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

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Abstract

We examine how firms *search*, i.e., solve problems, to create new products. Organizational learning research argues that firms position themselves on a uni-dimensional 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: s*earch depth* or how frequently the firm re-uses its existing knowledge, and *search scope* or how widely the firm explores new knowledge.

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

In this study we examine how firms *search*, i.e., 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 for organizations to diversify, adapt, and reinvent themselves in changing market and technical conditions (Schoonhoven, Eisenhardt, & Lyman, 1990). Research has also demonstrated how new products improve 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. In this paper we explain a firm's performance in creating products as a function of its search behavior.

Research in organizational learning has sometimes argued that in their search for solutions to problems firms position themselves on a uni-dimensional search space that spans the spectrum from exploitation to exploration (March, 1991). In this study we suggest that the firms' search, or problem-solving efforts, actually vary across two distinct dimensions rather than one. Firms can vary in their degree of usage and re-usage of their existing knowledge, just as they can vary in their exploration of new knowledge. We call the first dimension, which describes how deeply the firm re-uses its existing knowledge, s*earch depth.* We call the second dimension, which describes how widely the 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.

CONCEPTUAL BACKGROUND

Product innovation

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

New product search

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 best ways to implement new innovations (von Hippel & Tyre, 1995). In this study we focus on one specific type of search, that of search for new products. Based on Winter (1984), we define product search as the organization's problem-solving activities that involve creation and recombination of technological ideas. In using the search perspective and the view of 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 the current organizational routines and knowledge-bases (March, 1991). While this traditional characterization of search in terms of *scope*, i.e., 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*, i.e., in the degree to which existing knowledge is re-used 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 the firms' ability to craft new solutions. Huber presents a similar argument: "in prior work no distinction has been made between search for new solutions vs. search for more information about already identified solutions" (1991: 99). In sum, while the different levels of exploration of new knowledge are studied in relative detail in the literature (e.g., Rosenkopf & Nerkar, 2001), we know much less about the different levels of exploitation of existing knowledge.

Thus, in this paper 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 that guide firms on where to locate in this search space, i.e., hypotheses about the effects of different search approaches on new product introductions.

HYPOTHESES

Our general proposition is that search depth and scope are distinct dimensions of search, and the choice along, or a combination 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 introduced by each firm. *Search depth* is defined as the degree to which search revisits the 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 the search more predictable, as the knowledge to be searched is familiar and the requirements that should be met by the product 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 the firm's ability to identify valuable knowledge elements within them, to develop connections between 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 & Schon, 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 due to 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 complicated, leading to the costs of depth to eventually exceed its benefits. Second, depth can also hurt search since beyond a point, re-using the existing knowledge can make the 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 with the approach that has been traditionally used (Argyris & Schon, 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, but beyond a point, additional depth in search will cause a fall in product output. We suggest:

Hypothesis 1. *Search depth is curvilinearly (inverted U-shape) related to the number of new products introduced by the 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 the number of new products through enhancing recombinatory search (Fleming, 1998; Fleming & Sorenson, 2000; 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 to the 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 the organization (Henderson & Clark, 1990). Prior work argues 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). The firm's reliability (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 where the proportion of new knowledge is high are less likely to succeed than projects that search closely related knowledge (Cyert & March, 1963).

The above reviewed mechanisms suggest that search scope, as measured by the proportion of new knowledge elements in search, is curvilinearly (inverted U) related with subsequent product innovation. The following hypothesis is proposed:

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

Combination of depth and scope

The above hypotheses focused on the distinct effects of depth and scope on innovation. In this section we propose that these variables are mutually beneficial beyond their individual effects: Hypothesis 3 relates product introductions to the interactive effects of depth and scope. Below 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) argues 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 needed, and therefore assimilation and further development of the novelty requires complementary problem-solving efforts by the firm. Thus, existing knowledge may facilitate both 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 discussed the relationship between scope and new product output. However, increases in scope can be costly: the success probability of finding valuable new knowledge elements is small and even if the firm succeeds it is possible that the same product idea has already been discovered – resulting in an exact replica of an already existing product. In other words, the knowledge element or a recombination, although new to the firm, may have been previously used by other firms. 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 follows:

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

RESEARCH METHODS

Research setting and sample

The research sample was drawn from the population of industrial robotics companies in Europe, Japan, and North America. A number of considerations motivate 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 the industry lacks product standards (Dahlin, 1993), search activities in the industry require complex problem-solving. Finally, while the diffusion of robots, and the effects of robotization on workers are well-documented, few studies examine how robots are developed.

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

Data sources

We used two main data sources: new product introduction announcements and patent data. To assemble 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 editorially controlled new product announcement sections of robotics technical and trade magazines as well as from robotics product catalogues. The use of several sources for a single introduction assured the reliability of the data. As 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 the *Who owns whom* directories to create the patent portfolios for each firm. Yearly patent data, by application date, were used.

