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SOMETHING OLD, SOMETHING NEW: A LONGITUDINAL STUDY OF SEARCH BEHAVIOR AND NEW PRODUCT INTRODUCTION

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We examine how firms search, or solve problems, to create new products. According to organizational learning research, firms position themselves in a unidimensional search space that spans a spectrum from local to distant search. Our findings in the global robotics industry suggest that firms' search efforts actually vary across two distinct dimensions: search depth, or how frequently the firm reuses its existing knowledge, and search scope, or how widely the firm explores new knowledge.

In this study, we examined how firms *search*, or solve problems (Nelson & Winter, 1982), to create new products. The ability to create new products is an important component of firm innovative capabilities. New products are a central mechanism whereby organizations diversify, adapt, and reinvent themselves in changing market and technical conditions (Schoonhoven, Eisenhardt, & Lyman, 1990). Research has also demonstrated how new products improve the market share, market value, and survival of firms (Banbury & Mitchell, 1995; Chaney & Devinney, 1992). Yet, despite the attractiveness, firms find it difficult to create new products. Here, we explain a firm's performance in creating products as a function of its search behavior.

Organizational learning researchers have sometimes argued that in their search for solutions to problems, firms position themselves in a unidimensional search space that spans the spectrum from exploitation to exploration (March, 1991). We suggest that firms' search, or problem-solving efforts, actually vary on two distinct dimensions rather than one. Firms can vary in their degree of use and reuse of their existing knowledge, just as they can vary in their exploration of new knowledge. We call the first dimension, which describes how deeply a firm reuses its existing knowledge, *search depth*. We call the second dimension, which describes how widely a firm explores new knowledge, *search scope*. In the sections that follow, we develop and apply this framework to the context of new products and argue that a firm's ability to create new products is determined by the independent and interactive effects of search depth and search scope.

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CONCEPTUAL BACKGROUND

The core technical and user service features of a product are customarily called a product's design (Saviotti & Metcalfe, 1984). In this study, a *new product introduction* was defined as any change in a product's design. New products represent the potential commercial value of a firm's R&D activities; most innovations do not influence firm performance until they are introduced to the market. A construct of product introductions also complements other, more intermediate proxies for firm innovation, such as knowledge, R&D investment, and scientific publications. Yet relatively few longitudinal studies have explored the determinants of new product introductions.

Search in organizations is one part of the organizational learning process through which firms attempt to solve problems in an ambiguous world (Huber, 1991). Organizations engage in a wide variety of searches: they search for superior organizational designs (Bruderer & Singh, 1996), for optimal manufacturing methods (Jaikumar & Bohn, 1992), and for the best ways to implement new innovations (von Hippel & Tyre, 1995). We focused here on one specific type of search, search for new products. Drawing on the work of Winter (1984), we defined *product search* as an organization's problem-solving activities that involve the creation and recombination of technological ideas. In taking a search perspective and viewing firms as problem solvers, we build on research that describes product development as problem solving (e.g., Dougherty & Hardy, 1996).

Prior work has used two notions of search, local search and distant (exploratory) search. Organizations that search locally address problems by using knowledge that is closely related to their preexisting knowledge bases (e.g. Helfat, 1994; Martin & Mitchell, 1998; Stuart & Podolny, 1996). At the other end of the spectrum, exploratory search behaviors involve a conscious effort to move away from current organizational routines and knowledge bases (March, 1991; Miner, Bassoff, & Moorman, 2001). Although this traditional characterization of search in terms of scope—that is, the degree to which it entails the exploration of new knowledge—is useful, it is, however, incomplete. The search efforts of firms can vary not just in their scope (local versus distant) but also in their depth, which is the degree to which existing knowledge is reused or exploited. In the search for solutions to new problems, certain firms may use some of their existing elements of knowledge repeatedly, while others may use them only once. These differences in depth of search can lead to varying degrees of familiarity with the knowledge and eventually have implications for firms' ability to craft new solutions. Huber presented a similar argument: "No distinction has been made between focused search for solutions and focused search for information about already identified solutions" (1991: 99). In sum, although the different levels of exploration of new knowledge have been studied in some detail (e.g., Rosenkopf & Nerkar, 2001), relatively little is known about the different levels of exploitation of existing knowledge.

Thus, in this work we propose that instead of a single dimension that represents a trade-off between exploitation and exploration, there actually exist two distinct underlying dimensions of search, which we call depth and scope. In the following section, we develop hypotheses about the effects on new product introductions of firms' choices along these two search dimensions.

HYPOTHESES

Our general proposition is that search depth and scope are distinct dimensions of search and that the choice to pursue one or both of these dimensions affects a firm's ability to introduce new products. In the following hypotheses, *new product innovation* is defined as the number of new products a firm introduces. *Search depth* is defined as the degree to which search revisits a firm's prior knowledge. *Search scope* is defined as the degree of new knowledge that is explored.

Search Depth

Increase in the depth of search can positively affect product innovation through three kinds of experience effects. First, using the same knowledge elements repeatedly reduces the likelihood of errors and false starts and facilitates the development of routines, making search more reliable (Levinthal & March, 1981). Increased experience is also likely to make a search more predictable, as the knowledge to be searched is familiar and the requirements the product should meet are better understood. Consequently, the product development task can be effectively decomposed into solvable subproblems, activities can be sequenced in efficient order, and unnecessary steps can be eliminated (Eisenhardt & Tabrizi, 1995). Third, repeated usage of a given set of concepts can lead to significantly deeper understanding of those concepts and boost a firm's ability to identify valuable knowledge elements within them, to develop connections among them, and to combine them in many different and significant ways that are not apparent to less experienced users of those concepts.

