.34	0.34	0.34	0.34	0.20	0.33
Collaboration freq$_{it-1}$	0.03	0.05	0.03	0.04	0.04	0.04	0.04	0.03
	0.20	0.17	0.13	0.13	0.13	0.12	0.07	0.12
Technol diversification$_{it-1}$	-0.21	-0.69 **	-0.59 *	-0.72 *	-0.71 *	-0.73 *	-0.42 *	-0.77 **
	0.14	0.27	0.30	0.35	0.34	0.33	0.19	0.26
Product diversification$_i$	-0.63	-0.98 *	-1.16 **	-1.19 ***	-1.23 ***	-1.19 ***	-1.12 ***	-1.36 ***
	0.48	0.40	0.37	0.37	0.37	0.36	0.31	0.37
European firm$_i$	-1.79 ***	-1.62 ***	-1.28 ***	-1.25 ***	-1.21 **	-1.12 **	-1.27 ***	-1.21 **
	0.41	0.36	0.40	0.39	0.40	0.38	0.31	0.38
American firm$_i$	-1.61 ***	-1.65 ***	-1.68 ***	-1.64 ***	-1.67 ***	-1.53 ***	-1.60 ***	-1.66 ***
	0.37	0.36	0.35	0.35	0.35	0.34	0.27	0.35
Number of new products$_{it-1}$						0.05 *		
						0.02		
Experience$_{it-1}$								-0.06
								0.26
Experience$^2_{it-1}$								0.01
								0.04
Deviance	1586	1456	1391	1376	1376	1283	1360	1367
Difference in Log likelihoods vis-à-vis the base model		130***	195***	210***	210***	303***		219***
d.f.	20	25	27	32	31	32	31	33

† $p < 0.1$;
* $p < 0.05$;
** $p < 0.01$;
*** $p < 0.001$ (two-tailed tests for controls, one-tailed tests for hypothesized variables).

[a] The table gives parameter estimates; robust standard error is below each parameter estimate.
[b] 131 firms and 1255 firm-year observations. Year dummies are included, but not shown.

Bio statement

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