Dependent variable

Number of new products. To operationalize the dependent variable we use Martin and Mitchell's (1998) definition of a new product as change in the product's design characteristics. A product is defined to be new if there is a change in one or more of its design characteristics in comparison with the firm's previous products. Thus, introducing an existing design in a new geographical area, for example, does not qualify as a new product.

Independent variables

Obtaining data on intrafirm problem-solving behaviors over a 10-year period is a major challenge. Data to assess intrafirm search activities over time are usually not public, or, even if available, often extremely resource-consuming to assemble (Cohen, 1995). In this study we use firms' patenting activities to measure their depth and scope of search. Since patents, by definition, include 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, i.e., search. Recognizing these attributes, several authors have used patent data as an indicator of search activity (see 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 (see for example Cockburn & Griliches, 1987). However, this is not a problem in our study since we focus 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).

Search depth. This variable describes accumulation of search experience with the same knowledge elements. As defined previously, the more frequently the firm has used the knowledge, the more deeply it is defined to know it. Thus, search depth is measured as the average number of times the firm has repeatedly used the citations in its focal year's patents. The depth variable is created by calculating the number of times that, on average, each citation in year *t-1* has been 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 is used:

$$Depth_{it-1} = \frac{\sum_{y=t-6}^{t-2} Repetitioncount_{iy}}{Totalcitations_{it-1}}$$

Search scope. This variable corresponds to the theoretical notion of exploration of new knowledge. The scope variable is operationalized as the proportion of previously unused citations (*Newcitations* $_{it-1}$) in the firm's focal year's list of citations. A search scope variable is created as the share of citations in the focal year's citations that cannot be found in the previous five years' list of patents and citations by that firm. This variable ranges from 0 to 1.

$$Scope_{it-1} = \frac{Newcitations_{it-1}}{Totalcitations_{it-1}}$$

To illustrate the use of the search depth and scope measures, consider a firm with ten patents. Each of the ten patents further cites ten other patents. On average, eight out of the ten citations are new to the firm, i.e., the firm 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 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

Collaboration frequency. Firms often face constraints in developing all innovations in-house (e.g., Ahuja, 2000a), especially if the technology is complex. Thus, we include the number of sample firms' factory automation collaborations as a control.

Firm performance. 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 include return on assets ($\boldsymbol{ROA_{it-1}}$) as a firm performance measure. Return on assets has been used as a performance measure in other innovation studies (e.g., Ahuja, 2000b; Hitt, Hoskisson, Johnson, & Moesel, 1996), and its use in this research thus facilitates comparisons across studies.

Moreover, innovation studies have found that return on assets is highly correlated with other performance indicators, such as return on sales (see for example Steensma & Corley, 2000).

R&D expenditure. We use the firm's yearly R&D expenditure (M$) to proxy for the 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 patent data used in predictor variables.

Diversification. The 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 an economies of scope effect. On the other hand, Hoskisson and Hitt (1988) have shown that as firms become more diversified, corporate management understands the firm's R&D activities less, decreasing innovation. An entropy measure of diversification is used (Chatterjee & Blocher, 1992).

Nationality. Theoretically, national technological characteristics such as R&D infrastructure and historical resource endowments, intensity of competition, or national culture have been found to affect innovative behavior of firms (e.g. Nelson, 1993; Shane, 1992). The propensity to introduce new products versus new processes can also vary across nations (Hayes & Wheelwright, 1984; Teece, 1987). In this study we control for such effects by including dummy variables for European, American, and Japanese (omitted category) firms.

Firm size. The results on the effects of size on product innovation have been mixed. While most studies have reported a positive effect of size on product innovation (e.g. Chaney & Devinney, 1992), some studies have found a negative effect (Mansfield, 1968), or no effect at all (Clark, Chew, & Fujimoto, 1987). Our size measure was the number of corporate employees.

Time effects. 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 use year dummies (1985-1996). Year 1996 was the omitted category.

Statistical method

Since the dependent variable of the study, ***Number of new products$_{it}$***, includes counts of new products, we use a Panel Poisson regression (McCullagh & Nelder, 1989). The Poisson specification ensures that zero values of the dependent variable are incorporated into the model rather than implying truncation as 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 use the Generalized Estimating Equations (GEE) regression method. This method accounts for autocorrelation – due 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 is also included as an additional control for firm heterogeneity (Heckman & Borjas, 1980). Additionally, to account for any over-dispersion in the data we report all results with "robust" or empirical standard errors.

