

# Effects of Search Timing on Innovation: The Value of Not Being in Sync with Rivals

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This paper investigates the effects on product innovation of firms' search to innovate, taking into account how a firm's search relates to that of its competitors. Drawing on organizational learning theory, we hypothesize that search timing relative to competitors matters and test two seemingly contradictory views: 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. Results show that firms introduce more new products if they search after their competitors do, and they introduce more innovative new products if they search ahead of their competitors. The most innovative firms combine these two approaches, bridging their own and their rivals' hitherto isolated clusters of knowledge, but avoid engaging in learning contests in which they search at the same time as their rivals. The key insight for innovating firms, then, is not necessarily to strive to perform as well as possible in absolute terms, but to be different from the competition. ●

Innovation is an unpredictable 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 new product innovation is essential in technology-based firms. It represents the commercial potential of the firm's research and development (R&D) activities (King and Tucci, 2002; Katila and Shane, 2005) and is thus a source of competitive advantage and profits (Utterback, 1994).

But how do organizations obtain the knowledge necessary for innovation? Organization theorists have identified several ways, such as inheriting knowledge from founders (Romanelli, 1985; Eisenhardt and Schoonhoven, 1990), adding new members and organizations (Ahuja and Katila, 2001; Rao and Drazin, 2002), and, more recently, growing organically (Katila, 2002; Hess and Kazanjian, 2006). Prominent among such organic approaches is search, a problem-solving process in which organizations recombine, relocate, and manipulate existing knowledge to create new knowledge (March and Simon, 1958; Nelson and Winter, 1982). Search is particularly attractive when the needed knowledge was not inherited or cannot be readily added onto the organization's knowledge base.

A significant stream of research on search, and in particular on how firms search to innovate, has produced several insights. Researchers have found that successful searches are more frequent and further away from what the firm already knows (Greve, 2003), yet 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. Also, a 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

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and Ahuja, 2002; Siggelkow and Rivkin, 2005; Chen and Katila, 2008).

Yet despite these insights, the dominant view on innovation search has been primarily firm-centric. The firm's search activities are typically 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, without taking into account that the firm's competitors also search. 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. Overall, how firms search within an environment of other competing organizations and the implications of that environment for their search outcomes are poorly understood. Because firms do not search in isolation, to understand the search for innovation in depth, we need to incorporate competition, which can create constraints on and opportunities for learning.

In understanding how competitors' simultaneous or past search activities might influence the outcomes of a focal firm's search, we conceptualize search as a learning contest, focusing on the effects of three kinds of differences in the choice of search timing between the firm and its competitors. A focal firm may have a head start on competitors in searching a new area of knowledge, or it might search in sync with its competitors, racing to create innovative products. Finally, a firm may search an area after competitors have, playing catch-up. We test predictions of how these timing choices influence the performance of a firm's search over a 15-year period in a prominent subfield of the international industrial automation industry, namely, robotics.

## **INNOVATION SEARCH IN COMPETITIVE ENVIRONMENTS**

Studying innovation as search—that is, as the problem-solving process in which organizations manipulate knowledge to create new products—is particularly appropriate for understanding innovation in competitive environments. First, in-depth fieldwork has described innovation as problem solving (e.g., Clark, Chew, and Fujimoto, 1987; Dougherty and Hardy, 1996). For example, in the course of new product development, automotive engineers search for solutions to technical problems by translating information on technological possibilities into a set of designs, instructions, and information required for producing a product (e.g., Iansiti, 1995). Second, the search perspective explicitly focuses on attempts to solve problems in a world that is ambiguous and in which problems cannot be solved directly (Simon, 1957; Cyert and March, 1963; Nelson and Winter, 1982). Because a key element of such ambiguity for innovating firms is competition (Porter, 1985; Brown and Eisenhardt, 1998), innovation search relative to competitors is critical to understand.

Innovation search takes place in a knowledge space, also known as a knowledge pool. According to Levinthal and March (1981: 313), "search consists of sampling opportunities from the pool of technological possibilities." The firm recombines, relocates, and manipulates knowledge within this pool, an activity that researchers typically track using