Excessive depth can also have negative consequences. The literature identifies at least two negative effects of excessive depth: limits to improvement along a technological trajectory, and rigidity (Argyris & Schön, 1978; Dosi, 1988). We argue below that these negative effects of depth at some point exceed the benefits discussed above and, thus, the relationship between depth and innovation is, indeed, nonlinear. The first negative effect of depth is a consequence of diminishing returns to building on the same knowledge. It seems that improvement by focusing on the same knowledge elements is possible only until the intrinsic performance limit of that knowledge trajectory is encountered (Dosi, 1988). When the limits of the trajectory are approached, benefits from subsequent product development efforts increase at a declining rate. At some point, further developments based on the same knowledge elements become increasingly expensive and the solutions excessively complicated, leading to the costs of depth eventually exceeding its benefits. Second, depth can also hurt search since beyond a point, reusing existing knowledge can make an organization rigid: solutions and problem-solving strategies that once made firms great can turn into problems to be resolved. For example, to preserve a status quo, organization members may try to hide problems related to the approach that has been traditionally used (Argyris & Schön, 1978). Thus, rigidity can eventually lead to a decrease in product output.

Consequently, we propose that the number of new products will first increase with depth in search but that, beyond a point, additional depth in search will cause a fall in product output.

Hypothesis 1. Search depth is curvilinearly (taking an inverted U-shape) related to the number of new products introduced by a firm.

Search Scope

Search with high scope affects product innovation positively through at least two mechanisms. First, search with high scope enriches the knowledge pool by adding distinctive new variations. New variations are necessary to provide a sufficient amount of choice to solve problems (March, 1991). Evolutionary theorists call this effect the "selection effect of variation." Second, search scope increases a firm's number of new products through enhancing recombinatory search (Fleming & Sorenson, 2001; Nelson & Winter, 1982). There is a limit to the number of new ideas that can be created by using the same set of knowledge elements. An increase in scope adds new elements to the set, improving the possibilities for finding a new useful combination.

However, the literature also suggests two negative consequences of extremely high levels of scope: dynamically increasing knowledge integration costs, and decreasing reliability. First, high scope can hurt innovativeness through the dynamically increasing costs of integrating new knowledge. As the amount of search scope and, consequently, the proportion of new knowledge to be integrated into a firm's knowledge base increases, so do the technological and organizational challenges in integration. Technologically, common interfaces need to be established among knowledge elements. Organizationally, new knowledge requires changes in networks of relations and communication relationships both within and outside an organization (Henderson & Clark, 1990). In prior work, it has been argued that the wider the scope of the knowledge to be integrated, the more complex are the problems of creating and managing integration (Grant, 1996: 377). Thus, eventually, the costs of integration will exceed the benefits of acquiring new knowledge.

Second, researchers have argued that excessive increase in search scope can hurt product output through decreasing reliability (e.g., Martin & Mitchell, 1998). A firm's reliability (its ability to respond to new information correctly) is "a negative function [of distance] from an agent's immediate experience or from its local environmental situation" (Heiner, 1986: 84). Thus, innovation projects in which the proportion of new knowledge is high are less likely to succeed than projects that search closely related knowledge (Cyert & March, 1963).

The mechanisms described above suggest that search scope, as measured by the proportion of new knowledge elements in search, is curvilinearly related to subsequent product innovation. The following hypothesis is proposed:

Hypothesis 2. Search scope is curvilinearly (taking an inverted U-shape) related to the number of new products introduced by a firm.

Combination of Depth and Scope

The above hypotheses focus on the distinct effects of depth and scope on innovation. In this section, we propose that these variables are mutually beneficial and have interactive effects. We suggest two mechanisms that underlie this positive interaction: absorptive capacity and uniqueness.

The absorptive capacity literature discusses how firms can use their accumulated knowledge to recognize and assimilate new knowledge (e.g., Cohen & Levinthal, 1994). Relatedly, Winter (1984: 293) argued that the new knowledge firms typically obtain by searching their external environments is a collection of fragments of possibly useful knowledge. However, the number and quality of these fragments are likely to be less than what is needed, and therefore assimilation and further development of novelty require complementary problem-solving efforts by the acquiring firms. Thus, existing knowledge may facilitate both the absorption and further development of new knowledge, suggesting a positive relationship between relatively high levels of depth and scope, and product innovation.

A combination of depth and scope search can also increase the uniqueness of recombinations. In Hypothesis 2, we discuss the relationship between scope and new product output. However, increases in scope can be costly: the probability of finding valuable new knowledge elements is small and, even if a firm succeeds in doing so, it is possible that the same product idea has already been discovered. By combining firm-specific accumulated understanding of certain knowledge elements (depth) with new solutions (scope), firms are more likely to create new, unique combinations that can be commercialized (Winter, 1984: 293).

Hypothesis 3. The interaction of search depth and scope is positively related to the number of new products introduced by a firm.

