EFFECTS OF SEARCH TIMING ON PRODUCT INNOVATION: THE VALUE OF NOT BEING IN SYNC

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Abstract

This paper investigates how firms search for new products. While prior work takes a firm-centric view, we study how the firm's search depends on that of its competitors. Drawing on organizational learning theory, we argue and find that search timing relative to competitors matters. Two seemingly contradictory views are tested: that competitors take away the exclusivity of search and therefore suppress innovation, or, in contrast, sharpen and validate the focal firm's search and thus promote innovation. Our analysis of 15 years of longitudinal data on 124 Japanese, European, and U.S. industrial automation organizations reconciles these views. In particular, firms introduce *more* new products if they search after their competitors, and they introduce *innovative* new products if they search ahead of competitors. Interestingly, the most innovative firms combine these two out-of-sync approaches, but avoid searching in sync.

Key words: organizational search, innovation, new products.

How do organizations obtain the knowledge necessary for innovation? Organization theorists highlight several approaches, such as inheriting knowledge from founders (Romanelli, 1985; Eisenhardt and Schoonhoven, 1990), grafting on new members and organizations (Rao and Drazin, 2002; Song, Almeida, and Wu, 2003), and, more recently, growing organically (Hess and Kazanjian, 2006). Prominent among such organic approaches is search, i.e., a problem-solving process where organizations recombine, relocate and manipulate existing knowledge in order to create new knowledge (Nelson and Winter, 1982). Search is particularly attractive when the needed knowledge was not inherited and cannot be readily grafted on.

A significant stream of research has emerged to study search, and in particular, to study how firms search to innovate. There are several insights. One is that successful searches are more frequent and further away from what the firm already knows (Greve, 2003; Taylor and Greve, 2006). Another is that firms typically search in exactly the opposite way – too little and too close (Helfat, 1994; Benner and Tushman, 2002; Nerkar and Paruchuri, 2005) – and need to find effective strategies to avoid such local tendencies. A third insight is that successful search often combines knowledge that is known to the firm with knowledge that is new to it (March, 1991; Tushman and O'Reilly, 1996; Katila and Ahuja, 2002; Siggelkow and Rivkin, 2005).

Yet despite this variety in insights, the dominant view on innovation search is surprisingly firm-centric. The firm's search activities are measured in terms of its own past behavior, such as how new the search is relative to the search paths that the firm has tried before. But such studies, although valuable, do not take into account that the firm's competitors also search. These competitor searches are likely to create constraints and opportunities for search that are important but poorly understood.

We propose that the next step in search research, therefore, is to incorporate competition. Specifically, we ask: How do competitors' simultaneous or past search activities influence the outcomes of focal firm's search? In response, we build on research in organizational learning to examine how competitors search relative to one another and what the potential effects on innovation are. To assess the effects, we conceptualize search as a learning contest, map out differences in search timing between the firm and its competitors (head-start, in-synch, and catch-up), and form predictions of how these timing choices influence performance of search. We test the predictions over a 15-year period in a prominent subfield of the international industrial automation industry, namely robotics.

There are two main contributions. The first is adding the idea that firms do not search in isolation but in an ongoing interaction with their competitors. We show that a full understanding of the value of search requires understanding the competition. Of particular note is our unique temporal conceptualization of competition--what we term "learning contests"--that focus on search timing relative to that of competitors. The second contribution is novel findings about timing of search. Based on the learning contests that we observe, firms that time their search so that they are out-of-sync with their competitors succeed in innovation while firms that search in-sync often fail. The key insight, then, is not to strive to perform a well as possible in absolute terms, but to differentiate from the competition. We also find that in the context of these learning contests, the most innovative firms search along more than one path. When a firm engages in both types of out-of-sync search simultaneously, it can bridge its own and its rivals' hitherto isolated clusters of knowledge, and subsequently introduce more products and more innovative products than using either approach alone. The aggregate effect of our results is an interesting evolutionary path through which heterogeneity in the industry converges and diverges over time and through which industries can potentially overcome local search.

THEORETICAL BACKGROUND

Innovation is a tenuous activity: New products are developed through an inherently complex and ambiguous process. The path to an innovation includes many detours and dead-ends, and the technical and commercial promise of an innovation is poorly understood in advance. Yet, innovation is essential in technology-based firms. It represents the commercial potential of the firm's R&D activities (King and Tucci, 2002) and is thus a source of competitive advantage and profits (Utterback, 1994; Bayus and Agarwal, 2007). Understanding how firms search for innovation is thus important.

Innovation Search

Innovation search—the problem-solving process where organizations recombine, relocate and manipulate existing knowledge in order to create new products—is a particularly appropriate lens to study innovation. First, in-depth fieldwork (e.g., Clark et al., 1987; Dougherty and Hardy, 1996) describes innovation as problem-solving. For example, in the course of new product development, automotive engineers translate information on technological possibilities into a set of designs, instructions and information required for producing a product; in other words, they search for solutions to technical problems (e.g. Clark et al., 1987; Iansiti, 1995). Second, search is an appropriate lens to examine innovation because it explicitly focuses on attempts to solve problems in a world that is ambiguous and where problems cannot be solved directly (Simon, 1957; Cyert and March, 1963; Nelson and Winter, 1982). Innovation search is also intriguing to study because a key element of such environmental ambiguity is competition (Porter, 1985; Brown and Eisenhardt, 1998) yet prior work on innovation search has overlooked its influence.

Innovation search takes place in a knowledge space, also known as a knowledge pool. As Levinthal and March describe, "search consists of sampling opportunities from the pool of technological possibilities" (1981: 313). In other words, the firm recombines, relocates and manipulates knowledge within a technological knowledge space (c.f., Nelson and Winter, 1982), and researchers typically track this activity using patent citations (Rosenkopf and Nerkar, 2001; Benner and Tushman, 2002; Almeida et al., 2003; Singh, 2005).

The knowledge space where the firm searches has two distinct sectors: One is knowledge familiar to the searching firm (its current knowledge-base), and another is knowledge that is new to it (e.g., Levinthal and March, 1981; Katila and Ahuja, 2002). The firm may introduce new products because it explores entirely new areas that depart from its current knowledge-base, or because it productively translates knowledge from its existing knowledge-base into new products. Consequently, a relatively large stream of innovation search studies (anchored in organizational learning theory) has examined these two approaches, typically labeling them as exploration and exploitation.[1] *Exploring* areas that are new to the firm lowers the expected returns to search, i.e., the mean (because most new ideas are bad ones) and thus *reduces frequency* of new products. At the same time, however, exploration increases the variance of search and subsequently helps the firm introduce *more innovative* products (March, 1991; see also Campbell, 1977). In contrast, *exploiting* the firm's current knowledge-base leads to a relatively high mean (because the value of knowledge is already known) and thus *increases frequency* of new products. However, exploitation reduces variance of search (because variability declines with experience) and in the process makes search more reliable but substantively *less innovative* (Levitt and March, 1988; March, 1991). In short, the more

[1] Some authors use different labels such as innovation and refinement (Levinthal and March, 1981) or slack search and problemistic search (Cyert and March, 1963).

exploratory the search the more innovative but unreliable the output; and the more exploitative the search, the less innovative but more reliable the output.

Exploration and exploitation have been further characterized through empirical studies. For instance, Mezias and Glynn (1993) used simulation and Rosenkopf and Nerkar (2001) archival data to demonstrate that firms that explore are more likely to generate innovative technologies. In contrast, other empirical work shows that firms that exploit introduce new technologies more frequently (Greve, 2003; Rouse, 1999). Another empirical stream provides descriptive insights. The findings indicate that despite the benefits, firms avoid exploration (Romanelli, 1985; March, 1991), and that this tendency is especially strong and potentially detrimental in R&D (Helfat, 1994). Further, learning tends to crowd out exploration (Cyert and March, 1963; Levinthal and March, 1993; Sorensen and Stuart, 2000; Ahuja and Katila, 2004). Thus, as firms grow large and search more, they will typically explore less, thereby making their search more reliable at the expense of variation.

In sum, prior work on innovation search provides many useful insights. But these insights are predominantly firm-centric[2]. The studies typically assess a firm's search activities relative to its own behavior and do not consider how competitors search. Overall, how firms search within an environment (of other competing organizations) and the implications for search outcomes are poorly understood. For example, questions such as whether competitors' experience influences search in a similar way as the firm's own experience remain unexplored. And yet, firms do not search in isolation: in order to understand search in detail, we need to incorporate competition. This is the task we undertake in this paper.

Effects of Competition on Innovation Search

[2] The few studies that include competition (e.g., Greve and Taylor, 2000) are typically descriptive and use high-level proxies, such as co-location in the same market for competition, and successful outcomes for search.

As noted above, innovation search literature explains innovation but focuses on the firm and seldom deals with competition. In contrast, both organizational economists and sociologists have long been interested in the relationship between competition and innovation (e.g., Schumpeter, 1934; Scherer, 1980; Porter, 1990). These literatures suggest several logics through which competition may influence search. We focus on two, learning and racing, that are particularly significant for innovation search.

Effects of competitor search: learning. Competitors can influence the search of the focal firm through *learning*: The firm can learn from its competitors, and the competitors can learn from the firm. First, the focal firm can learn from its competitors in several ways. One is learning mimetically, that is, selective copying of other organizations. Some authors argue that, in competitive industries, large firms in particular often adopt a 'fast second' strategy and commercialize the discoveries of their smaller competitors (e.g., Baldwin and Childs, 1969; Markides and Geroski, 2005). In another form of learning, firms observe a variety of R&D attempts by their competitors, and decipher rules that link their experiences to consequences (Miner and Mezias, 1996). Such inferential learning—informed observation and active interpretation of others' search—may thus lead to more innovation. Research also notes that by selecting to search in some areas and *not* in others, competitors "set the agenda" and "influence judgment" in R&D (Greve and Taylor, 2000; Zollo and Winter, 2002). In other words, competitors' R&D efforts may provide clues to executives that certain areas are viable and timely in the market, or they may validate (or cast doubt on) the firm's current R&D focus. Overall, the implication is that the focal firm learns what works (and what does not) by observing the results of innovation search of others, with a likely positive effect on the product *frequency* of the focal firm.