## Search Timing

patent citations (Rosenkopf and Nerkar, 2001; Benner and Tushman, 2002; Katila, 2002; Katila and Ahuja, 2002). This pool of knowledge 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. A relatively large stream of innovation search studies anchored in organizational learning theory has examined these two approaches. Some authors have labeled them slack search and problemistic search (Cyert and March, 1963) or scope search and depth search (Katila and Ahuja, 2002), though they are often referred to as exploration and exploitation. Exploring areas that are new to the firm lowers the expected returns to search, because most new ideas are bad ones, and thus reduces the frequency of creating 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 relatively high returns to search, because the value of the knowledge is already known, and thus increases the frequency of creating new products. But exploitation reduces the variance of search, because variability declines with experience, and in the process, makes search more reliable but also makes it substantively less innovative (Levitt and March, 1988; March, 1991). In short, the more 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 also been studied empirically. Mezas and Glynn (1993) used a simulation and Rosenkopf and Nerkar (2001) used archival data to demonstrate that firms that explore generate more innovative new technologies. In contrast, other empirical work has shown that firms that exploit generate new technologies more frequently (Katila, 2002; Greve, 2003). Another empirical stream provides descriptive insights. The findings indicate that despite the benefits, firms avoid exploration (Romanelli, 1985) and that this tendency is especially strong and potentially detrimental in R&D (Helfat, 1994). Further, learning tends to crowd out exploration (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. To add to the complexity, competition is also likely to affect the search for innovation.

## Effects of Competition on Innovation Search

Both organizational economists and sociologists have long been interested in the relationship between competition and innovation (e.g., Schumpeter, 1934; Scherer, 1980; Porter, 1990) and have suggested several logics through which com-

petition may influence search. We focus on two, learning and racing, that are particularly significant for innovation 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, by selectively copying 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; Katila, 2002). Such inferential learning—informed observation and active interpretation of others’ search—may thus lead to more innovation. Researchers have also noted 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 others’ search, with a likely positive effect on the frequency of the focal firm’s introductions of new products.

On the flipside, competitors will also learn from the focal firm. They typically start searching in the same area and crowd it (cf. Katila, Rosenberger, and Eisenhardt, 2008). 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, Stuart, and Hannan, 1996; Swaminathan, 1996). In contrast, if the focal firm searches first and alone, it does not have to invent around competitors. The 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 the innovativeness of the focal firm’s introductions of new products.

**Racing.** Search by competitors can also induce racing behavior, in which the focal firm searches simply 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). Because 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, Oxley, and Silverman, 1998; Sull, 2001), thus killing the variation in search (e.g., March, 1991; Romanelli, 1999). As a result, innovation may become

## Search Timing

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 introductions of new products.

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. Competitors' 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 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 the 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. Further, understood as racing, competition derails the focal firm's search by forcing it to expend resources to match its rivals rather than to innovate. This logic is particularly acute in situations in which 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 a focal firm's search hinges on which logic will help a firm meet its goals and therefore what timing of the search is more appropriate. Searching after competitors do is likely to be a significant determinant of search success when the goal of the search is to introduce new products more frequently, while searching ahead of competitors is likely to be a significant determinant when the goal is to introduce more innovative new products. Firms are likely to achieve neither outcome by searching simultaneously with competitors in the same area.

### The Timing of Search Relative to Competitors

To analyze the effects of search timing in more detail, we constructed a model, shown in figure 1, in which the different competitive situations are categorized by juxtaposing the focal firm's and its rivals' innovation search behavior over time. For brevity, two baseline situations—firm no longer searches and rivals no longer search—are not shown in the figure but served as omitted categories in our empirical tests. 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 figure, although all paths may not follow all the same steps along the way. For instance, in head start, 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, we have labeled the three paths as three learning con-

**Figure 1. Search of the focal firm over time relative to competitors.\***

	Rivals do not search	Rivals explore	Rivals exploit
Firm exploits	Firm's exclusive exploitation	Rivals' late exploration	Synchronous exploitation
Firm explores	HEAD START Firm's exclusive exploration	IN SYNC Synchronous exploration	Firm's late exploration
Firm does not search		CATCH UP Rivals' exclusive exploration	Rivals' exclusive exploitation

\* Curved arrows illustrate possible search paths. For brevity, two baseline situations—firm no longer searches and rivals no longer search—are not shown here but served as omitted categories in the empirical tests.

tests. The first two are out-of-sync contests, in which a focal firm is not searching with rivals, while the third is a synchronous contest. The first, a 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, a 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, a synchronous contest, starts when both the firm and its rivals use a particular knowledge first (i.e., exploring) simultaneously and possibly keep searching it at the same time (i.e., exploiting).

Innovation in video games provides a great illustration of these three contests. In the 1970s Atari had a clear head start over its 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 graphics. In contrast, Microsoft and Sony engage in synchronous competition, with relentless lock-step introductions of faster processors, snazzier graphics, and more complex games.

### Out of Sync: Searching with a Head Start

**Focal firm's exclusive exploration and exploitation.** When the focal firm has a head start over its competitors in the industry in searching for new knowledge, there is no prior experience to learn from, 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 may reduce the frequency of product introductions.