METHODS

Sample and Data

The research sample was drawn from the population of industrial robotics companies in Europe, Japan, and North America. A number of considerations motivated the choice of industrial robotics as the setting of the study. The high research intensity of the robotics industry makes it a good place to analyze the effects of new product search (Katila, 2000). And since robotics technology is a combination of multiple rapidly changing technological disciplines such as electronics, new materials, and optics, and since the industry lacks product standards (Dahlin, 1993), search activities in the industry require complex problem solving. Finally, although the diffusion of robots and the effects of robotization on workers are well documented, few studies have examined how robots are developed.

We searched through robotics trade magazines and catalogues and talked to industry experts to form a comprehensive list of companies in the industrial robotics industry. This method assured that we were not sampling on the dependent variable: all relevant companies were included, whether or not they were innovative. Availability of yearly data on the control variables reduced the final sample to 124 firms, of which 78 were Japanese, 27 were American, and 19 were European. The firms varied widely in size: the average firm had 39,000 employees, and the smallest had fewer than 100 employees. Industry entry and exit data for each company were collected from *Predicasts*, trade journals, and industry reports.

We used two main data sources: new product introduction announcements and patent data. In assembling the product data, a method introduced by Coombs, Narandren, and Richards (1996) was applied. Following this method, we obtained product introductions and their characteristics from both editorially controlled new product announcement sections of robotics technical and trade magazines and from robotics product catalogues. The use of several sources for a single introduction assured the reliability of the data. For a final verification, we contacted our sample companies and asked them to verify their individual product records in our data. To collect the patent data for the search variables, we used data from the United States Patent and Trademark Office. We went through *Who Owns Whom*, a set of directories, to create the patent portfolios for each firm. Yearly patent data, by application date, were used.

Measures

Dependent variable: Number of new products. To measure the dependent variable we used Martin and Mitchell's (1998) definition of a new product as change in design characteristics. A robot was defined as new if one or more of its design characteristics differed from those of the producing firm's previous products. Thus, an existing design introduced into a new geographical area, for example, did not qualify as a new product.

Independent variables. Obtaining data on intrafirm problem-solving behaviors over a ten-year period is a major challenge. Data with which to assess intrafirm search activities over time are usually not public, or, even if they are available, are often extremely resource-consuming to assemble (Cohen, 1995). In this study, we used firms' patenting activities to measure their depth and scope of search. Since a patent by definition includes a description of a technical problem and a solution to that problem (Walker, 1995), patent data gave us a detailed and consistent chronology of how firms solve problems—or search. Recognizing these attributes, several authors have used patent data as an indicator of search activity (see Katila, 2002; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996).

Using patent data as a measure of search also has some limitations. Previous studies have shown that the propensity for patenting varies considerably across industries (e.g., Cockburn & Griliches, 1987). However, this was not a problem in our study since we focused on one industry, industrial robotics. Patents have been shown to be an important appropriability mechanism in the robotics industry (Grupp, Schwitalla, Schmoch, & Granberg, 1990) and in the industrial machinery industry in general (Arundel & Kabla, 1998; Cockburn & Griliches, 1987).

The variable *search depth* describes accumulation of search experience with the same knowledge elements. We argued above that the more frequently a firm has used knowledge, the more deeply it knows it. Thus, search depth was measured as the average number of times a firm repeatedly used the citations in the patents it applied for. We created the depth variable by calculating the number of times that, on the average, each citation in year $t-1$ was repeatedly used during the past five years. Prior research has shown that organizational memory in high-technology companies is imperfect: knowledge depreciates sharply, losing significant value within approximately five years (Argote, 1999). The following formula was used:

$$Depth_{it-1} = \frac{\sum_{y=t-6}^{t-2} repetition\ count_{iy}}{total\ citations_{it-1}}.$$

The variable *search scope*, which corresponds to the theoretical notion of exploration of new knowledge, was the proportion of previously unused citations (*new citations*$_{it-1}$) in a firm's focal year's list of citations. We assessed the share of citations in a focal year's citations that could not be found in the previous five years' list of patents and citations by that firm. Values for this variable, which was calculated as follows, range from 0 to 1:

$$Scope_{it-1} = \frac{new\ citations_{it-1}}{total\ citations_{it-1}}.$$

The use of the search depth and scope measures can be illustrated by considering a firm with ten patents. Each of the ten patents further cites ten other patents. On the average, eight out of the ten citations are new to the firm; that is, it has not used them during the past five years. The firm's search scope is thus 0.8. Of the remaining two "old" citations in each patent, on the average, the firm has used one of them twice and the other three times. Thus, the search depth for this firm is 0.5.

Control variables. Firms often face constraints in developing innovations in-house (e.g., Ahuja, 2000a), especially if the technology is complex. Thus, we included the number of a sample firm's factory automation collaborations as a control, labeling the variable *collaboration frequency*.

Prior work suggests that financial performance may affect innovation in two ways. Search theorists argue that increase in performance encourages exploration for new innovations (Levinthal & March, 1981). Prospect theorists, on the other hand, predict the opposite: when financial performance is good, managers are less likely to explore (Cyert & March, 1963). We thus included return on assets (ROA) as a *firm performance* measure. Other innovation studies (e.g., Ahuja, 2000b; Hitt, Hoskisson, Johnson, & Moesel, 1996) have used ROA as a performance measure, and its use in this research thus facilitates comparisons across studies. Moreover, innovation studies have shown that return on assets is highly correlated with other performance indicators, such as return on sales (e.g., Steensma & Corley, 2000).