On the flipside, competitors will also learn from the focal firm. They typically start searching in the same area, and crowd it. The area quickly becomes 'picked over', and innovative opportunities start to disappear. This is because the best technological opportunities are typically exploited first, and the remaining opportunities are more difficult to find (Podolny et al., 1996; Swaminathan, 1996). In contrast, if the focal firm searches alone, it does not have to invent around competitor search. Knowledge space is less crowded and there are ample opportunities to draw on knowledge that does not overlap with competitors. Overall, the implication is that when competitors start learning from the focal firm, there is a likely negative effect on *innovativeness* of the focal firm's new products.

Effects of competitor search: racing. Search by competitors can also induce *racing* behavior, where the focal firm searches simply in order to keep up with its competitors. This behavior is particularly likely when firms engage in simultaneous searches with similar resources (Paredis, 1997). In the extreme, competitors' achievements provide a continuously moving target for the focal firm, establishing a Red Queen effect (i.e., the firm has to run just to stay in place; Van Valen, 1973; Barnett, 1997). Since racing is likely to focus the firm's efforts on matching those of its competitors', it may make it harder for the firm to introduce new products frequently. Also, firms that race often start thinking alike about implementation, instead of adopting unique R&D paths (Mowery et al., 1998; Sull, 2001), thus killing the variation in search (e.g., March, 1991; Romanelli, 1999). As a result, innovation may become stifled. The overall implication is that racing makes innovation more difficult because the firm's efforts are focused on staying even rather than on innovating, with a likely negative effect on both the *frequency* and *innovativeness* of the focal firm's product introductions.

Theoretical Framework

The learning and racing logics can be used to frame our arguments on how competition affects search. Understood as a positive influence, learning from competitors augments the focal firm's search by increasing the amount of experience from which the focal firm can draw. Competitor searches provide raw material for search as well as examples of what not to do, and they influence the judgment of where the opportunities are. This logic suggests that it is advantageous to search when experience from competitors' searches is already available, that is, *after* competitors have already searched. By contrast, understood as a negative influence, competitors' learning from the focal firm crowds the search space and restricts the opportunities for focal firm's innovation. The very searches by competitors that provide material for learning also block opportunities for innovation that the focal firm could have reached first. Thus, it suggests that it is advantageous to search *ahead* of competitors.

Second, understood as racing, competition derails the focal firm's search by forcing it to expend resources to match the rivals rather than to innovate. This logic is particularly acute in situations where firms engage in simultaneous head-to-head searches, and thus suggests that it is disadvantageous to search *simultaneously* with competitors.

Altogether, the answer to the question of how competitors influence search hinges on which logic is more appropriate. Our purpose in this paper is to show that searching after competitors is a significant determinant of search success when the goal of the search is to introduce new products more frequently, and that searching ahead of competitors is a significant determinant when the goal is to introduce more innovative new products. Firms achieve neither outcome by searching simultaneously with competitors.

--- Insert Table 1 about here ---

In order to analyze the effects of search timing in more detail, we construct a model where the different competitive situations are categorized by juxtaposing the focal firm's and its rivals' innovation search behavior over time (table 1).[3] Three (illustrative) paths emerge, differentiated based on when the focal firm starts searching relative to its competitors. Each path starts from a distinct starting position and then proceeds toward the top right corner of the table. Note that all paths may not visit all the same steps along the way. For instance, firms may move directly from firm's exclusive exploration to rivals' late exploration if rivals catch up fast.

Consistent with our theoretical focus on organizational learning, the three paths are labeled as three learning contests (see also Amburgey et al., 2000): The first two are out-of-sync contests while the third is a synchronous contest. The first, *head-start* contest, starts when the focal firm uses a particular knowledge first in the industry, first exploring, and then (possibly but not necessarily) exploiting exclusively. The rivals may join this contest later. The second, *catch-up* contest, starts when rivals use a particular knowledge first in the industry, first exploring, and then (possibly also) exploiting it exclusively without the focal firm. The focal firm may catch up and join this contest later. The third, *synchronous* contest, starts when both the firm and its rivals use a particular knowledge first (i.e., exploring) simultaneously and possibly keep searching it together (i.e., exploiting).

Innovation in video games provides a great illustration of these three contests. In the 1970's Atari had a clear *head start* over competition. It was a technological front-runner and led the market until its slower competitors caught up. In subsequent decades Nintendo, Sega and Sony, each in turn, were the firms pushing the technological frontier with a head start approach. More recently, Nintendo has succeeded with a *catch-up* strategy, with simple games and no-frills

[3] For brevity, two baseline situations ('Firm no longer searches', 'Rivals no longer search') are not shown in the table but serve as omitted categories in our empirical tests.

graphics. In contrast, Microsoft and Sony engage in *in-sync* competition with relentless lock-step introductions of faster processors, snazzier graphics and more complex games.

In the next section, these three contests form the basis of our hypotheses. The effects of search are examined on two dependent variables: how frequently new products are introduced and how innovative they are. Italicized terms in the next section refer to cells in table 1.

HYPOTHESES

Out-of-Sync: Searching with a Head Start

The first set of hypotheses focuses on the situation where the focal firm has a head start over its competitors. In hypothesis 1, *firm's exclusive exploration* makes product introductions less frequent (H1a) but more innovative (H1b). Because the firm is searching the knowledge first in the industry, there is no prior experience to learn from (March, 1991), and it is unclear whether the returns are high enough to warrant further development into a commercializable product. On average, exclusive exploration is unlikely to generate new products reliably and thus reduces product frequency.

In contrast, the variability of outcomes from exclusive exploration is likely to be high, precisely because there is no prior experience (March, 1991). Such variability will extend the range of available technological options from which the firm can select (Madsen et al., 1997). Since these options are *not* known to one's competitors (and so there is no risk of crowding), they are particularly important when the firm competes for a relative position within a group of competitors (March and Simon, 1958). This is the case here; the firms try to introduce a product that offers more value to customers than competing products. We thus propose that exclusive exploration is likely to yield innovative new products.

When the firm with the head start is able to exploit the knowledge exclusively, i.e., continue to search it without any of its rivals joining the race, such *firm's exclusive exploitation* modifies the above-documented negative (on frequency) and positive (on innovativeness) effects on product innovation. First, the traditional argument is that exploitation will increase the expected returns from search (March, 1991). At the same time, however, competitors have had the opportunity to join the search but have not done so, possibly because they do not believe that the knowledge area provides enough opportunities for them (e.g., scales up easily) or perhaps because the knowledge may not be as valuable as the focal firm believes (Kirzner, 1973). In other words, competitors may not be interested because the potential returns from this area are uncertain. Taken together, these arguments suggest that firm's exclusive exploitation has a negative but weaker effect on focal firm's product frequency than firm's exclusive exploration.

In contrast, while firm's exclusive exploitation is likely to result in fewer products, the products that are generated may be even more innovative than those generated by exclusive exploration. It often takes multiple attempts to get an innovative product 'right'. While the first attempt (through exclusive exploration) may have been relatively rough, the firm that has a chance to continue searching free of competition has complete control of the search process. There is no need to reconcile findings with those of rivals or to keep track of others' search efforts in the same area. Thus, the firm is free to select any knowledge combinations it returns to search. Further, product development engineers that search a particular knowledge element repeatedly, for a variety of purposes, often come to understand it better, and learn to combine the knowledge effectively into new, innovative combinations (Mezias and Glynn, 1993; Galunic and Rodan, 1998). Thus, exclusive exploitation may result in more innovative products than exclusive exploration. Based on these arguments, we propose:

H1a. Firm's exclusive search (exploration and exploitation) has a *negative* effect on the *frequency* of its new product introductions.

H1b. Firm's exclusive search (exploration and exploitation) has a *positive* effect on the *innovativeness* of its new product introductions.

While hypothesis 1 focused on solitary searches by the focal firm, at some point the firm's competitors are likely to join this race (i.e., *rivals' late exploration*). Rivals' search may provide an opportunity for learning making product introductions more frequent (H2a) but it also increases crowding making them less innovative (H2b). First, by joining the search, competitors can help confirm that an area is viable and timely for search. In other words, competitors indicate (indirectly, through their own search) that selecting the knowledge for further development is worthwhile, i.e., expected returns are high relative to other possible projects. Thus, from the focal firm's perspective, there is a lower chance that the development will fail or that the project needs to be shelved. Competitors' search also provides opportunities for learning because the focal firm can see what competitors do with the knowledge and may get new product ideas. Taken together, when competitors join the race they will provide opportunities for learning and so increase frequency of new product innovation.

However, once competitors start searching the knowledge, it is less and less likely to lead to innovative products that differentiate the focal firm from its rivals. The reason is that rivals also start learning from the focal firm and soon the knowledge space becomes crowded: the new knowledge combinations that the focal firm can select are constrained by the combinations that its rivals are now forming using the same knowledge (March, 1991). So, while rivals' joining the search may lower the risk of poor outcomes, it may make it harder to find innovative outcomes that others would not also find.

H2a. Rivals' delayed search (late exploration) has a *positive* effect on the *frequency* of the firm's new product introductions.

H2b. Rivals' delayed search (late exploration) has a *negative* effect on the *innovativeness* of the firm's new product introductions.