## Search Timing

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, Mosakowski, and Zaheer, 1997). Because 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), trying to introduce an innovative product that offers more value to customers than competing products.

When the firm with the head start is able to exploit the knowledge exclusively, continuing to search it without any of its rivals joining the race, its exclusive exploitation modifies the above-described negative effect on the frequency and positive effect on the innovativeness of products. 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. That is, competitors may not be interested because the potential returns from this area are uncertain. Taken together, these arguments suggest that a firm's exclusive exploitation has a negative but weaker effect on a focal firm's product frequency than a firm's exclusive exploration.

In contrast, though a 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. Although 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; Katila and Ahuja, 2002). Thus exclusive exploitation may result in more innovative products than exclusive exploration does. Based on these arguments, we propose:

**Hypothesis 1a (H1a):** A firm's exclusive search (exploration and exploitation) will have a negative effect on the frequency of its new product introductions.

**Hypothesis 1b (H1b):** A firm's exclusive search (exploration and exploitation) will have a positive effect on the innovativeness of its new product introductions.

**Rivals' late exploration.** Hypothesis 1 focused on solitary searches by the focal firm, but at some point the firm's com-

petitors are likely to join this race. Rivals' search may provide an opportunity for learning, but it also increases crowding. First, by joining the search, competitors can help confirm indirectly that an area is viable and timely for search and that selecting the knowledge for further development is worthwhile because expected returns are likely to be high relative to other possible projects. Thus, from the focal firm's perspective, there is less chance that the development will fail or that the project will need 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, these arguments imply that when competitors join the race, they will provide opportunities for learning and so increase the frequency of new product innovation.

But once competitors start searching the knowledge, it is less and less likely to lead to innovative products for the focal firm that differentiate it from its rivals. Rivals 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 (Katila, 2002). So, though 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.

**Hypothesis 2a (H2a):** Rivals' delayed search (late exploration) will have a positive effect on the frequency of the focal firm's new product introductions.

**Hypothesis 2b (H2b):** Rivals' delayed search (late exploration) will have a negative effect on the innovativeness of the focal firm's new product introductions.

### **Out of Sync: Searching to Catch Up**

**Rivals' exclusive exploration and exploitation.** When a firm's rivals search first, the focal firm's product introductions are likely to be more frequent but less innovative. First, technical breakthroughs and new problem-solving approaches that rivals discover may leak to the rest of the industry (cf. Nelson and Winter, 1973) and so may become available to the focal firm without its doing any direct search of its own, through passive search (Huber, 1991). Such knowledge leaks may, for instance, remove bottlenecks in the innovation process that hold up 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 and save the costs of search 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 focal 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 cus-



## Search Timing

tomers' problems. In general, then, 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 focal firm from its rivals (Kogut and Zander, 1992), for two reasons. First, rivals' searches make the knowledge space crowded. Without a firm's own search effort and the intricate knowledge that it provides (e.g., about 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 (Romanelli, 1999). The result is that while rivals' exclusive search may lower the risk of poor outcomes, it will make it harder for the focal firm to introduce particularly innovative products that would surpass those of competitors.

When rivals continue to exploit the knowledge exclusively, and the focal firm does not join the race, their exclusive exploitation intensifies both the above-described positive effect on the frequency and the negative effect on the innovativeness of the focal firm's 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 as they 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' exclusive 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.

**Hypothesis 3a (H3a):** Rivals' exclusive search (exploration and exploitation) will have a positive effect on the frequency of the focal firm's new product introductions.

**Hypothesis 3b (H3b):** Rivals' exclusive search (exploration and exploitation) will have a negative effect on the innovativeness of the focal firm's new product introductions.

**Focal firm's late exploration.** Although knowledge that is available from rivals' searches 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. Because of this, a firm's late exploration can make product introductions more frequent. First, the firm that joins the race late is likely to introduce more new products because competitors' prior searches provide reliable raw material for sub-

sequent searches. By observing competitors' searches first and only then forming its 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 and may have high expected returns. In addition, rivals' simultaneous search of the focal knowledge indicates that the knowledge remains a valuable source for new product introductions. Together, these effects should have a positive effect on the frequency of a focal firm's new product introductions.

At the same time, it is less likely that the new products 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 the focal firm's search output. Thus, we propose a negative effect on innovativeness:

**Hypothesis 4a (H4a):** A firm's delayed search (late exploration) will have a positive effect on the frequency of the firm's new product introductions.