We used a firm's yearly *R&D expenditure* in millions of dollars as a proxy for a firm's total R&D inputs to the innovation process. These data can also describe the amount of the firm's search activities (Cohen, 1995), complementing the patent data used in predictor variables.

A firm's degree of product *diversification* can have both positive and negative effects on new products. Since diversified firms possess more opportunities for the internal use of new knowledge, innovativeness may increase through economies of scope. On the other hand, as Hoskisson and Hitt (1988) showed, as firms become more diversified, corporate management understands the firm's R&D activities less, so innovation decreases. We used an entropy measure (Chatterjee & Blocher, 1992).

National technological characteristics such as R&D infrastructure and historical resource endowments, intensity of competition, and national culture affect the innovative behavior of firms (e.g., Nelson, 1993; Shane, 1992). The propensity to introduce new products rather than new processes can also vary across nations (Hayes & Wheelwright, 1984; Teece, 1987). In this study, we controlled for such effects by including dummy variables for nationality; *European firm* and *American firm* were the categories, with "Japanese firm" as the omitted category.

Previous research findings on the effects of size on product innovation have been mixed. Although most studies have reported a positive effect of size on product innovation (e.g., Chaney & Devinney, 1992), some studies have shown a negative effect (Mansfield, 1968), or no effect at all (Clark, Chew, & Fujimoto, 1987). Our measure of *firm size* was number of corporate employees.

Market conditions and the general economic environment can vary over time, making it more or less attractive to introduce new products. To control for such period effects, we used year dummies (1985–95). "Year 1996" was the omitted category.

Statistical Method and Analysis

Since the dependent variable of the study, number of new products, included counts of new products, we used a panel Poisson regression (McCullagh & Nelder, 1989). A Poisson specification ensures that zero values of the dependent variable are incorporated into a model rather than implicitly truncated, as they are in OLS regression. This estimation technique is common in new product introduction studies (e.g., Blundell, Griffith, & Van Reenen, 1995).

To control for firm heterogeneity, we used the generalized estimating equations (GEE) regression method. This method accounts for autocorrelation—owing to repeated yearly measurements of the same firms—by estimating the correlation structure of the error terms (Liang & Zeger, 1986). A one-period-lagged dependent variable was also included as an additional control for firm heterogeneity (Heckman & Borjas, 1980). Additionally, to account for any overdispersion in the data, we report all results with robust, or empirical, standard errors.

Table 1 shows the descriptive statistics and correlations for all variables. All independent and control variables are lagged by one year. Grupp and colleagues (1990) provided qualitative evidence of one- to two-year lags in introductions of robotics products to market. As the descriptive statistics on the control variables indicate, the companies in the sample differ widely in size, R&D efforts, and performance. The low, nonsignificant correlation (−.003) between search depth and search scope is also noteworthy: it suggests that these two variables represent two distinct dimensions of search. The correlation matrix suggests that the collinearity among the main variables is low. However, firm size and R&D expenditure are exceptions, and subsequently we entered these variables into separate models.

A regression approach was used for testing the hypotheses. The regression analysis pertains to the years 1985–96. As several authors have recommended, we centered the independent variables, search depth and search scope, on their means before creating the interaction term (e.g., Cronbach, 1987).

In total, 1,898 new robotics introductions were included in the analysis. On the average, the sample companies introduced about one new robot yearly. Some companies had no new introductions in a given year, while others introduced over 20 new robots. About three-quarters of the patent citations that the firms used were new (average search scope), and each citation was repeatedly used about 0.22 times within the next five years (average search depth).

RESULTS

Hypothesis Tests

Table 2 reports the results of the GEE Poisson regression analysis. Two of our three hypotheses

TABLE 1
Descriptive Statistics and Correlations[a]

Variable	Mean	s.d.	Min.	Max.	1	2	3	4	5	6	7	8	9
1. Number of new products	0.92	2.36	0.00	24.00									
2. Search depth	0.22	0.24	0.00	1.74	.04								
3. Search scope	0.74	0.30	0.00	1.00	.08**	−.003							
4. Collaboration frequency	0.16	0.50	0.00	6.00	.33***	.02	.07*						
5. Firm performance	0.02	0.05	−0.73	0.45	−.01	.04	.03	.04					
6. R&D expenditure	0.32	0.78	0.01	6.78	.07*	.22***	.07*	.07*	.03				
7. Diversification	0.64	0.37	0.00	1.62	−.02	.20***	.15***	.03	−.02	.11***			
8. European firm	0.15	0.36	0.00	1.00	−.06*	−.06*	.06*	−.01	.03	.17***	.20***		
9. American firm	0.22	0.41	0.00	1.00	−.15***	−.02	−.06*	.01	.04	.05	−.19***	−.22***	
10. Firm size	39.66	100.77	0.03	876.80	−.03	.15***	.08**	.06*	.05	.86***	.14***	.29***	.17***

[a] $n = 1{,}185$.
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 2
Results of Regression Analysis for Number of New Products[a, b]