Out-of-Sync: Searching to Catch Up

The second set of hypotheses focuses on the situation where the rivals search first and the focal firm then has to catch up. In hypothesis 3, *rivals' exclusive exploration* makes the focal firm's product introductions more frequent (H3a) but less innovative (H3b). First, technical breakthroughs and new problem-solving approaches that rivals discover may leak to the rest of the industry (c.f., Nelson and Winter, 1973) and so may become available to the focal firm without any direct search by it, i.e., through 'passive search' (Huber, 1991). Such knowledge leaks may, for instance, remove bottlenecks in the innovation process that hold back better products (Hughes, 1983), and may thus make a larger number of new products possible. More broadly, rivals' exclusive exploration may provide clues to where the opportunities are that are worth developing. "Borrowing saves the costs of search, the costs of testing and the costs of evaluating feasibility" (March and Simon, 1958). For instance, rivals' exclusive exploration may provide hints of up-and-coming areas and thus increase expected returns from search (Romanelli, 1999). The firm may then react, for example, by introducing shelved products that respond to the new trend (Utterback, 1994). The focal firm may also scan its competitors' patent documents to get new insight into its own development problems or become informed of possible solutions to customers' problems. Altogether, rivals' exploration of new knowledge may suggest which product development projects should be completed (i.e., which have high expected returns) and thus may allow the focal firm to introduce new products more often.

In contrast, rivals' exclusive exploration is likely to hurt innovativeness. Simple imitation of what rivals already know is unlikely to lead to innovative products that differentiate the firm from its rivals (Kogut and Zander, 1992), for two reasons. First, rival searches make the knowledge space crowded. Without its own search effort and the intricate knowledge that it provides (e.g., causality, failed approaches, promising leads), innovation is difficult. Second, imitation typically has a low variance – variations that might have developed from the organization's idiosyncratic search may never emerge (Leonard-Barton et al., 1994; Romanelli, 1999). The result is that while rivals' exclusive search may lower the risk of poor outcomes, it will make it harder to introduce particularly innovative outcomes that would surpass those of competitors.

When the rivals continue to exploit the knowledge exclusively, i.e., the focal firm does not join the search, such *rivals' exclusive exploitation* intensifies both the above-documented positive (on frequency) and negative (on innovativeness) effects on product innovation. First, rivals' repeated use of knowledge is an implicit sign that the knowledge is valuable, and provides reliable material for learning, from which new products can be created (March, 1991). Observing rivals' repeated search also allows the firm's own engineers to identify possible dead-ends in product development and to avoid the mistakes of prior searches (i.e., to learn what *not* to do). Overall, rivals' exclusive exploitation may make new product introductions even more frequent than rivals' exclusive exploration does.

In contrast, rivals' exploitation is likely to have a negative effect on innovativeness. The gap between the firm's and its rivals' products widens as rivals return to search the same knowledge and start to perfect it, but the focal firm has yet to join the search. We propose:

> H3a. Rivals' exclusive search (exploration and exploitation) has a *positive* effect on the *frequency* of the firm's new product introductions.
>
> H3b. Rivals' exclusive search (exploration and exploitation) has a *negative* effect on the *innovativeness* of the firm's new product introductions.

While knowledge that is available from rivals' searches (H3) can be useful, it is often incomplete—a collection of fragments of possibly useful knowledge (Winter, 1984: 293)—and typically requires complementary problem-solving efforts by the focal firm. Hypothesis 4 centers on these efforts. We propose that *firm's late exploration* makes product introductions more frequent (H4a) but less innovative (H4b). First, the firm that joins the race late is likely to introduce more new products because competitors' prior searches provide reliable raw material for subsequent searches. By observing competitor searches first and only then forming their own combinations, the focal firm's engineers learn how a particular knowledge element behaves in combination with other elements, and what approaches to search are the most promising (i.e., have high expected returns). In addition, the rivals' simultaneous search of the focal knowledge indicates that the knowledge remains a valuable source for new product introductions. Taken together, we thus propose a positive effect on frequency of new products.

While firms that explore late are likely to introduce more new products, it is less likely that they will be innovative. Although the focal firm may identify a knowledge combination that is new to it, the same combination may have already been used by one of the rivals, thus limiting the variability of focal firm's search output. Thus, we propose a negative effect on innovativeness.

> H4a. Firm's delayed search (late exploration) has a *positive* effect on the *frequency* of the firm's new product introductions.

> H4b. Firm's delayed search (late exploration) has a *negative* effect on the *innovativeness* of the firm's new product introductions.

In-Sync: Searching Simultaneously

The third set of hypotheses focuses on synchronous search where the firms start at the same time and race together. In hypothesis 5, searching simultaneously with competitors makes it difficult to introduce a large number of products (H5a) as well as products that are innovative (H5b). First, *synchronous exploration* lowers product frequency because it is risky. The firm can neither learn from its competitors' nor from its own prior experiences, making the search unreliable. Even more significantly, both synchronous exploration and *synchronous exploitation* lead to fewer new products because racing behavior is likely to develop. Rivals become locked into head-to-head races where they try to stay competitive with relatively homogeneous resources (Barnett, 1997; Lieberman and Asaba, 2006). New product ideas are often commercialized prematurely (fearing that the competitors get there first) or not at all (waiting for the competition to move first). As a result, fewer products are introduced.

Second, synchronous search is likely to make the firm's products less innovative. With rivals searching the same knowledge at the same time, neither synchronous exploration nor synchronous exploitation is likely to lead to unique product ideas. Instead, the rivals are likely to engage in a race where product innovation is constantly improved in rapid but minor steps in order to outcompete one another. In these situations, competitors' achievements provide a continuously moving target for the focal firm, establishing a Red Queen effect (Van Valen, 1973; Barnett, 1997). Since the target is constantly moving, it is difficult to keep up, and particularly difficult to introduce major innovations (Paredis, 1997). Firms may also end up developing product concepts or technical improvements that respond to their competitors' moves rather than the needs of the customer. Both the firm and its rival(s) invest in costly search, but neither ends up being particularly innovative.

H5a. Synchronous search (exploration and exploitation) has a *negative* effect on the *frequency* of the firm's new product introductions.

H5b. Synchronous search (exploration and exploitation) has a *negative* effect on the *innovativeness* of the firm's new product introductions.

METHOD

Sample

We test the hypotheses in the industrial automation industry by studying companies that developed industrial robots between 1984 and 1998, inclusive. We limited our analysis to three large geographical areas, namely Japan, Europe, and the U.S., because they accounted for over 95% of the world's robot supply during this period (World industrial robots, 1996) and because high-quality data were available for each of them. There were 124 companies in the sample during this 15-year period, although some of these companies participated in the industry for a shorter time period only. Of the 124 firms, seventy-three were Japanese, nineteen were European, and twenty-seven were U.S. firms.

We chose to focus on firms that develop robots, for three reasons. First, these firms make substantial R&D investments and develop complex products (Klepper, 1988). As a result, it is difficult to compete in robotics, and so there is a greater need for search behavior that is effective. We also chose robotics because if search is influenced by competition, it should be possible to observe this process in robotics. In our interviews[4], robotics engineers and their managers told us that they regularly scan public sources of information to identify ideas for new products. One interviewee who had worked both in the automobile and in the robotics industry pointed out that whereas automobile companies routinely made reciprocal agreements to exchange information, robotics companies knew surprisingly little about each others' R&D, and instead relied on public information such as scanning of competitors' patents. Third, we chose robotics because it is a competitive market where users require high product performance

[4] As part of this study, we conducted informational interviews with engineers and executives of nine U.S., two European and seven Japanese robotics organizations.

(because robots are a critical part of their manufacturing process). Understanding how firms create innovative products is thus important.

To identify the sample of industrial robotics companies for this study, a list of candidates was formed through an extensive search of robotics trade magazines and databases, and then verified through discussions with industry experts. Only those companies in the population that developed or had announced that they will develop industrial robots were included. Companies that developed automation systems or appliances, or robots in other than industrial application areas were excluded, as were companies that sold or licensed robots, but did not develop them. We also excluded private companies because we did not have complete data on them. Seventy-one firms in our sample had introduced at least one industrial robot during the study period. These firms represent a wide range: one company introduced new products 14 years in a row, whereas 22 of these firms introduced products in only one year. On average, the firms introduced new products in 4.1 firm-years.

Data Sources

Three primary sources of data were used. For new products, trade publications and product catalogs were the main source, and the data were assembled using a "literature-based innovation output indicator" method (Coombs, Narandren, and Richards, 1996). In this method, editorially-controlled new product announcement sections of technical and trade journals (such as *Assembly Automation*, *Industrial Robot*, *Japan Robot News*, *Robotics Today*, and *Robotics World)* as well as product catalogs and databases (such as *Robotics new product database* and *Robotics product specifications in Japan)* were combed through systematically to assemble data on new product introduction dates and specifications. This data collection was particularly painstaking because while some of these sources were electronic, many others, especially in early years, were available only in hard copy format in remote library locations. Altogether, over 30 different publications over a 15-year period were searched, and multiple sources were used whenever possible to validate the data.

For patents, we retrieved the data from the U.S. Patent and Trademark Office database, and used Who owns whom directories to track subsidiaries so that patents could be assigned to each firm. We then used custom-programmed C code to assemble the data into the independent variables. These programs were particularly time-consuming to design and run because they combined a large number of citation variables, interactions between various rivals, and long time periods.[5]

For firm financial and operational indicators, we assembled the data from databases including Compustat, Worldscope and DIR Analyst's guide.

The primary, archival data was supplemented with eighteen interviews. We interviewed industry participants and observers, including robotics executives and engineers, suppliers, customers, university scientists and industry experts, on three continents (Japan, Europe, U.S.). These interview data grounded our thinking about the industry. In particular, it strengthened our understanding of the causal mechanisms underlying successful innovation and helped us choose more accurate measures. It also helped in interpreting the results.