**Hypothesis 4b (H4b):** A firm's delayed search (late exploration) will have a negative effect on the innovativeness of the firm's new product introductions.

### **In Sync: Searching Simultaneously**

Competing firms can also search synchronously, starting at the same time and racing together. Searching simultaneously with competitors, however, makes it difficult for a focal firm to introduce a large number of products or products that are innovative. 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 in which they try to stay competitive, with relatively homogeneous resources (Barnett, 1997; Lieberman and Asaba, 2006). New product ideas are often commercialized prematurely (for fear that competitors will 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 area at the same time, neither synchronous exploration nor synchronous exploitation is likely to lead to unique product ideas. Instead, rivals are likely to engage in a race in which 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). Because 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 to the needs of the customer. Both the firm and

## Search Timing

its rivals invest in costly search, but none of them ends up being particularly innovative.

**Hypothesis 5a (H5a):** Synchronous search (exploration and exploitation) will have a negative effect on the frequency of the focal firm's new product introductions.

**Hypothesis 5b (H5b):** Synchronous search (exploration and exploitation) will have a negative effect on the innovativeness of the focal firm's new product introductions.

## METHOD

### Sample

We tested 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 percent of the world's robot supply during this period (United Nations et al., 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. As part of the study, we conducted informational interviews with engineers and executives of seven Japanese, two European, and nine U.S. robotics organizations.

We chose to focus on firms that develop robots, for three reasons. First, these firms make substantial R&D investments to develop complex products, so there is a greater need for effective search behavior. Second, if search is influenced by competition, it should be possible to observe this process in robotics. In our interviews, 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, robotics is a competitive market in which users require high product performance, because robots are a critical part of their manufacturing process. These firms should thus be a good sample in which to observe the search to create innovative products.

To form the sample of industrial robotics companies for this study, we identified a list of candidates through an extensive search of robotics trade magazines and databases, which we then verified through discussions with industry experts. Only those companies in the population that developed or had announced that they would 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

We used three primary sources of data. For new products, we assembled data from trade publications and product catalogs, using a “literature-based innovation output indicator” method (Coombs, Narandren, and Richards, 1996; Katila, 2000). In this method, we systematically combed 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 the *Robotics New Product Database* and *Robotics Product Specifications in Japan*), 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, we searched over 30 different publications over a 15-year period and used multiple sources whenever possible to validate the data.

We retrieved patent 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.<sup>1</sup> We collected data on firms’ financial and operational indicators from databases, including COMPUSTAT, Worldscope, and DIR Analyst’s guide.

We supplemented the primary archival data with interviews with 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, they strengthened our understanding of the causal mechanisms underlying successful innovation and helped us choose more accurate measures. They also helped in interpreting the results.

### Dependent Variables

We examined two outcomes of innovation search: (1) the number of new product introductions (*product frequency*) and (2) the innovativeness of these introductions (*product innovativeness*). We measured *product frequency* as the number of new industrial robots introduced by each sample firm each year. To qualify as new, each product had 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

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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 two 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.

## Search Timing

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.

We measured *product innovativeness* annually for each firm as the improvement in those product design characteristics that were important to users, which is a well-established method (Sahal, 1985; Keeney and Lilien, 1987). For example, Dodson (1985) used the method to compare rocket motors (delivered impulse, thrust, and motor weight), and Trajtenberg (1989) used it 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 of robots that users value fulfill both of these criteria.

There are four such characteristics of robots: repeatability, speed, load capacity, and degrees of freedom. 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 in which the robot is able to move and thus determines how complex its movements can be. 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. Because we did not have price data for all products in the sample, we restricted the hedonic analysis to a smaller set yet were able to confirm that we had chosen the right characteristics (see Appendix, table A.1). Further, the four design characteristics that we used were 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, 1999). These data are also highly reliable because we used multiple data sources.

To construct the product innovativeness measure, we compared 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, we compared the repeatability of the firm's robots with the repeatability of all robots introduced in the previous year. Consistent with prior work using a similar composite measure, we constructed the innovativeness variable 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.

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

We compiled an alternative measure of product innovativeness that included only those firm-years in which the firm introduced better-performing robots than its prior introductions. The intuition was that once a firm introduced a robot with certain performance characteristics, it had the ability to innovate at that level and that we should not penalize it if it chose to introduce a robot with inferior characteristics in some future years. We also constructed an alternative measure by comparing year  $t$  values with the first robot introduced in the industry (instead of year  $t-1$  values) 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 give us a detailed and consistent chronology of search (Almeida, Song, and Grant, 2002; Katila, 2002). Citation patterns in patents track the knowledge used over time and, because of their legal nature, are precise (Walker, 1995). Thus two of our key features of search, competitors' search and its timing, can be measured accurately. Third, patent measures are particularly appropriate for testing hypotheses that include learning. Because one of the requirements for patenting is novelty, each time an existing patent is cited as an antecedent for a new patent, it is used in a different context 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, because 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), they 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, according to our interviews, 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 studied. Third, patents have long been used to describe technology developments in robotics (e.g., Brossia, 1983; Grupp et al., 1990), and we followed this tradition.