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	−0.58	−0.57	−0.57	−0.57	−0.57	−0.63	−0.62	−0.63	−0.53	−0.51
	(0.39)	(0.40)	(0.39)	(0.40)	(0.41)	0.42	0.42	0.42	0.42	0.42
Search depth		0.55†		0.59*	0.95*	3.07***	2.70	3.11***	3.45***	3.24***
		(0.34)		(0.34)	(0.44)	(1.04)	(3.24)	(1.05)	(0.96)	(0.90)
Search scope			0.14	0.22†	1.34**	0.76*	1.32	0.76*	0.85*	0.82*
			(0.15)	(0.16)	(0.49)	(0.44)	(4.25)	(0.45)	(0.42)	(0.39)
Search depth × search scope					5.69**	3.10†	3.33†	3.08†	3.48*	3.43*
					(2.22)	(1.97)	(2.13)	(2.01)	(1.83)	(1.70)
Search depth squared						−3.05*	−2.71	−3.12*	−3.32**	−2.99**
						(1.35)	(2.92)	(1.40)	(1.22)	(1.09)
Search scope squared							−0.51			
							(4.05)			
Collaboration frequency	0.30**	0.30**	0.30***	0.30**	0.29**	0.25*	0.25*	0.26*	0.23*	0.21
	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.12)	(0.13)
Firm performance	−1.42	−1.46	−1.39	−1.43	−1.44	−1.46	−1.47	−1.46	−1.12	−1.14
	(1.07)	(1.08)	(1.08)	(1.11)	(1.14)	(1.21)	(1.21)	(1.22)	(1.26)	(1.20)
R&D expenditure	0.40**	0.40*	0.40**	0.40*	0.40*	0.30*	0.30*	0.30*		
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)		
Diversification	−0.50	−0.54	−0.51	−0.55	−0.56	−0.58	−0.58	−0.58	−0.60	−0.59
	(0.36)	(0.38)	(0.36)	(0.38)	(0.38)	(0.38)	(0.38)	(0.37)	(0.39)	(0.39)
European firm	−1.14*	−1.08*	−1.14*	−1.07*	−1.05*	−1.05*	−1.04*	−1.03*	−0.97†	−1.01†
	(0.50)	(0.50)	(0.50)	(0.50)	(0.51)	(0.51)	(0.51)	(0.50)	(0.57)	(0.58)
American firm	−2.05***	−2.04***	−2.05***	−2.03***	−1.97***	−1.97***	−1.97***	−1.95***	−1.82***	−1.86***
	(0.43)	(0.43)	(0.43)	(0.43)	(0.40)	(0.40)	(0.41)	(0.39)	(0.39)	(0.40)
Number of new products (lagged)								0.01		−0.03
								(0.03)		(0.06)
Firm size									0.0001	0.0001
									(0.002)	(0.001)
Deviance	2,694.1	2,685.2	2,679.4	2,667.2	2,646.8	2,618.8	2,617.5			
Difference in log likelihood vis-à-vis the base model		8.9**	14.7***	26.9***	47.3***	75.3***	76.6***			
df	19	20	20	21	22	23	24	24	23	24

[a] The table gives parameter estimates; the standard error is below each parameter estimate in parentheses.
[b] There were 124 firms and 1,185 firm-year observations. Year dummies were included but are not shown.

† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

Two-tailed tests for controls, one-tailed tests for hypothesized variables.

were supported (Hypotheses 1 and 3), but the curvilinear relationship predicted in the second hypothesis was not fully borne out in that we found a linear rather than a curvilinear relationship between search scope and new products. In the analysis presented in Table 2, number of new products is the dependent variable. The first column reports the baseline model in which collaboration frequency, ROA, R&D expenditure, diversification, and the nationality and year dummies were included as control variables. In models 2–4, we introduced search depth and search scope to assess those variables' possible effects on new products. In model 5, we included the interaction of search depth and search scope, and in models 6 and 7 we added the squared terms of the two search variables. Although we hypothesized a curvilinear effect for search scope, the inclusion of search scope squared did not significantly improve model fit (model 7). Accordingly, we dropped the squared term from the final model. We therefore base our discussion of the results on the full model, model 6.

In Hypothesis 1, we propose that search depth will have a curvilinear (inverted U-shaped) relationship with new product innovation. In model 6 in Table 2, the coefficient for search depth is positive and that for the squared term of depth is negative and significant, supporting the hypothesis. Hypothesis 2 proposes a curvilinear relationship between search scope and new products. This hypothesis was not supported, since the squared term of scope fails to provide a good fit in model 7. However, the linear coefficient for scope in model 6 is positive and significant, thus suggesting a positive, linear relationship between scope and product innovation. We examine the possible explanations for the linear effect of scope in the discussion section. In Hypothesis 3, we predict that search depth and search scope leverage each other, yielding a combined positive effect on product innovation. The estimated positive interaction between depth and scope in model 6 provides support for this hypothesis. Finally, the log-likelihood statistics provide evidence that adding depth and the interaction variables (models 4–6) significantly improves the model fit over the model with the scope variable only (model 3), supporting the idea that search is indeed a two-dimensional construct. The effects are also substantively significant. For a hypothetical firm at the mean of the depth (0.22) and scope (0.74) variables, a 10 percent increase in depth (an increase of 0.022) leads to a 10 percent increase in new product introduction. For the same firm, a 10 percent increase in search scope (an increase of 0.074) leads to an 11 percent increase in new product introduction.

Overall, the effects of the control variables were as expected: R&D expenditure and collaboration frequency were found to increase the number of robotics product introductions. The result that Japanese robotics firms innovated more than their competitors in Europe and in the United States supports previous findings reported in the literature (e.g., Mansfield, 1988).