Dependent Variables

We examined two outcomes of innovation search: (1) number of new product introductions (*product frequency*) and (2) innovativeness of these introductions (*product innovativeness*). We measured *product frequency* as the number of new industrial robots

[5] This computationally intensive and complex task was accomplished by parallelizing the code and running it on a high-performance Linux cluster computer. There were 244,616 patents and 12,047,365 patent citations in the data. One run of the program took approximately 2 days on the cluster with 346 CPUs; the same task would have required over 100 days on a single-CPU computer. In total, running the different versions of the program and their revisions required over eight years of CPU time.

introduced by each sample firm each year. To qualify as new, each product was required to differ in technical or physical characteristics from the producing firm's previous products (Martin and Mitchell, 1998). An existing product introduced in a new geographical area, for example, did not qualify. To qualify as an industrial robot, a product needed to be programmable to move a gripper or tool through space to accomplish a useful industrial task (Hunt, 1983). All our data sources used this definition.

Product innovativeness was measured annually for each firm as the improvement in those product design characteristics that were important to users. This user design characteristic method is well-established (Sahal, 1985; Keeney and Lilien, 1987). For example, Dodson (1985) used it to compare rocket motors (delivered impulse, thrust, and motor weight), and Trajtenberg (1989) to compare medical imaging equipment (scan time, image quality, and reconstruction time). In general, several scholars such as Alexander and Mitchell (1985) have concluded that to qualify, performance measures of products need to be both valuable to users and make sense to engineers in the field. Design characteristics that users value fulfill both of these criteria.

There are four such characteristics of robots: repeatability, speed, load capacity, and degrees of freedom[6]. According to industry sources, customers used these four characteristics to decide which new robot to buy during the time period of this study (McDermott and Alexander, 1984; Booth, Khouja, and Hu, 1992). A hedonic price analysis, which determines the value that buyers place on characteristics of products (e.g., Henderson, 1993), also confirmed that these characteristics were important. Since we did not have price data for all products in the sample,

[6] Repeatability of each robot is defined as a closeness of agreement of repeated position movements under the same conditions to the same location. Speed is defined as the maximum velocity at which the robot (i.e., its tool tip or end effector) can move, producing a satisfactory result. Load capacity is the maximum weight or mass of a material that the robot can handle without failure. Degrees of freedom (or dexterity) defines the space where the robot is able to move and thus determines how complex its movements can be.

the hedonic analysis was restricted to a smaller set yet confirmed that we had chosen the right characteristics (see Appendix, table 1A).

The four design characteristics that we used are reliably measured and consistently reported in the product catalogs during the period of the study (Booth, Khouja, and Hu, 1992). Robotics associations have guidelines for measuring these characteristics, and both U.S. and international standards exist to enforce that the measurements are comparable (Dagalakis, 1998). These data are also highly reliable since multiple data sources were used.

In order to construct product innovativeness, we compare the average performance characteristics of the firm *i*'s new products in year t (c_{ijt}) with the average performance characteristics of new products introduced in the industry the previous year (c_{jt-1}), where *j* identifies one of the four characteristics. For example, the repeatability of the firm's robots is compared with the repeatability of all robots introduced last year. Consistent with prior work that uses a similar composite measure, the innovativeness variable is constructed by identifying the differences between year t and year t-1 values divided by year t-1 values for each of the four characteristics, and taking the average of these four ratios. We also used several alternative measures, noted below.

$$Product\ \ innovativeness_{it} = \frac{\sum_{j=1}^{4} [(c_{ijt} - c_{jt-1}) / c_{jt-1}]}{4}$$

We compiled an alternative measure of product innovativeness that included only those firm-years in which the firm introduced better-performing robots (relative to its prior introductions).[7] The intuition was that once a firm introduces a robot with certain performance characteristics, it has the ability to innovate at that level. Thus, to avoid penalizing firms that

[7] We appreciate the advice of our anonymous reviewer regarding this point.

chose to introduce a robot with inferior characteristics in some future years, we dropped these 'inferior' firm-years from the analysis (see Appendix, table 2A). We also constructed an alternative measure by comparing year t values with the first robot introduced in the industry, and, in another unreported regression, used only the most innovative products of each year. Together, all these alternative measures confirmed the original results (unreported results available from the authors).

Independent Variables

Assembling longitudinal data to measure innovation search is a major challenge. We chose patents as a data source for several reasons. First, patent data provide an accurate description of such search (i.e., problem-solving), because each patent is required to describe a technological problem and a solution to that problem (Walker, 1995). Second, patent data are one of the few sources that gives us a detailed and consistent chronology of search (Almeida, Song, and Grant, 2002). Citation patterns in patents track the knowledge used over time, and are due to their legal nature, precise (Walker, 1995). Thus, two of our key features of search, competitor search and its timing, can be measured accurately. Third, patent measures are particularly appropriate for testing hypotheses that include learning. Since one of the requirements for patenting is novelty, each time an existing patent is cited as an antecedent for a new patent, the cited patent is used in a different combination of citations than before. Thus, each repeat use of a citation serves as a distinct source for learning.

Patents are also a particularly good measure of search in our empirical setting. First, patents are an important appropriability mechanism in robotics (Marklund, 1986), as well as in the industrial machinery industry in general (Cockburn and Griliches, 1987; Arundel and Kabla, 1998). Therefore, patents are a comprehensive source for search. Second, patent documents report functional details about robot design that make them a uniquely rich and useful source both for competitors and for researchers. In fact, prior art patent searches of the U.S. Patent and Trademark Office database are a common part of robotics R&D in all geographical areas we interviewed. Third, patents have long been used to describe technology developments in robotics (e.g. Brossia, 1983; Grupp et al., 1990), and we continue this tradition.

The patents for our independent variables were assembled following Podolny et al.'s (1996) procedure for comparing technological knowledge-bases of firms (see also Nelson and Winter, 1982). We first identified all patents that the focal firm (firm *i*) had applied for each year (and subsequently received), and made a list of all prior-art patents cited in these patents. These data (patents and the citations in them) form each firm's technological knowledge-base yearly. We then took all prior art citations for the focal firm each year and placed these citations into the categories shown in table 2, by comparing the firm's and its rivals' current and prior years' knowledge-bases. Table 2 thus shows how search categories in table 1 are operationalized. In these operationalizations, all 123 other firms that participated in the industry were included as rivals, and this year's vs. past five years' citations were used to measure present vs. past. A five-year window is used since organizational memory in high-technology companies is imperfect: Knowledge depreciates sharply, losing significant value within approximately five years (Argote, 1999).

To control for the expanding risk set (Podolny and Stuart, 1995), fractions were used when constructing the variables. We divide the citation counts in each category with the firm's total number of citations that year, or with the rivals' citations in the bottom row where the firm has not cited any of the patents. Because fractions sum to a whole, capturing the effects of different types of search requires caution, i.e., we cannot include all categories simultaneously in the regression models. In order to estimate the models, we focus on the eight categories shown in table 2, and omit the remaining four categories that are not pictured (but are shown in the example in figure 1). The categories that are omitted are: patents that the focal firm searches at the present time (explores or exploits) but rivals no longer search, and patents that rivals search at the present time (explore or exploit), but the focal firm no longer searches. We also ran the models by including these categories and omitting others, with no change in the main results.

If the firm does not apply for patents in a year, making the denominator in our variables zero (under 4% of observations), the search variables are set to zero.[8] Similar results were obtained when these observations were dropped. We also constructed alternative measures by excluding the focal firm's self-citations (i.e., citations to one's own patents) from the variables, thus eliminating the potential advantages that the firms that have created the patents themselves might have in searching them. These results exhibited the same pattern as the original results. The measures are described in detail below and a hypothetical example of the various categories is provided in figure 1.

--- Insert Table 2 and Figure 1 about here ---

Head-start variables. We measured *Firm's exclusive exploration* (firm uses for the first time, rivals have never used) as the proportion of those prior art patent citations in the focal firm's current year patents that are neither in its own or its rivals' past five years' knowledge bases nor in its rivals' knowledge bases this year. The denominator in this fraction is thus the total number of prior art patents that the focal firm is citing in the current year. For example, if the focal firm cites 10 different prior art patents this year, is using two of them for the first time, and competitors have never used these two either, firm's exclusive exploration takes a value of

[8] We appreciate the advice of our anonymous reviewer to include this clarification.

0.2. [*Firm's exclusive exploration = Citations exclusively explored by the focal firm / Total citations by the focal firm*]

We measured *Firm's exclusive exploitation* as the proportion of those prior art patent citations in the focal firm's current year patents that are not in its rivals' but are in its own past five years' knowledge bases. [*Firm's exclusive exploitation = Citations exclusively exploited by the focal firm / Total citations by the focal firm*]

We measured *Rivals' late exploration* as the proportion of those prior art patent citations in the focal firm's current year patents that are not in its rivals' but are in the firm's own past five years' knowledge base, and are used this year by both. [*Rivals' late exploration = Late citations by rival / Total citations by the focal firm*]

Catch-up variables. We measured *Rivals' exclusive exploration* (rivals use for the first time, focal firm has never used) as the proportion of those prior art patent citations in firm's rivals' current year patents that cannot be found in the rivals' past five years' technological knowledge bases nor in the focal firm's knowledge bases this year or earlier. The denominator in this fraction is thus the total number of prior art patents that rivals are citing in the current year. For example, if the rivals cite 100 different prior art patents this year, and are using 50 of them for the first time and the focal firm has never used these 50, rivals' exclusive exploration takes a value of 0.5. [*Rivals' exclusive exploration = Citations exclusively explored by rivals / Total citations by rivals*]

We measured *Rivals' exclusive exploitation* as the proportion of those prior art patent citations in the rivals' current year patents that are in the rivals' but not in the focal firm's past five years' knowledge bases, and are not used by the focal firm this year either. [*Rivals' exclusive exploitation = Citations exclusively exploited by rivals / Total citations by rivals*]

We measured *Firm's late exploration* as the proportion of those prior art patent citations in the focal firm's current year patents that are in the rivals' knowledge bases during the past five years but not in the firm's knowledge base, and are used this year by both. [*Firm's late exploration = Late citations by the focal firm / Total citations by the focal firm]*

In-sync variables. We measured *Synchronous exploration* as the proportion of those prior art patent citations in the focal firm's current year patents that are not in its own nor in its rivals' past five years' knowledge bases but are used this year by both. [*Synchronous exploration = Citations explored by the focal firm and rivals in sync / Total citations by the focal firm*]

We measured *Synchronous exploitation* as the proportion of those prior art patent citations in the focal firm's current year patents that can be found in its own and in its rivals' past five years' knowledge bases, and are used again this year by both. [*Synchronous exploitation = Citations exploited by the focal firm and rivals in sync / Total citations by the focal firm*]

All independent variables were lagged so that search was measured before the products were introduced. As did Beckman and Haunschild (2002), we conducted various analyses with different lag structures and found approximately the same pattern of results. We report a five-year lag (moving average of years t-1 through t-5) for the search timing variables. Our interview data guided this choice because it usually took a few years to introduce a robot after the knowledge was developed, and the most innovative products had lags up to 4-5 years. Podolny et al. (1996) used a similar 5-year lag.