## Search Timing

**Figure 2. Operationalization of the search variables using patent data.\***

	Rivals do not search	Rivals explore	Rivals exploit
Firm exploits	Firm's exclusive exploitation (H1) 	Rivals' late exploration (H2) 	Synchronous exploitation (H5) 
Firm explores	Firm's exclusive exploration (H1) 	Synchronous exploration (H5) 	Firm's late exploration (H4) 
Firm does not search		Rivals' exclusive exploration (H3) 	Rivals' exclusive exploitation (H3) 

\* A rectangle indicates that this patent was searched in the past five years. A square indicates that this patent was searched in the current year. The dark color indicates search by the focal firm, white indicates search by rivals.

The patents for our independent variables were assembled following Podolny, Stuart, and Hannan's (1996) procedure for comparing the 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 figure 2, by comparing the firm's and its rivals' current and prior years' knowledge bases. Figure 2 thus shows how search categories in figure 1 were operationalized. In these operationalizations, all 123 other firms that participated in the industry were included as rivals, and this year's vs. the past five years' citations were used to measure present vs. past. A five-year window was used because 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), we used fractions when constructing the variables. We divided the citation counts in each category by the firm's total number of citations that year or by the rivals' citations in the bottom row when the firm did not cite 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. To estimate the models, we focused on the eight categories shown in figure 2 and omitted the remaining four categories that are not pictured but are shown in the example in figure 3. The categories that are omitted are as follows: 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 did not apply for patents in a given year, making the denominator in our variables zero (under 4 percent of

**Figure 3. Example illustrating how patent citations (represented by capital letters) are categorized, based on how the focal firm and its rivals cited them in the past and in the current year.**

	Rivals do not search	Rivals explore	Rivals exploit	Rivals no longer search
Firm exploits	Firm's exclusive exploitation A	Rivals' late exploration E	Synchronous exploitation I	M
Firm explores	Firm's exclusive exploration B	Synchronous exploration F	Firm's late exploration J	N
Firm does not search	C	Rivals' exclusive exploration G	Rivals' exclusive exploitation K	O
Firm no longer searches	D	H	L	P

Patents Cited in the Past

By Focal Firm:

A, D, E, H, I, L, M, P

By Rivals:

I, J, K, L, M, N, O, P

Patents Cited in the Current Year

By Focal Firm:

A, B, E, F, I, J, M, N

By Rivals:

E, F, G, H, I, J, K, L

observations), the search variables were set to zero. We obtained similar results 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 3.

**Head-start variables.** We measured a *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 were neither in its own or its rivals' past five years' knowledge bases nor in its rivals' knowledge bases in the current 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, the firm's exclusive exploration takes a value of 0.2 (Firm's exclusive exploration = Citations exclusively explored by the focal firm / Total citations by the focal firm).

We measured the *firm's exclusive exploitation* as the proportion of those prior-art patent citations in the focal firm's current-year patents that were not in its rivals' but were 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 were not in its rivals' but were in the firm's own

## Search Timing

past five years' knowledge base and were used in the current 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 the firm's rivals' current-year patents that could not be found in the rivals' past five years' technological knowledge bases nor in the focal firm's knowledge bases in the current 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 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 rivals' current-year patents that were in the rivals' but not in the focal firm's past five years' knowledge bases and were not used by the focal firm in the current year either (Rivals' exclusive exploitation = Citations exclusively exploited by rivals / Total citations by rivals).

We measured the *firm's late exploration* as the proportion of those prior-art patent citations in the focal firm's current-year patents that were in rivals' knowledge bases during the past five years but not in the firm's knowledge base and were used in the current 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 were not in its own nor in its rivals' past five years' knowledge bases but were used in the current 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 could be found in its own and in its rivals' past five years' knowledge bases and were used again in the current 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 of up to four to five years. Podolny, Stuart, and Hannan (1996) used a similar five-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 the 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 applied for (Griliches, 1990; Deng, Lev, and Narin, 1999).