Data analysis

Table 1 shows the descriptive statistics and correlations for all variables. All independent and control variables are lagged by one year. Grupp et al. (1990) provide qualitative evidence of 1-2 year lags in introducing robotics products to market. As indicated by the descriptive statistics on the control variables (Table 1), the companies in the sample differ widely in size, R&D efforts, and performance. The low, non-significant correlation (-.003) between ***Search depth$_{it-1}$*** and ***Search scope $_{it-1}$*** 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 these variables were entered in separate models.

A regression approach is used for testing the hypotheses. Regression analysis pertains to years 1985-1996. As recommended by several authors, we centered search depth and search scope variables on their means before creating the interaction term (e.g., Cronbach, 1987).

--- Insert Table 1 about here ---

In total, 1898 new robotics introductions were included in the analysis. On average, the sample companies introduced approximately 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), while each citation was repeatedly used about 0.22 times within the next five years (average search depth).

RESULTS

Results of hypothesis tests

Table 2 reports the results of the GEE Poisson regression analysis. Two of our three hypotheses were supported (H1 and H3), while the curvilinear relationship predicted in the second hypothesis (H2) was not fully borne out in that we find a linear, rather than a curvilinear relationship between search scope and new products. In Table 2 ***Number of new products***$_{it}$ is used as the dependent variable. The first model reports the baseline model where ***Collaboration frequency***$_{it-1}$, ***ROA***$_{it-1}$, ***R&D expenditure***$_{it-1}$, ***Diversification***$_{it-1}$, and nationality and year dummies are included as control variables. Models 2 - 4 introduce ***Search depth***$_{it-1}$ and ***Search scope***$_{it-1}$ variables to assess their possible effects on new products. In Model 5 we include the interaction of ***Search depth***$_{it-1}$ and ***Search scope***$_{it-1}$ variables, and in Models 6 and 7 the square terms (***Search depth***$^{2}_{it-1}$ and ***Search scope***$^{2}_{it-1}$). Although we hypothesized a curvilinear effect for Search scope, the inclusion of the ***Search scope***$^{2}_{it-1}$ variable does not significantly improve model fit (Model 7). Accordingly, the square term is dropped from the final model. We discuss the results based on the full model (Model 6) in Table 2.

--- Insert Table 2 about here ---

In Hypothesis 1 we proposed that search depth has a curvilinear (inverted U) relationship with new product innovation. In Model 6 in Table 2 the coefficient for the search depth variable is positive, while that for the squared term of depth is negative and significant, supporting the hypothesis. Hypothesis 2 proposed a curvilinear relationship between search scope and new products. This hypothesis is 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 predicted that search depth and search scope leverage each other, resulting in 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 improve the model fit over the model with the scope variable only (Model 3), supporting the idea that search indeed is 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% increase in depth (increase of 0.022) leads to a 10.1% increase in new product introduction. For the same firm a 10% increase in search scope (increase of 0.074) leads to an 11.3% increase in new product introduction.

Control variables

Overall, the effects of the control variables are as expected: ***R&D expenditure***$_{it-1}$ and ***Collaboration frequency***$_{it-1}$ are found to increase the number of robotics product introductions (Table 2). The results that ***Japanese*** robotics firms innovate, as evidenced by robotics product introductions, more than their competitors in Europe and in the US supports previous findings 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 that measures demand for industrial robots (***Demand***$_{t-1}$), operationalized through 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***$_{it-1}$ instead of the R&D expenditure measure. The results from this sensitivity test are reported in Model 9 (Table 2), and consistently support the main findings of the study. We also ran additional analyses by a) including both R&D and firm size in the same model, b) substituting R&D expenditure with R&D intensity (R&D divided by sales; Helfat, 1994), and, c) using 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). In all these tests the main results were consistently supported.

We also used several alternative data sources to test the validity of our search depth and scope measures. In addition to US patent citations used in the original results, we also ran the analysis by including both US and foreign citation data. We also measured the search variables by including six past years of patents (instead of 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 (World Robotics, 1999). All of these results exhibited a similar pattern to those results reported previously.

Finally, we tested the robustness of the results against unobserved heterogeneity. Theoretically, 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 that capture the 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, Griffith, & Van Reenen, 1995). In Table 2 in Model 8 we report the results using a lagged dependent variable method. We also ran the results by including a presample control variable. This presample covariate is constructed from the dependent variable values in the periods immediately preceding the study period, and serves as a 'fixed-effect' for the firms in the panel. Both of these results strongly support the original findings. Second, we applied a commonly used parametric approach to handling unobserved heterogeneity in Poisson regressions: we presumed that the unobserved error follows 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 paper we examined how firms search for new products, and made a distinction based on two dimensions of search: depth and scope. We provided a detailed description of the mechanisms underlying the different search approaches, and distinguished their effects on performance.

This study has theoretical implications for organizational learning and resource-based perspectives. From the perspective of the organizational search and learning literature, we provide a contribution to the 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: “We know relatively more about knowledge retention and transfer than we know about knowledge creation in organizations” (Argote, 1999: 203).