Control Variables

Prior studies suggest several control variables that are important for our analyses. First, we controlled for the firm's *search intensity* (i.e., search effort) because the amount of search performed is likely to influence frequency of innovation (e.g., Cyert and March, 1963; Greve, 2003). Consistent with prior work, we measured each firm's search intensity annually by the number of patents it applies for (Griliches, 1990; Deng, Lev, and Narin, 1999).

We also controlled for the technical similarity of this effort relative to firm's previous searches (*search distance*) because prior work suggests that if the firm searches technological areas that are new to it, it will be more innovative (e.g., Rosenkopf and Nerkar, 2001). We measured search distance by the proportion of those technological sub-classes to which the firm's current-year patents have been assigned but none of its patents during the past five years has. We used sub-classes as a measure because they characterize the technological areas where the firm is searching; similar measures have been corroborated in prior work (e.g., Jaffe, 1989; Patel and Pavitt, 1997). This measure was constructed annually for each firm in the sample.

We also controlled for *firm size* and used a commonly accepted measure: number of corporate employees (in thousands). Same results were obtained with firm size either as a linear term or in its square root transformation. In addition, given that several innovation scholars report a relationship between R&D expenditures and innovation, although often in opposite directions (Mansfield, 1964; Henderson, 1993), we controlled for it. We measured *firm R&D* for each firm annually by dividing corporate R&D expenditure by corporate sales. In an unreported regression we also controlled for firm profitability (ROA) but did not find a significant effect, or any changes in our main results. The coefficient was negative in equations that predict innovativeness, however, as suggested by Greve (2003). The data for these variables were annual and obtained from Compustat, Worldscope and DIR Analyst's Guide.

Because *firm diversification* can influence innovation in a number of ways, we controlled for it. Diversified firms may have more opportunities to use their existing technologies and so economies of scope effects can increase frequency of innovation (Kamien and Schwartz, 1982). At the same time, top executives in diversified firms may be more detached from R&D activities and therefore be less committed to pursuing innovative technologies (Hoskisson and Hitt, 1988).

We measured firm diversification by a time-variant variable entropy; i.e., $\sum_j p_j \log p_j$ where p_j is the fraction of the firm's sales in the *j*th 4-digit SIC code (Jacquemin and Berry, 1979). We collected yearly 4-digit SIC sales data for each company from annual reports, company databases, and directories such as Worldscope and Japan Company Handbook.

Since the sample firms were from different geographical areas, we included a variable to control for geography. Culture and technological infrastructure can cause geographical differences in innovation (e.g., Shane, 1992). For example, Mansfield (1989) found that Japanese robotics companies emphasized product improvements, whereas U.S. companies were more skilled at developing entirely new products. We used region dummies which were set to one if the firm originated in a particular area (*European, U.S. firm*) and zero otherwise. Japanese firms were the omitted category.

We also controlled for temporal effects because technological factors and the availability of skills to innovate may vary over time. For instance, the firms may become better at introducing innovative products over the observation window, and this temporal pattern would be captured by the outcome variables in the absence of temporal effects. Temporal effects were incorporated using dummy variables for the calendar years 1984-1996 (1997 is the omitted year). We also ran models in which we substituted the year dummies with cumulative new product introductions by all firms in the industry annually (as a measure of the skill base; Haleblian, Kim, and Rajagopalan, 2006), with no change in the results.

Statistical Method

The data consist of a panel of observations on firm-years. The first set of data includes 1,304 firm-years and is used to test models with *product frequency* as the dependent variable. Since this dependent variable consists of counts of new products and has many zero values, we use a negative binomial regression. To control for repeated observations for the same firm, we employ the Generalized Estimating Equations (GEE) regression method. This method accounts for autocorrelation that may arise because each firm is measured repeatedly across multiple years (Liang and Zeger, 1986). The standard errors that we report are derived from the Huber/White robust estimator of variance that is insensitive to the choice of the correlation structure in GEE. To further ensure that unobserved heterogeneity did not affect the results, we included earlier values of the dependent variable in unreported regressions, i.e., presample and lagged dependent variables (Heckman and Borjas, 1980; Blundell et al., 1995). Our results held independently of the model (results available from authors).

The second set of data includes 285 firm-years and is used to test models with *product innovativeness* as the dependent variable. We employed a random-effects GLS regression because there were multiple observations for each firm.[9] This dataset is a subset of the first because 1,019 of our original observations occurred in firm-years in which the firms did not introduce any products and the product innovativeness variable could therefore not be calculated. To be sure that excluding these observations did not bias our results, we ran the analyses using the Heckman (1979) selection model to estimate the likelihood of product introductions in the initial sample (124 firms). We then used the parameter estimates (the inverse Mills ratio scores) from that model in a second stage model to predict the effects of search on innovativeness for those firms that had at least one product introduction during a year (71 firms). The hazard rate from the selection model is labeled *selection* and effectively controls for the likelihood that an observation is included in the subsample. To facilitate causal inference, the independent and

[9] Random-effects is a more appropriate method than fixed-effects because there are many firms in the sample but each has only relatively few observations, potentially causing inconsistent fixed-effects estimates. The fixed-effects model also excludes variables such as geography that do not vary over time within each firm panel (Greene, 2000). Despite the limitations, the fixed-effects estimator confirmed the original results. We also ran a tobit model with similar results. Both results are available from the authors.

control variables were lagged, search timing variables by a five-year moving average as described above and controls by one year. The last dependent variable year was 1998.

RESULTS

Main analyses. Descriptive statistics and correlations for all the key variables are reported in table 3 for product frequency and in table 5 for product innovativeness samples. Overall, the independent and control variables show considerable variance and most correlations among the variables range from small to moderate. There are two exceptions in table 3: the correlation between rivals' exclusive exploration and rivals' exclusive exploitation (r=-.98), and the correlation between firm's exclusive exploration and firm's late exploration (r=-.73). Consequently, these variables are entered in the models both separately and simultaneously. In the first case (rivals' search) the results are unaffected, but differ in the second (as will be discussed below). Overall, since potential collinearity between variables may inflate the standard errors, but does not invalidate the significant parameter estimates that are found (Darlington, 1990), multicollinearity does not pose a threat to the results that we report.

--- Insert Tables 3 and 5 about here ---

Tables 4 and 6 test hypotheses 1-5. Table 4 reports results for the frequency of product introductions while table 6 reports results for innovativeness. In both tables *head-start*, *catch-up*, and *in-sync search* variables are predictors, and control variables in each model include *search intensity*, *search distance*, and operational controls. Chi-squares and log likelihoods are reported at the bottom of the table, indicating how each model improves upon the base model.

--- Insert Tables 4 and 6 about here ---

In both tables 4 and 6, model 1 shows the results with control variables only. Year dummies were also included in this and the other models but are not reported to save space (results available from the authors). Models 2, 3 and 4 add the head-start, catch-up and in-sync variables, respectively. Models 5, 6, and 7 are the full models used for interpreting the results, with the firm's exclusive exploration variable added separately from firm's late exploration (models 5 and 6 in table 4) to avoid risks of multicollinearity. Two of the results reported below (H1a on exclusive exploration and H4a on late exploration) should thus be interpreted with caution. A conservative interpretation suggests that at least one of these hypotheses is supported (possibly both), but the data do not allow adjudication between these two mechanisms.

In H1, we argued that searching ahead of competitors results in fewer but more innovative products. To test H1a on product frequency, we examined the coefficients for firm's exclusive exploration and firm's exclusive exploitation in table 4, model 5. Both coefficients are negative, and the first is significant ($p<0.01$) and the second moderately significant ($p<0.1$). Together, the results confirm that exclusive search makes product introductions less frequent.[10] Similarly, we tested H1b on innovativeness by examining the coefficients for firm's exclusive exploration and firm's exclusive exploitation in table 6, model 5. The coefficient for exploration is non-significant, but the coefficient for exploitation is positive and significant ($p<0.001$). These results show that firms indeed introduce innovative products when they are able to search knowledge exclusively *and* keep the competitors out. Exploration of new knowledge does not make the firm innovative immediately, but the benefits are realized over time through repeated search. Thus, we find partial support for H1b as well as support for the idea that the positive effects of firm's exclusive exploitation are stronger than those of exclusive exploration. Intriguingly, these findings are consistent with those of Taylor and Greve (2006) and

[10] As expected, we also find that the negative effect attenuates rather than intensifies as the focal firm returns to exploit the same knowledge element. A one standard deviation increase in firm's exclusive *exploration* decreased the rate of product frequency by 33% whereas one standard deviation increase in firm's exclusive *exploitation* decreased frequency only by 21%. Because the negative binomial model is log-linear, we exponentiated coefficients to get these estimated multiplier effects.