We also controlled for the technical similarity of this effort relative to the 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 subclasses to which the firm's current-year patents have been assigned but none of its patents during the past five years has. We used subclasses as a measure because they characterize the technological areas in which the firm is searching; similar measures have been corroborated in prior work (e.g., Jaffe, 1989; Katila and Shane, 2005). 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). The 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 have reported 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 (return on assets) 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 the 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 products (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 Standard Industrial Classification (SIC) code (Jacquemin and Berry, 1979). We collected yearly 4-digit SIC sales data for each company from annual reports, company databases, and

## Search Timing

directories such as Worldscope and Japan Company Handbook.

Because 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 that were set to one if the firm originated in a particular area (*European firm*, *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 by 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 consisted of a panel of observations on firm-years. The first set of data included 1,304 firm-years and was used to test models with product frequency as the dependent variable. Because this dependent variable consisted of counts of new products and had many zero values, we used a negative binomial regression. To control for repeated observations for the same firm, we employed the Generalized Estimating Equations (GEE) regression method, which 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, which 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, Griffith, and Van Reenen, 1995). Our results held irrespective of the model (results are available from the authors).

The second set of data included 285 firm-years and was 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.<sup>2</sup> 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 esti-

### 2

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 sets of results are available from the authors.

mates (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 was labeled *selection* and effectively controlled for the likelihood that an observation was included in the subsample.

To facilitate causal inference, the independent and 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.

Descriptive statistics and correlations for all the key variables are reported in table 1 for product frequency and in table 2 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 1: 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 were entered in the models both separately and simultaneously. In the first case (rivals' search), the results are unaffected, but they differ in the second, as discussed below. Overall, because 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.

Table 1

<b>Descriptive Statistics and Correlations for the Key Study Variables for the Frequency Models (N = 1304)</b>										
Variable	Mean	S.D.	1	2	3	4	5	6	7	
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	
10. Search distance	.65	.27	.05	.05	-.06	.08	-.05	-.02	.04	
11. Firm size	33.29	74.30	-.06	.08	.13	.07	-.14	-.003	-.05	
12. Firm R&D	.04	.03	-.21	.07	.24	-.02	-.06	.17	-.06	
13. Firm diversification	1.00	.44	-.09	.09	.07	-.05	.02	.01	.11	
14. European firm	.15	.35	.07	-.09	.004	-.01	.004	-.01	-.10	
15. U.S. firm	.19	.39	.14	.15	-.08	.14	-.13	-.20	-.09	
16. Product frequency	.94	2.33	.03	.002	-.07	.17	-.01	.14	-.02	
Variable	8	9	10	11	12	13	14	15		
9. Search intensity	.27									
10. Search distance	-.02	-.16								
11. Firm size	.05	.40	.01							
12. Firm R&D	.10	.37	-.01	.26						
13. Firm diversification	.10	.19	.06	.14	.08					
14. European firm	-.06	.03	.05	.44	.15	.17				
15. U.S. firm	-.13	-.07	.04	.07	.05	-.34	-.20			
16. Product frequency	.01	.14	.03	-.001	.08	.15	-.06	-.12		



## Search Timing

Table 2

<b>Descriptive Statistics and Correlations for the Key Study Variables for the Innovativeness Models (N = 285)</b>									
Variable	Mean	S.D.	1	2	3	4	5	6	7
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
10. Search distance	.66	.24	.11	-.01	-.21	.07	.02	-.03	.10
11. Firm size	38.42	65.14	.06	.12	.05	.06	-.14	-.17	-.07
12. Firm R&D	.04	.03	-.14	.18	.26	-.07	-.02	.05	-.17
13. Firm diversification	1.11	.43	-.04	.15	.14	-.08	.02	-.09	.04
14. European firm	.12	.32	.09	-.11	.14	-.07	.09	-.07	-.05
15. U.S. firm	.14	.35	.28	.09	-.12	.26	-.23	-.23	-.18
16. Product innovativeness	.28	.66	.06	.07	-.08	.11	-.11	-.05	-.06
Variable	8	9	10	11	12	13	14	15	
9. Search intensity	.35								
10. Search distance	-.11	-.29							
11. Firm size	-.001	.41	-.04						
12. Firm R&D	.13	.37	-.11	.31					
13. Firm diversification	.02	.30	.09	.38	.13				
14. European firm	-.11	-.06	.03	.49	.22	.31			
15. U.S. firm	-.21	-.08	.04	.11	.07	-.34	-.15		
16. Product innovativeness	-.08	-.02	.11	-.02	-.02	-.04	.004	.10	

## RESULTS

**Main analyses.** Tables 3 and 4 test the hypotheses. Table 3 reports results for the frequency of product introductions, while table 4 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.