Sensitivity Analyses

The sensitivity of the results was also tested in several ways. We tested the sensitivity of the regression models by including additional measures of the industry-level effects. Adding a variable for demand for industrial robots, measured as yearly worldwide industrial robot installations, did not change the results. To examine the effect of firm size on product introductions, we tested the model by including firm size instead of the R&D expenditure measure. The results from this sensitivity test, reported in model 9 of Table 2, consistently support the main findings of the study. We also ran additional analyses by (1) including both R&D and firm size in the same model, (2) replacing R&D expenditure with R&D intensity (R&D divided by sales; Helfat, 1994), and (3) adding a size-R&D factor (using factor analysis to reduce the highly correlated firm size and R&D variables to a single factor). We also modified the models by controlling for the number of firms that each sample firm had acquired. This control was included since acquisitions can potentially substitute for internal innovation search (Ahuja & Katila, 2001). All of these tests consistently supported the main results.

We also used several alternative data sources to test the validity of our search depth and scope measures. In addition to the U.S. patent citations used in the original results, we also conducted the analysis by including both U.S. and foreign citation data. We also measured the search variables by including six past years of patents (instead of the five years used in the original measures) and by excluding the company's self-citations from the search measures to account for any differences between external and internal citations. We also used robotics application area data to substitute for the patent data used in the search measures (International Federation of Robotics, 1999). All of these results exhibited a pattern similar to that of the results reported previously.

Finally, we tested the robustness of the results against unobserved heterogeneity. Theoretically, the organizational learning and search literatures are based on the premise that firms differ in their search behaviors and that most firms do not search in perfect ways: organizations learn at different rates and forget (Argote, 1999), and their search actions are inertial and rationality-bounded (Cyert & March, 1963). We used three separate approaches to control for such unobserved heterogeneity. First, we included proxy variables to capture unobserved influence; this is most commonly done by using previous values of the dependent variable as an additional regressor. Second, we modeled the unobserved heterogeneity parametrically, by assuming a statistical distribution. Third, we corrected and controlled for the serial correlation that arises if unobserved heterogeneity is not directly accounted for.

In the first approach, we constructed two types of proxy variables: the lagged dependent variable (Heckman & Borjas, 1980) and the presample variable (Blundell et al., 1995). In Table 2 in model 8 we report the results obtained using a lagged dependent variable method. We also performed an analysis by including a presample control variable. This presample covariate was constructed from the dependent variable values in the periods immediately preceding the study period and served as a fixed effect for the firms in the panel. Both of these results strongly supported the original findings. Second, we applied a commonly used parametric approach to handling unobserved heterogeneity in Poisson regressions: we presumed that the unobserved error followed a gamma distribution and estimated a negative binomial model. The negative binomial results again exhibited the same pattern as the original results. Third, as discussed earlier, to account for any remaining serial correlation we used a generalized estimating equations (GEE) method in all models.

DISCUSSION

In this study, we examined how firms search for new products and made a distinction based on two dimensions of search: depth and scope. We have described the mechanisms underlying the different search approaches in detail and distinguished their effects on performance.

This study has theoretical implications for the organizational learning and resource-based perspectives. From the perspective of the organizational search and learning literature, we contribute to knowledge on new product search and its components. Few authors have examined the performance effects of search approaches as is done in our study. This contribution is important, since, as Argote stated, "We know relatively more about knowledge retention and transfer than we know about knowledge creation in organizations" (1999: 203).

Prior work on search has frequently focused on the exploration/exploitation dichotomy (e.g., March, 1991). A key contribution of our study is the idea that exploitation is a more comprehensive concept than it is usually considered to be. Specifically, we have distinguished levels of exploitation, or search depth. We argue that firms can differentiate themselves not only as to the extent to which they explore new things, but also as to the extent to which they master the old ones. Thus, we extend the unidimensional concept of exploitation versus exploration into a two-dimensional framework. Relatedly, we draw attention to the fact that exploitation is important, not just for fine-tuning and economizing the efficiency of an existing technology (Levinthal & March, 1981: 311), but also for creating new knowledge. Although exploratory search has a key role in knowledge creation, that of providing *completely new solutions,* exploitation also has a role, that of *combining existing solutions to generating new combinations* (Schumpeter, 1934).

This study also expands the work on the dynamic capabilities of firms by examining in detail one such capability: that of problem solving, or search. The study supports the notion that a firm's dynamic problem-solving capabilities can be an important source of resource heterogeneity. Our results also indicate that firms differ in how they search and that these variations can lead to variations in performance. Further, finding a statistically significant effect of the interaction term of depth and scope suggests that at least some organizations are able to engage in both search approaches simultaneously. Thus, this study contributes to an understanding of search processes within organizations. However, we examined search processes largely through archival patent data. Although this limitation was almost unavoidable in our longitudinal setting, it suggests the need for future research using complementary approaches to measure search, such as surveys and case studies. Understanding the differences between organizations that manage the productive combination of scope and depth in relation to those that fail may be a fruitful direction for further research in this area.

The unexpected result of this study, the linear effect of search scope on new product innovation, instead of the expected nonlinear effect, deserves more attention. A possible explanation is that in the empirical sample of this study, few companies "oversearched" along this dimension, because intensive scope search was costlier than extensive depth search. Consequently, instead of a curvilinear relationship, only the linear, increasing part of the curve was detected. This result is also in line with the proposition that firms search locally (Helfat, 1994; Stuart & Podolny, 1996), and with the human tendency to try to reduce uncertainty. We would expect this tendency to be especially strong in innovation search when firms need to decide between searching in known, well-tried directions and searching in uncertain, new directions. As Thompson observed: "If such tendencies appear in puzzle-solving as well as in everyday situations, we would especially expect them to be emphasized when responsibility and high stakes are added" (1967: 4). More explanations for this result should be explored in future work.