Csikszentmihalyi (1996) who emphasized that inventors' deep rather than shallow expertise leads to fundamentally new discoveries. We return to these results in the discussion.

In H2, we proposed that once competitors enter, the focal firm will introduce more new products but fewer innovative ones. To test H2a on frequency we examined the coefficient for rivals' late exploration in table 4, model 6. The positive and significant ($p<0.05$) coefficient confirms H2a, indicating that firms can indeed learn indirectly from their rivals' choices. Searching with a head start that used to hurt product frequency turns into a positive effect as rivals join the search.[11] Regarding innovativeness, consistent with H2b that predicted that when rivals catch up the firm becomes less innovative, the coefficient for rivals' late exploration variable has a negative sign (albeit not significant) in table 6, model 6.

In H3, we argued that when rivals search alone, the focal firm will introduce more new products but less innovative ones. To test H3a on frequency, we examined coefficients for rivals' exclusive exploration and exploitation in table 4, model 6. Both coefficients are positive, and exploration is significant ($p<0.05$) but exploitation does not reach significance at the $p<0.1$ level. These results show that rivals' search makes the focal firm's search more productive if the rivals are exploring the knowledge for the first time. Similarly, we tested H3b on innovativeness by examining coefficients for rivals' exclusive exploration and exploitation in table 6, model 6. The coefficients are negative and positive, respectively, but non-significant. Thus, there is no significant support for the hypothesis, although the signs on rivals' exclusive exploration are consistently negative, as we expected.

[11] In separate (unreported) regressions, we also assessed whether firms that have a bigger head start (of using the knowledge ahead of rivals) have an advantage. We interacted firm's prior exclusive experience (using a continuous variable of cumulative citations) with rivals' late exploration. The coefficient for this interaction was positive but it did not reach significance at the $p<0.1$ level.

In H4, we predicted that when the firm joins a search that was previously dominated by rivals, it will introduce a larger number but less innovative products. To test H4a on frequency, we examined the firm's late exploration coefficient in table 4, model 6. The positive and significant ($p<0.001$) coefficient supports H4a.[12] Similarly, we tested H4b on innovativeness in table 6, model 6. We expected a negative effect on innovativeness, but this prediction was not borne out as the coefficient on firm's late exploration is non-significant.

In H5, we focused on the detrimental effects of in-sync search. To test H5a and H5b, we examined coefficients for synchronous exploration and synchronous exploitation in tables 4 and 6. The coefficients have mostly negative (but non-significant) signs in both tables. Although only synchronous exploration significantly hurts product frequency (table 4, model 6), the overall conclusion is as expected: successful innovators do not search simultaneously with their rivals.

Control variables support prior findings. As expected, diversified (*firm diversification*), Japanese (*Japanese firm*), search-intensive (*search intensity*) firms introduce new products more frequently (table 4). Also as expected, searching technologically further away from prior searches (*search distance*) results in more innovative products (table 6) but does not make product introductions any more frequent (table 4). Further, although the effects of dummies for European firm and U.S. firm fall short of statistical significance in table 6, the coefficients are in the direction suggesting that European and U.S. firms introduce more innovative products than Japanese firms, as we expected. Overall, the conclusion is that even after controlling for the traditional predictors of search success—i.e., search intensity and search distance, in particular—search by competitors has a significant influence.

[12] In separate (unreported) regressions, we also assessed whether rivals' bigger head start (of using the knowledge ahead of the focal firm) mattered. We interacted rivals' prior exclusive experience (using a continuous variable of cumulative citations) with firm's late exploration. It leveraged the original positive effect, further supporting H4a.

Additional analyses. Our results were robust to a variety of additional analyses. The first such analysis explored firms that simultaneously combined different search approaches (c.f., Gulati and Gargiulo, 1999). In our original hypotheses, search approaches were treated as separate and distinct sources of new products. In additional tests (results available from the authors), we created interaction terms by pairing each of the broad categories of search (head-start, in-sync and catch-up) with one another.[13] Following March's (1991) idea that the strongest effects on performance are borne by balancing opposite extremes of the search spectrum, we expected that head-start and catch-up search would leverage each other so that firms that bring these two distinct but beneficial search paths together would introduce both more products and more innovative products. We also expected that the interactions of in-sync with either head-start or catch-up search would have a negative effect. The results broadly support these expectations while confirming our original results. Participation in the two out-of-sync races simultaneously (head-start and catch-up) boosts frequency of product innovation while the interactions with in-sync searches are not significant. Innovativeness results have a similar pattern. In additional tests, we interacted the original variables instead of the broad categories. These results again confirmed the pattern. For example, an especially intriguing result is a positive and significant interaction between rivals' late exploration (head-start) and firm's late exploration (catch-up) variables which makes new products both more frequent and more innovative. Curiously, by forming a two-way bridge between its own and its rivals' search efforts, the focal firm is able to locate a sweet spot that boosts both qualities. One reason for these results may be that such bridges help the firm see old knowledge differently, that is, to use knowledge from one part of the knowledge domain to challenge "accepted believes" in another (Lant and Mezias, 1992). For example, the firm can use experiences from its exclusive searches to challenge the way that

[13] We appreciate the advice of our anonymous reviewer to address this issue.

rivals have viewed and used their exclusive knowledge in the industry, resulting in new combinations (c.f., Zajac and Bazerman, 1991). In fact, one of the oft-cited robotics designs in our interviews was a robot that was developed by a relatively novice team by simply turning a common design on its side (from vertical to horizontal). Altogether, the interaction results show that not all search approaches create tradeoffs between introducing more products and introducing more innovative products. These findings provide interesting avenues for future work.

Second, we explored the boundary conditions for search. Since the firm's late exploration variable had such a strong positive effect on product frequency (table 4) but the measure was dichotomous, we measured whether it mattered if the knowledge was used by a niche population of rivals or by the majority, before the focal firm joined the search. We found that the positive effect was stronger the fewer rivals had searched the knowledge (i.e., the interaction between firm's late exploration and the proportion of rivals who had used the knowledge in the past was negative and significant at the $p<0.01$ level). A possible explanation is that it is easier to learn from a few firms that use the knowledge repeatedly than it is from several isolated uses by a large number of firms. Note that this result is the opposite of what firms tend to do: Organizations often imitate larger (rather than smaller) numbers of other organizations (Haunschild and Miner, 1997). Our results thus show that when the goal is to innovate, it is better to build on knowledge that is known to few rather than to many.

Third, a sensitivity analysis was conducted to understand the scope of search. Instead of using all corporate patents to measure search, we included only each sample firm's patents in robotics (separated using a comprehensive approach that included both word and technology class searches; see also Grupp et al., 1990). Using all corporate patents assumes that the searches in other divisions may be valuable (Henderson and Cockburn, 1996), whereas restricting search to robotics patents means that knowledge is "sticky" and transfers relatively poorly across divisions (Szulanski, 1996). The latter approach also assumes that it is possible to accurately isolate the search efforts that contribute to new robotics products. In any case, the robotics patent results (available from the authors) exhibit the same pattern as the original results, and thus show that the results are robust regarding the scope of search.

DISCUSSION

In this paper we extended the traditional firm-centric search theory to incorporate an overlooked but critical dimension, competition. An analysis of 124 global robotics organizations over a 15-year period supports our theoretical predictions. Firms do not search in isolation; instead, they are strongly influenced by competitors, and in particular by their timing. First, we find that out-of-sync search both accentuates and diminishes product innovation: Searching after competitors helps firms introduce a larger number of new products whereas staying one step ahead of them helps firms introduce more innovative new products. These findings are not contradictory but reflect tradeoffs between introducing a larger number but less innovative products (catch-up) and introducing fewer but more innovative products (head-start). Second, we show that most frequent innovators participate in these two out-of-sync searches, but avoid searching in sync. Our results have interesting implications for theories of search, competition, and innovation.

Innovation Search

We started this paper by proposing that the next step for search research is to incorporate competition. In particular, we identified the focal firm's search timing relative to that of competitors as a significant open issue. By juxtaposing the firm's own search with its rivals' search over time in what we termed as a "learning contest", we then examined and tested the relationship between innovation and search timing relative to competitors.

Several key findings support our theoretical predictions. The first set of findings is consistent with the theoretical arguments that competition stimulates learning. Indeed, firms that search to catch up can be frequent innovators: By observing competitors, firms learn what not to do and where future opportunities might be, and can thus introduce new products more frequently.

The second set of findings highlights the unexpected tension that is caused by the flipside of learning. While competitors stimulate learning in the focal firm, their reciprocal learning from the focal firm blocks innovativeness. Thus, firms are particularly likely to introduce innovative products when they have a head start over their competitors, and especially when their competitors are then slow to catch up.

The third set of findings shows that the best innovators combine the two out-of-sync approaches. They search simultaneously with head-start and catch-up logics. By participating in both contests simultaneously, the same firm can introduce both a larger number and more innovative products. Firms that search in-sync with competitors attain neither. Altogether, our results provide strong empirical evidence that the value of search cannot be understood independently of the competitive context in which the firm operates. The results also make an interesting connection to evolutionary theory: They show that in competitive interactions it is not necessarily most advantageous to perform as well as possible in absolute terms; rather it pays to differentiate from the opponent.

Overall, the findings extend the innovation search theory to include competition. They suggest that it matters not only whether firms are searching locally or distally with respect to their own past, but also whether and when they are searching with respect to their rivals. We thus add to previous empirical search studies that have started to incorporate external elements, and in particular to that of Greve and Taylor (2000), who found that changes in competitors' markets triggered changes in the focal firm. However, these authors used successful search outcomes such as market entry to approximate search, and suggested that further work was needed to identify the actual search processes and resource allocations. We addressed this issue, and also extended the theory to different types of search timing and their effects on search performance that have not been studied. The results thus provide empirical evidence that understanding search requires understanding the dynamics of competition. It matters not only where you search, but with whom.