In both tables 3 and 4, 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 are 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 3) to avoid risks of multicollinearity. Two of the results reported below, H1a on firm's 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 the firm's exclusive exploration and its exclusive exploitation in table 3,

Table 3

**Negative Binomial GEE Regression Analysis of Product Frequency (N = 1304)\***

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

•  $p < .10$ ; ••  $p < .05$ ; •••  $p < .01$ ; ••••  $p < .001$ ; two-tailed tests.

\* Standard errors are in parentheses below parameter estimates. All models include unreported dummy variables for year.

**3**

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 a firm's exclusive exploration decreased the rate of product frequency by 33 percent, whereas a one-standard-deviation increase in a firm's exclusive exploitation decreased product frequency only by 21 percent. Because the negative binomial model is log-linear, we exponentiated coefficients to get these estimated multiplier effects.

model 5. Both coefficients are negative, and the first is significant ( $p < .01$ ) and the second marginally significant ( $p < .10$ ). Together, the results confirm that exclusive search makes product introductions less frequent.<sup>3</sup> Similarly, we tested H1b on innovativeness by examining the coefficients for a firm's exclusive exploration and its exclusive exploitation in table 4, model 5. The coefficient for exploration is non-significant, but the coefficient for exploitation is positive and significant ( $p < .001$ ). These results show that firms do introduce innovative products when they are able to search knowledge exclusively

## Search Timing

Table 4

### Random-effects GLS Regression Analysis of Product Innovativeness (N = 285)\*

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

•  $p < .10$ ; ••  $p < .05$ ; •••  $p < .01$ ; ••••  $p < .001$ ; two-tailed tests.

\* Standard errors are in parentheses below parameter estimates. All models include unreported dummy variables for year.

and keep their 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 a firm's exclusive exploitation are stronger than those of its exclusive exploration.

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 3, model 6. The positive and significant ( $p < .05$ ) coefficient confirms H2a, indicating that firms can learn indirectly from their rivals' choices. Searching with a head start that hurts product frequency turns into a positive effect as rivals join the search.<sup>4</sup> Regarding innovativeness, consistent with H2b, which 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 4, 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 3, model 6. Both coefficients are positive, and exploration is significant ( $p < .05$ ), but exploitation does not reach significance. These results show that rivals' search makes the focal firm's product introductions more frequent if 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 4, model 6. The coefficients are negative and positive, respectively, but non-significant. Thus there is no significant support for hypothesis 3b, although the signs on rivals' exclusive exploration are consistently negative, as we expected.

In H4, we predicted that when the firm joins a search that was previously dominated by rivals, it will introduce a larger number of but less innovative products. To test H4a on frequency, we examined the firm's late exploration coefficient in table 3, model 6. The positive and significant ( $p < .001$ ) coefficient supports H4a.<sup>5</sup> Similarly, we tested H4b on innovativeness in table 4, model 6. We expected a negative effect on innovativeness, but this prediction was not borne out; the coefficient on a 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 3 and 4. The coefficients have mostly negative, but non-significant, signs in both tables. Although only synchronous exploration significantly hurts product frequency (table 3, model 6), the overall conclusion is as expected: successful innovators do not search simultaneously with their rivals.

Results for the control variables support prior findings. As expected, diversified (firm diversification), Japanese (Japanese firm), search-intensive (search intensity) firms introduce new products more frequently (table 3). Also as expected, searching technologically further away from prior searches (search distance) results in more innovative products (table 4) but does not make product introductions any more frequent (table 3). Further, although the effects of dummies for European firm and U.S. firm fall short of statistical significance in table 4, the coefficients are in the predicted direction, suggesting that European and U.S. firms introduce more innovative products than Japanese firms. Overall, the conclusion is that even after controlling for the traditional predictors of

#### 4

In separate (unreported) regressions, we also assessed whether firms that have a bigger head start in using the knowledge ahead of rivals have an advantage. We interacted a 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.

#### 5

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

## Search Timing

search success—i.e., search intensity and search distance, in particular—search by competitors has a significant influence.

**Additional analyses.** Our results were robust to a variety of additional analyses. The first such analysis explored firms that simultaneously combined different search approaches (cf. Gulati and Gargiulo, 1999). In our original hypotheses, we treated search approaches 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. 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 the frequency of product innovation, while the interactions with in-sync searches are not significant. Results for innovativeness 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, there is a positive and significant interaction between rivals' late exploration (head-start) and firm's late exploration (catch-up) variables, which makes a focal firm's new products both more frequent and more innovative. 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.