The robotics industry was an interesting empirical setting for the study, given the complexity of the innovation search activities in the industry and the lack of prior large-scale organizational research in the industry. Although our findings are likely to generalize to other high-technology industries, such as pharmaceuticals, telecommunications, and the computer industry, where search problems are complex and the ability to bring new products to the market is a key determinant of success, future research to confirm how the framework developed in this study applies to these industries would be helpful. Further research is also needed to examine the usefulness of our propositions for other types of organizational search.

A better understanding of new product search also has important implications for managers. Mastering internal search can provide a source for competitive advantage: internal capabilities such as the ability to search effectively can be a more stable basis for strategy formulation than those acquired externally (Grant, 1996). Two aspects of this study make it especially useful in this context. First, prior research suggests that many organizations are likely to develop a natural tendency to specialize in one form of search behavior—they either exploit or they explore (Levinthal & March, 1993). This study's arguments and results draw managers' attention to the notion that the most fruitful approach lies at the intersection of these two activities and that some firms are able to achieve this balance and are rewarded for it. This reminder of the importance of balance is especially relevant in the context of the two mutually conflicting prescriptions often presented to practitioners: "stick to the knitting" and work to improve, or cast aside all that is familiar and work to develop revolutionary new products and modes of thought. In contrast, we suggest that search is most likely to be productive when it uses both familiar and unfamiliar elements. Second, we provide a practical mechanism managers can use to monitor the degree to which a firm is able to maintain this balance, both longitudinally and cross-sectionally. The patent-based metrics for depth and scope developed in this study can be computed from public information for any firm and its leading competitors over time, and it can help provide a frame of reference that managers can use for tracking, focusing, and redirecting search efforts.

REFERENCES

Ahuja, G. 2000a. The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. ***Strategic Management Journal,*** 21(special issue): 317–343.

Ahuja, G. 2000b. Collaboration networks, structural holes, and innovation: A longitudinal study. ***Administrative Science Quarterly,*** 45: 425–455.

Ahuja, G., & Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. ***Strategic Management Journal,*** 22: 197–220.

Argote, L. 1999. ***Organizational learning: Creating, retaining and transferring knowledge.*** Boston: Kluwer Academic.

Argyris, C., & Schön, D. 1978. ***Organizational learning.*** Reading, MA: Addison-Wesley.

Arundel, A., & Kabla, I. 1998. What percentage of innovations are patented? Empirical estimates for European firms. ***Research Policy,*** 27: 127–141.

Banbury, C., & Mitchell, W. 1995. The effect of introducing important incremental innovations on market share and business survival. ***Strategic Management Journal,*** 16(special issue): 161–182.

Blundell, R., Griffith, R., & Van Reenen, J. 1995. Dynamic count data models of technological innovation. ***Economic Journal,*** 105: 333–344.

Bruderer, E., & Singh, J. 1996. Organizational evolution, learning, and selection: A genetic-algorithm-based model. ***Academy of Management Journal,*** 39: 1322–1349.

Chaney, P., & Devinney, T. 1992. New product innovations and stock price performance. ***Journal of Business Finance & Accounting,*** 19: 677–695.

Chatterjee, S., & Blocher, J. 1992. Measurement of firm diversification: Is it robust? ***Academy of Management Journal,*** 35: 874–888.

Clark, K., Chew, B., & Fujimoto, T. 1987. Product development in the world auto industry. ***Brookings Papers on Economic Activity,*** special issue on microeconomics (3): 729–771.

Cockburn, I., & Griliches, Z. 1987. ***Industry effects and appropriability measures in the stock market's valuation of R&D and patents.*** Working paper no. 2465, NBER, Cambridge, MA.

Cohen, W. 1995. Empirical studies of innovative activity. In P. Stoneman (Ed.), ***Handbook of the economics of innovation and technological change:*** 182–264. Oxford, England: Blackwell.

Cohen, W., & Levinthal, D. 1994. A fortune favors the prepared firm. ***Management Science,*** 40: 227–251.

Coombs, R., Narandren, P., & Richards, A. 1996. A literature-based innovation output indicator. ***Research Policy,*** 25: 403–413.

Cronbach, L. 1987. Statistical tests for moderator variables: Flaws in analyses recently proposed. ***Psychological Bulletin,*** 102: 414–417.

Cyert, R., & March, J. 1963. ***A behavioral theory of the firm.*** Englewood Cliffs, NJ: Prentice-Hall.

Dahlin, K. 1993. Diffusion and industrial dynamics in the robot industry. ***International Journal of Technology Management,*** 8(3–5): 259–281.

Dosi, G. 1988. Sources, procedures, and microeconomic effects of innovation. ***Journal of Economic Literature,*** 26: 1120–1171.

Dougherty, D., & Hardy, C. 1996. Sustained product innovation in large, mature organizations: Overcoming innovation-to-organization problems. ***Academy of Management Journal,*** 39: 1120–1153.

Eisenhardt, K. M., & Tabrizi, B. N. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. ***Administrative Science Quarterly,*** 40: 84–110.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: Evidence from patent data. ***Research Policy,*** 30: 1019–1039.