While many of our hypotheses are supported, a few results are surprising and offer unexpected insights. Creativity research argues that deep expertise is a source of truly novel innovations (Csikszentmihalyi, 1996; Taylor and Greve, 2006). However, this observation has not been easy to reconcile with the exploration/exploitation perspective that connects old and familiar knowledge with lack of innovation. This paper brings together these two observations in a unique way: We show that searchers with deep expertise (firm's exclusive exploitation) rather than those exploring entirely new knowledge (firms' exclusive exploration) introduce the most innovative products. Further, innovation is a race: the firm is innovative as long as it has exclusive access to the knowledge, but loses its edge once rivals move in (rivals' late exploration). These results thus prompt us to reconsider some of our traditional assumptions about exploration and exploitation. While exploration is traditionally believed to lead to innovation, our results show that such novelty may be overrated. Exploration does not lead to innovative products immediately; the benefits are realized over time through repeated, competitor-free exploitation. Examining this phenomenon in detail is an intriguing avenue for future work.

Beyond Search

Evidence of how competitor searches influence the focal firm's search will also provide one answer to the enduring question in organizational research; whether competition spurs or stifles innovation. Prior work in economics suggests that there is a tension, some arguing for positive effects (Porter, 1990) and others suggesting negative ones (Blundell et al., 1999). While economists often use broad time-independent measures of competition, this paper demonstrates that it is important to go beyond proxy measures of monopolists or industry concentration to examine how competition evolves over time and to pinpoint the specific search approaches that firms use. With such a dynamic search perspective, the results show that it is not competition per se, but timing of the search relative to competitors, that gives rise to differences in innovation.

Our findings also contribute to research on innovation more generally. First, as Drazin and Schoonhoven (1996: 1067) note, "researchers have usually portrayed innovation as a universally useful and productive end in and of itself; they have typically not distinguished between types of innovations". By contrast, we examine both frequency and innovativeness of new products and thus expand to examine more diverse types of innovation. Second, by incorporating competition, this research contributes to understanding external factors that influence innovation. Drazin and Schoonhoven further note, "certain to influence a given organization in its decision to innovate or not would be actions taken by its competitors" (1996: 1077), yet according to these authors such external factors have received less attention than the internal ones and should be brought back to the center stage. Our approach also responds to calls for more "integrated, multilevel models of innovation" (Brown and Eisenhardt, 1995; Drazin and

Schoonhoven, 1996; Lepak, Smith, and Taylor, 2007) that integrate innovation activities at the organizational level with macro processes that operate at the environmental level (i.e., competitor searches). Third, we also contribute to innovation research by examining spillovers (a.k.a. passive search). As did Jaffe (1989), we find that when competitors are active innovators, the firm is also more likely to innovate. Extending these prior results, we show specifically when spillovers are useful, i.e., that they need to be captured fast before they depreciate. Because our study focuses on the effects of spillovers on new products rather than inventions, it also provides more direct evidence of the commercial benefits of spillovers than prior studies. In light of these benefits, another question arises: why would firms invest in costly search when they could borrow (knowledge spilled over) from their competitors, that is, “exploit the successful exploration of others” (Levinthal and March, 1993)? Our results provide a unique answer: they show that focal firm’s own (exclusive) search is the only way to create innovative products, and that such search is protected from imitators who cannot create them from spillovers. Together, these three contributions on innovation types, external influences and spillovers lead to a more integrated and complete view of factors leading to innovation.

There are also several methodological contributions. First, our analysis is based on a unique dataset that tracks product development and product introduction behaviors of robotics companies over time and across three continents. This dataset combines numerous hardcopy and electronic sources as well as several informative interviews with industry participants to provide a comprehensive history of the robotics firms’ search efforts. Consequently, it provides a rare opportunity to test hypotheses about search timing. We hope that this study will encourage further research on compiling such longitudinal data on other industries.

Second, our method was novel and extensive: Measures of technological knowledge (patents) were combined with measures of commercialization (products), thus uniquely tracking the innovation process from invention to its commercial introduction. Usually longitudinal studies focus on one end or the other, but do not link the two. We were also able to develop more comprehensive and detailed measures of search than prior studies, instead of deciphering the process from its outcomes. In particular, patent measures made it possible to accurately express central features of search vis-à-vis competitors.

Third, we set necessary boundary conditions for the methodology and for the paper that suggest avenues for future work. The periods of discontinuous change as defined for example by Anderson and Tushman (1990)—that potentially introduce a whole new set of product attributes and have been relatively well-studied in organizational literature—are beyond the scope of this study. While such discontinuities are intriguing, most innovation activities in organizations take place in-between discontinuities. Improvements along the existing product attributes (such as those studied in this paper) often play an equally important role in technical advance.

CONCLUSION

To understand how competitors influence innovation search, we theorized about and modeled product innovation as a combination of opportunities *and* constraints created by competitors. A longitudinal study on the worldwide robotics industry provided intriguing results. We found that searching later than competitors boosts product frequency whereas searching ahead of them helps the firm introduce innovative products. Overall, the findings show how an approach that incorporates both organizational and inter-organizational factors, not as contrasting but as complementary explanations, can provide a richer understanding of search and innovation.

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TABLE 1

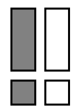
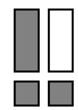
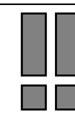
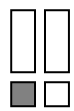
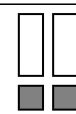
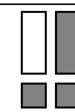
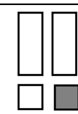
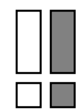
Search of the focal firm over time relative to competitors[1]

RIVALS → ↓ **FOCAL FIRM**	**Rivals do not search**	**Rivals explore**	**Rivals exploit**
Firm exploits	H1 Firm's exclusive exploitation **HEAD-START**	H2 Rivals' late exploration	Synchronous exploitation H5
Firm explores	H1 Firm's exclusive exploration	Synchronous exploration **IN-SYNC** H5	Firm's late exploration **CATCH-UP** H4
Firm does not search		Rivals' exclusive exploration H3	Rivals' exclusive exploitation H3

[1] Curved arrows illustrate possible search paths.

TABLE 2

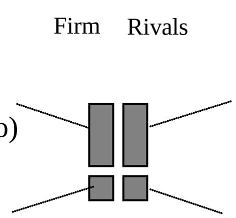
Operationalization of the search variables using patent data

RIVALS → FOCAL FIRM ↓	**Rivals do not search**	**Rivals explore**	**Rivals exploit**
Firm exploits	Firm’s exclusive exploitation 	Rivals’ late exploration 	Synchronous exploitation 
Firm explores	Firm’s exclusive exploration 	Synchronous exploration 	Firm’s late exploration 
Firm does not search		Rivals’ exclusive exploration 	Rivals’ exclusive exploitation 

Legend:

The focal firm has searched this patent in the **past** 5 years (dark rectangle=yes, white=no)

Rivals have searched this patent in the **past** 5 years (dark=yes, white=no)



The focal firm searches this patent **this year** (dark=yes, white=no)

Rivals search this patent **this year** (dark=yes, white=no)

TABLE 3

Descriptive Statistics and Correlations for the Key Study Variables (Frequency models)[a].

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Firm's exclusive exploration	.58	.19															
2	Firm's exclusive exploitation	.08	.06	-.10														
3	Rivals' late exploration	.01	.01	-.33	.39													
4	Rivals' exclusive exploration	.57	.07	.24	-.12	-.13												
5	Rivals' exclusive exploitation	.42	.07	-.21	.09	.07	-.98											
6	Firm's late exploration	.07	.06	-.73	-.27	.08	-.13	.10										
7	Synchronous exploration	.07	.11	-.55	-.23	-.12	.02	-.01	.34									
8	Synchronous exploitation	.02	.03	-.58	-.02	.26	-.19	.12	.40	.42								
9	Search intensity	108.61	236.36	-.26	.11	.38	-.10	-.09	.13	-.05	.27							
10	Search distance	.65	.27	.05	.05	-.06	.08	-.05	-.02	.04	-.02	-.16						
11	Firm size	33.29	74.30	-.06	.08	.13	.07	-.14	.00	-.05	.05	.40	.01					
12	Firm r&d	.04	.03	-.21	.07	.24	-.02	-.06	.17	-.06	.10	.37	-.01	.26				
13	Firm diversification	1.00	.44	-.09	.09	.07	-.05	.02	.01	.11	.10	.19	.06	.14	.08			
14	European firm	.15	.35	.07	-.09	.00	-.01	.004	-.01	-.10	-.06	.03	.05	.44	.15	.17		
15	U.S. firm	.19	.39	.14	.15	-.08	.14	-.13	-.20	-.09	-.13	-.07	.04	.07	.05	-.34	-.20	
16	Product frequency	.94	2.33	.03	.002	-.07	.17	-.01	.14	-.02	.01	.14	.03	-.001	.08	.15	-.06	-.12

[a] N=1304.