Second, we explored the boundary conditions for search. Because the firm's late exploration variable had such a strong positive effect on product frequency (table 3) 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 on frequency was stronger the fewer the number of rivals that 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  $p < .01$  level). Though prior research has shown that a natural tendency is to imitate larger (rather than fewer) numbers of other firms (Haunschild and Miner, 1997), our results show that it is more advantageous to do the opposite: it may be 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. 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; Katila, 2000). 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 to the scope of search.

## **DISCUSSION AND CONCLUSION**

In this paper, we extended the traditional firm-centric search theory to incorporate competition, an overlooked but critical dimension. 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 found 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 of but less innovative products (catch-up) and introducing fewer but more innovative products (head-start). Second, we found that the 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 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. 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, 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 simultane-



## Search Timing

ously with head-start and catch-up logics. By participating in both out-of-synch contests simultaneously, the same firm can introduce both a larger number of and more innovative products. Firms that search in sync with competitors attain neither. One reason for these results may be that participation in both contests helps the firm use knowledge from one part of the knowledge domain to challenge accepted beliefs in another (Lant and Mezias, 1992). For example, the firm can use experiences from its exclusive searches to challenge the way that rivals have viewed and used their exclusive knowledge in the industry, resulting in new combinations (cf. Zajac and Bazerman, 1991). In fact, one of the robotics designs often cited 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.

Together, our three sets of 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 be different from the opponent.

Overall, the findings extend 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 where 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. Those authors used successful search outcomes such as market entry to approximate search, however, 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 a firm searches, but with whom.

Though many of our hypotheses were supported, a few results were surprising and offer unexpected insights. Creativity researchers have argued that deep expertise is a source of truly novel innovations (Csikszentmihalyi, 1996; Taylor and Greve, 2006), but 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 showed that searchers with deep expertise (a firm's exclusive exploitation), rather than those exploring entirely new knowledge (a firm's exclusive exploration), introduce the most innovative products. Further, inno-

vation 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. Though 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 competitors' searches influence the focal firm's search will also provide one answer to the enduring question in organizational research of 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, Griffith, and Van Reenen, 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 the 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) noted, "... 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 examined both the frequency and the innovativeness of new products and thus examined more diverse types of innovation. Second, by incorporating competition, this research contributes to understanding external factors that influence innovation. Drazin and Schoonhoven (1996: 1077) further noted that "certain to influence a given organization in its decision to innovate or not would be actions taken by its competitors," yet according to these authors, such external factors have received less attention than the internal ones and should be brought back to center stage. Our approach also responds to calls for more integrated, multilevel models of innovation (Brown and Eisenhardt, 1995; 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 (also referred to as passive search). As did Jaffe (1989), we found that when competitors are active in search, the focal firm is also more likely to benefit. Extending these prior results, we showed that for such spillovers to be useful, they need to be captured fast, before they depreciate. Because our study focused on the effects of spillovers on new product innovation rather than on inventions, it also provides more direct evidence of the commercial benefits of spillovers than prior studies. In light of these benefits, another

## Search Timing

er question arises: why would firms invest in costly search when they could borrow (knowledge spilled over) from their competitors and exploit the successful exploration of others? Our results provide a unique answer: they show that a 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 the 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 hard-copy and electronic sources as well as 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 of the process 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.

Finally, the boundary conditions for this study suggest avenues for future work. The study focused on improvements along existing product attributes with current rivals, which typically account for the majority of technical advances. To explain how firms make such improvements, we focused on the opportunities and constraints that rivals create for the innovating firms. In the future, this approach can be extended to examining the search for innovation in periods of discontinuous change, which introduce a whole new set of product attributes and often a whole new set of competitors. In such discontinuous periods, in which new competitors often have a significant head start in critical areas of new knowledge, a focal firm might often be better off by exploring completely new areas with a head-start approach rather than engaging in destructive synchronous or long catch-up races. Studying innovation in the midst of the confusion that discontinuous change creates and incorporating both organizational and interorganizational factors, not as contrasting but as complementary explanations, can provide a richer understanding of search and innovation.

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## Search Timing

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## APPENDIX

Table A.1

### Hedonic Analysis of Price of 126 Industrial Robots: GLS Regression of Log(Product Price)\*

Variable	
Repeatability†	-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)
-2xLog likelihood	578.90
D.f.	20

•  $p < .10$ ; \*\*  $p < .05$ ; \*\*\*  $p < .01$ ; \*\*\*\*  $p < .001$ .

\* Standard errors are in parentheses below parameter estimates. Year dummies are included but not shown. Price is recorded when the product is first introduced and is inflection-corrected.

† Lower values of repeatability indicate better performance.