Grant, R. 1996. Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. ***Organization Science,*** 7: 375–387.

Grupp, H., Schwitalla, B., Schmoch, U., & Granberg, A. 1990. Developing industrial robot technology in Sweden, West Germany, Japan, and the U.S.A. In J. Sigurdson (Ed.), ***Measuring the dynamics of technological change:*** 106–129. London: Pinter Publishers.

Hayes, R., & Wheelwright, S. (Eds.) 1984. ***Restoring our competitive edge: Competing through manufacturing.*** New York: Wiley.

Heckman, J., & Borjas, G. 1980. Does unemployment cause future unemployment? ***Economica,*** 47: 247–283.

Heiner, R. 1986. Uncertainty, signal-detection experiments, and modeling behavior. In R. Langlois (Ed.), ***Economics as a process: Essays in the new institutional economics:*** 59–115. Cambridge, England: Cambridge University Press.

Helfat, C. 1994. Evolutionary trajectories in petroleum firm R&D. ***Management Science,*** 40: 1720–1747.

Henderson, R., & Clark, K. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. ***Administrative Science Quarterly,*** 35: 9–30.

Hitt, M., Hoskisson, R., Johnson, R., & Moesel, D. 1996. The market for corporate control and firm innovation. ***Academy of Management Journal,*** 39: 1084–1119.

Hoskisson, R., & Hitt, M. 1988. Strategic control systems and relative R&D investment in large multi-product firms. ***Strategic Management Journal,*** 9: 605–621.

Huber, G. 1991. Organizational learning: The contributing processes and a review of the literatures. ***Organization Science,*** 2: 88–115.

International Federation of Robotics. 1999. ***World robotics.*** Geneva: International Federation of Robotics.

Jaikumar, R., & Bohn, R. 1992. A dynamic approach to operations management: An alternative to static optimization. ***International Journal of Production Economics,*** 27: 265–282.

Katila, R. 2000. ***Innovation search determinants of new product introductions and their radicality: The case of industrial robotics.*** Unpublished doctoral dissertation, University of Texas at Austin.

Katila, R. 2002. New product search over time: Past ideas in their prime? ***Academy of Management Journal,*** 45: 995–1010.

Levinthal, D., & March, J. 1981. A model of adaptive organizational search. ***Journal of Economic Behavior and Organization,*** 2: 307–333.

Levinthal, D., & March, J. 1993. The myopia of learning. ***Strategic Management Journal,*** 14: 95–113.

Liang, K.-Y., & Zeger, S. L. 1986. Longitudinal data analysis using generalized linear models. ***Biometrika,*** 73: 13–22.

Mansfield, E. 1968. ***The economics of technological change.*** New York: Norton.

Mansfield, E. 1988. The speed and cost of industrial innovation in Japan and the United States; External vs. internal technology. ***Management Science,*** 34: 1157–1168.

March, J. 1991. Exploration and exploitation in organizational learning. ***Organization Science,*** 2: 71–87.

Martin, X., & Mitchell, W. 1998. The influence of local search and performance heuristics on new design introduction in a new product market. ***Research Policy,*** 26: 753–771.

McCullagh, P., & Nelder, J. 1989. ***Generalized linear models.*** New York: Chapman & Hall.

Miner, A., Bassoff, P., & Moorman, C. 2001. Organizational improvisation and learning: A field study. ***Administrative Science Quarterly,*** 46: 304–337.

Nelson, R. 1993. (Ed.). ***National innovation systems.*** New York: Oxford University Press.

Nelson, R., & Winter, S. 1982. ***An evolutionary theory of economic change.*** Cambridge, MA: Harvard University Press.

Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disc industry. ***Strategic Management Journal,*** 22: 287–306.

Saviotti, P., & Metcalfe, J. 1984. A theoretical approach to the construction of technological output indicators. ***Research Policy,*** 13: 141–151.

Schoonhoven, C., Eisenhardt, K., & Lyman, K. 1990. Speeding products to market: Waiting time to first product introduction in new firms. ***Administrative Science Quarterly,*** 35: 177–207.

Schumpeter, J. 1934. ***The theory of economic development.*** Cambridge, MA: Harvard University Press.

Shane, S. 1992. Why do some societies invent more than others? ***Journal of Business Venturing,*** 7: 29–46.

Steensma, K., & Corley, K. 2000. On the performance of technology-sourcing partnerships: The interaction between partner interdependence and technology attributes. ***Academy of Management Journal,*** 43: 1045–1067.

Stuart, T. E., & Podolny, J. M. 1996. Local search and the evolution of technological capabilities. ***Strategic Management Journal,*** 17(special issue): 21–38.

Teece, D. J. 1987. Capturing value from technological innovation: Integration, strategic partnering, and licensing decisions. In B. Guile & H. Brooks (Eds.), ***Technology and global industry:*** 65–95. Washington, DC: National Academy Press.

Thompson, J. 1967. ***Organizations in action.*** New York: McGraw-Hill.

von Hippel, E., & Tyre, M. 1995. How learning by doing is done: Problem identification in novel process equipment. ***Research Policy,*** 24: 1–12.

Walker, R. 1995. ***Patents as scientific and technical literature.*** Metuchen, NJ: Scarecrow Press.

Winter, S. 1984. Schumpeterian competition in alternative technological regimes. ***Journal of Economic Behavior and Organization,*** 5: 287–320.

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