TABLE 4

Negative Binomial GEE Regression Analysis of *Product Frequency* [a,b]

Variable	1	2	3	4	5	6
Head-start						
Firm's exclusive exploration		-0.71			-2.08 ***	
		(0.60)			(0.83)	
Firm's exclusive exploitation		-2.96 *			-3.85 *	-1.22
		(2.18)			(2.28)	(1.95)
Rivals' late exploration		28.09 *			26.90 *	33.55 **
		(15.29)			(15.86)	(14.56)
Catch-up						
Rivals' exclusive exploration			25.99 *		31.12 ***	30.44 **
			(13.99)		(12.57)	(13.33)
Rivals' exclusive exploitation			7.91		14.77	13.11
			(9.72)		(9.91)	(10.06)
Firm's late exploration			5.32 ****			6.82 ****
			(1.59)			(1.51)
In-sync						
Synchronous exploration				-0.88	-3.00 ***	-1.76 **
				(0.76)	(1.03)	(0.86)
Synchronous exploitation				1.52	-2.18	-3.45
				(3.53)	(4.10)	(3.96)
Search controls						
Search intensity	0.001 **	0.001	0.001 **	0.001 *	0.001 **	0.001 **
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Search distance	0.006	0.15	0.01	-0.03	0.19	0.15
	(0.18)	(0.20)	(0.19)	(0.18)	(0.20)	(0.22)
Operational controls						
Firm size	-0.001	-0.001	-0.001	0.001	-0.001	-0.0001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Firm r&d	7.03 ***	5.75 **	6.32 **	6.57 ***	4.74	4.18
	(2.46)	(2.64)	(2.71)	(2.53)	(2.89)	(2.89)
Firm diversification	0.54 **	0.68 **	0.64 **	0.59 **	0.74 ***	0.72 **
	(0.27)	(0.28)	(0.29)	(0.27)	(0.28)	(0.29)
European firm	-0.66	-0.79 *	-0.72	-0.65	-0.83 *	-0.86 **
	(0.51)	(0.43)	(0.45)	(0.51)	(0.41)	(0.39)
U.S. firm	-0.96 ***	-0.81 **	-0.73 **	-0.94 ***	-0.80 **	-0.76 **
	(0.33)	(0.34)	(0.33)	(0.33)	(0.33)	(0.34)
Constant	-2.24 ****	-2.02 ***	-19.45 *	-2.19 ****	-23.71 **	-24.41 **
	(0.45)	(0.65)	(10.81)	(0.47)	(10.36)	(10.71)
Chi-square	1453	1265	1255	1408	1199	1184

* p < 0.1; ** p < 0.05; *** p < 0.01; **** p < 0.001; two-tailed tests.

[a] Standard errors are in parentheses below parameter estimates.

[b] All models include unreported dummy variables for year. 1304 observations.

TABLE 5

Descriptive Statistics and Correlations for the Key Study Variables (Innovativeness models)[a].

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Firm's exclusive exploration	.56	.18															
2	Firm's exclusive exploitation	.08	.05	.01														
3	Rivals' late exploration	.01	.01	-.28	.21													
4	Rivals’ exclusive exploration	.60	.07	.43	-.05	-.25												
5	Rivals’ exclusive exploitation	.39	.07	-.35	.01	.15	-.97											
6	Firm's late exploration	.08	.07	-.74	-.38	.02	-.23	.22										
7	Synchronous exploration	.06	.10	-.55	-.25	-.14	-.02	.03	.36									
8	Synchronous exploitation	.02	.02	-.59	-.01	.31	-.34	.23	.37	.34								
9	Search intensity	184.08	303.54	-.27	.14	.34	-.17	-.07	.02	-.06	.35							
10	Search distance	.66	.24	.11	-.01	-.21	.07	.02	-.03	.10	-.11	-.29						
11	Firm size	38.42	65.14	.06	.12	.05	.06	-.14	-.17	-.07	-.001	.41	-.04					
12	Firm r&d	.04	.03	-.14	.18	.26	-.07	-.02	.05	-.17	.13	.37	-.11	.31				
13	Firm diversification	1.11	.43	-.04	.15	.14	-.08	.02	-.09	.04	.02	.30	.09	.38	.13			
14	European firm	.12	.32	.09	-.11	.14	-.07	.09	-.07	-.05	-.11	-.06	.03	.49	.22	.31		
15	U.S. firm	.14	.35	.28	.09	-.12	.26	-.23	-.23	-.18	-.21	-.08	.04	.11	.07	-.34	-.15	
16	Product innovativeness	.28	.66	.06	.07	-.08	.11	-.11	-.05	-.06	-.08	-.02	.11	-.02	-.02	-.04	.004	.10

[a] N=285.

TABLE 6

Random-effects GLS Regression Analysis of *Product Innovativeness* [a,b]

Variable	1	2	3	4	5	6	7
Head-start							
Firm's exclusive exploration		-0.16			-0.17		-0.20
		(0.36)			(0.50)		(0.73)
Firms' exclusive exploitation		4.29 ****			4.40 ****	4.74 ****	2.98 ***
		(1.13)			(1.21)	(1.12)	(1.26)
Rivals' late exploration		-2.95			-2.15	-0.42	-6.37
		(7.13)			(7.61)	(7.28)	(7.89)
Catch-up							
Rivals' exclusive exploration			-1.12		-0.21	-1.41	-0.15
			(5.61)		(9.32)	(8.71)	(9.36)
Rivals' exclusive exploitation			-2.99		1.98	2.51	0.32
			(8.90)		(5.96)	(5.59)	(6.11)
Firm's late exploration			-0.37			0.78	-0.05
			(0.83)			(0.94)	(1.57)
In-sync							
Synchronous exploration				-0.42	-0.01	0.08	-0.27
				(0.58)	(0.81)	(0.65)	(0.80)
Synchronous exploitation				0.24	0.14	-0.27	0.31
				(2.44)	(2.80)	(2.62)	(2.78)
Search controls							
Search intensity	0.0003	0.0003	0.0002	0.0002	0.0004	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Search distance	0.62 ***	0.71 ****	0.63 ***	0.63 ****	0.71 ****	0.72 ****	0.54 ***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.18)	(0.21)
Operational controls							
Firm size	-0.001	-0.002	-0.001	-0.001	-0.002	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm r&d	-1.36	-1.84	-1.12	-1.37	-1.82	-1.61	-2.01
	(1.72)	(1.85)	(1.79)	(1.79)	(1.91)	(1.80)	(1.79)
Firm diversification	-0.06	-0.14	-0.05	-0.03	-0.14	-0.14	-0.12
	(0.16)	(0.17)	(0.16)	(0.16)	(0.18)	(0.17)	(0.17)
European firm	0.28	0.45 *	0.28	0.26	0.47 *	0.45	0.44 *
	(0.23)	(0.27)	(0.24)	(0.24)	(0.28)	(0.27)	(0.24)
U.S. firm	0.20	0.15	0.20	0.19	0.15	0.09	0.21
	(0.18)	(0.21)	(0.19)	(0.19)	(0.21)	(0.21)	(0.19)
Selection							0.04
							(0.14)
Constant	-0.01	-0.26	1.98	-0.05	-1.17	-1.06	-0.13
	(0.33)	(0.38)	(6.46)	(0.34)	(6.91)	(6.47)	(7.03)
-2*Log likelihood	638.7	605.8	612.7	620.7	589.3	618.6	

* p < 0.1; ** p < 0.05; *** p < 0.01; **** p < 0.001; two-tailed tests.

[a] Standard errors are in parentheses below parameter estimates.

[b] All models include unreported dummy variables for year. 285 observations.

FIGURE 1

Example illustrating how patent citations are categorized, based on how the focal firm and its rivals cite them in the past and the current year. Each capital letter stands for a different patent.[1]

RIVALS → **↓ FOCAL FIRM**	**Rivals do not search**	**Rivals explore**	**Rivals exploit**	**Rivals no longer search**
Firm exploits	Firm's exclusive exploitation X	Rivals' late exploration Z	Synchronous exploitation C	H
Firm explores	Firm's exclusive exploration D	Synchronous exploration E	Firm's late exploration A	G
Firm does not search	O	Rivals' exclusive exploration F	Rivals' exclusive exploitation B	M
Firm no longer searches	L	Y	K	N

Patents cited in the past		**Patents cited during the current year**	
By Focal Firm	By Rivals	By Focal Firm	By Rivals
X, Y, Z, C, H, K, L, N	A, B, C, G, H, K, M, N	A, C, X, D, Z, E, G, H	A, B, C, Z, E, F, Y, K

[1]This is an expanded version of the 3x3 matrix pictured in table 1. For brevity, 'Firm no longer searches' and 'Rivals no longer search' dimensions were excluded from the graph in table 1.

APPENDIX.

TABLE 1A

Hedonic Analysis of Robot Price.

GLS Regression of Log(Product Price)[a,b]

Variable		
Repeatability[c]	-0.19	***
	(0.06)	
Speed	0.10	***
	(0.04)	
Load capacity (log)	0.33	****
	(0.04)	
Degrees of freedom	0.13	****
	(0.04)	
Constant	8.92	****
	(0.79)	
-2Log likelihood	578.90	
d.f.	20	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$

[a] Standard errors are in parantheses below parameter estimates.
[b] Price is recorded when the product is first introduced, and is inflection-corrected.
[c] Lower values of repeatability indicate better performance.

Year dummies are included but not shown.
126 products.

TABLE 2A

Sensitivity Analysis Results on Product Innovativeness [a,b]

Variable	Inferior products dropped	
Head-start		
Firm's exclusive exploration	-0.20	
	(0.60)	
Firm's exclusive exploitation	4.47	***
	(1.24)	
Rivals' late exploration	-1.86	
	(7.61)	
Catch-up		
Rivals’ exclusive exploration	-3.54	
	(9.74)	
Rivals’ exclusive exploitation	0.34	
	(6.70)	
Firm's late exploration		
In-sync		
Synchronous exploration	-0.06	
	(0.89)	
Synchronous exploitation	0.26	
	(2.84)	
Search controls		
Search intensity	0.0002	
	(0.0004)	
Search distance	0.73	***
	(0.20)	
Operational controls		
Firm size	-0.001	
	(0.001)	
Firm r&d	-1.76	
	(1.86)	
Firm diversification	-0.13	
	(0.19)	
European firm	0.53	*
	(0.29)	
U.S. firm	0.13	
	(0.23)	
Constant	1.31	
	(7.53)	
-2*Log likelihood/Chi-sq.	591.9	

* p < 0.1; ** p < 0.05; *** p < 0.01; **** p < 0.001; two-tailed tests

[a] Standard errors are in parantheses below parameter estimates.

[b] All models include unreported dummy variables for year.