Prior work on search has frequently focused on the exploration/exploitation dichotomy (e.g., March, 1991). One of the key contributions of this paper is the idea that exploitation is a more comprehensive concept than is usually considered. Specifically, we distinguish between different levels of exploitation, or search depth. We argue that firms can differentiate themselves not only to the extent they explore new things, but also to the extent that they master the old ones. Thus, we extend the uni-dimensional categorization of exploitation and exploration to a two-dimensional framework. Relatedly, we draw attention to the fact that exploitation is important not just in fine-tuning and economizing the efficiency of an existing technology (Levinthal & March, 1981: 311), but also in creating new knowledge. While exploratory search has a key role in knowledge creation by providing *completely new solutions*, exploitation also has a role in *combining existing solutions to generating new combinations* (Schumpeter, 1934).

This paper also expands the work on 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. The results of the study 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 paper contributes to an understanding of search processes within organizations. However, related to this contribution is the limitation that we examine search processes largely based on archival patent data. Although this limitation is 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, a 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 only few companies "over-search" in this dimension, due to high costs of this search approach in comparison with over-searching with high depth, for example. Consequently, instead of observing a curvilinear relationship, only the linear, increasing part of the curve is 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 decide between searching in known, well-tried directions vs. searching in uncertain, new directions. As Thompson observes: "if such tendencies appear in puzzle-solving and every day life, we would especially expect them to be experienced when responsibility and high stakes are added" (1967: 4). More explanations for this result should be explored in future work.

The robotics industry is 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 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 would be helpful to confirm how the framework developed in this study applies to these industries. 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 literature 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 both of these 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 two mutually conflicting prescriptions often presented to practitioners – to either "stick to the knitting", or to 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 for managers for monitoring 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 both the firm over time, as well as for its leading competitors, and can help provide a frame of reference that can be used by managers for tracking, focusing and redirecting the search efforts.

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TABLE 1

Descriptive statistics and correlations[a].

		Mean	s.d.	Min.	Max.	1	2	3	4	5	6	7	8	9
1	Number of new products_{it}	0.92	2.36	0	24									
2	Search depth_{it-1}	0.22	0.24	0	1.74	0.04								
3	Search scope_{it-1}	0.74	0.30	0	1	0.08 **	-0.003							
4	Collaboration freq_{it-1}	0.16	0.50	0	6	0.33 ***	0.02	0.07 *						
5	Return on assets_{it-1}	0.02	0.05	-0.73	0.45	-0.01	0.04	0.03	0.04					
6	R&D $\text{expenditure}_{it-1}$	0.32	0.78	0.01	6.78	0.07 *	0.22 ***	0.07 *	0.07 *	0.03				
7	$\text{Diversification}_{it-1}$	0.64	0.37	0	1.62	-0.02	0.20 ***	0.15 ***	0.03	-0.02	0.11 ***			
8	European firm_{i}	0.15	0.36	0	1	-0.06 *	-0.06 *	0.06 *	-0.01	0.03	0.17 ***	0.20 ***		
9	American firm_{i}	0.22	0.41	0	1	-0.15 ***	-0.02	-0.06 *	0.01	0.04	0.05	-0.19 ***	-0.22 ***	
10	Firm size_{it-1}	39.66	100.77	0.03	876.8	-0.03	0.15 ***	0.08 **	0.06 *	0.05	0.86 ***	0.14 ***	0.29 ***	0.17 ***

[a] N=1185.

* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

TABLE 2

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

	Model									
Variable	1	2	3	4	5	6	7	8	9	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$_{it-1}$		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$_{it-1}$			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$_{it-1}$* Search scope$_{it-1}$					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$^2_{it-1}$						-3.05 *	-2.71	-3.12 *	-3.32 **	-2.99 **
						1.35	2.92	1.40	1.22	1.09
Search scope$^2_{it-1}$							-0.51			
							4.05			
Collaboration freq$_{it-1}$	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
Return on assets$_{it-1}$	-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$_{it-1}$	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$_{it-1}$	-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$_i$	-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$_i$	-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$_{it-1}$								0.01		-0.03
								0.03		0.06
Firm size$_{it-1}$									0.0001	0.0001
									0.002	0.001
Deviance	2694.1	2685.2	2679.4	2667.2	2646.8	2618.8	2617.5			
Difference in Log likelihoods vis-à-vis the base model		8.9**	14.7***	26.9***	47.3***	75.3***	76.6***			
d.f.	19	20	20	21	22	23	24	24	23	24

[a] The table gives parameter estimates; standard error is below each parameter estimate.

[b] 124 firms and 1185 firm-year observations. Year dummies included, but not shown.

† $p < 0.1$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$ (two-tailed tests for controls, one-tailed tests for hypothesized variables).

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