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Untangling the Effects of Overexploration and Overexploitation on Organizational Performance: The Moderating Role of Environmental Dynamism†

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Because a firm's optimal knowledge search behavior is determined by unique firm and industry conditions, organizational performance should be contingent on the degree to which a firm's actual level of knowledge search deviates from the optimal level. It is thus hypothesized that deviation from the optimal search, in the form of either overexploitation or overexploration, is detrimental to organizational performance. Furthermore, the negative effect of search deviation on organizational performance varies with environmental dynamism; that is, overexploitation is expected to become more harmful, whereas overexploration becomes less so with an increase in environmental dynamism. The empirical analyses yield results consistent with these arguments. Implications for research and practice are correspondingly discussed.

Keywords: *overexploitation/overexploration; consistency in search; environmental dynamism; organizational performance*

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Knowledge search is a fundamental mechanism by which firms learn and organizational knowledge evolves (Huber, 1991; March, 1991). Search is often broadly classified into two types: exploitative (local) search and explorative (distant) search (Levinthal & March, 1981; March, 1991; Martin & Mitchell, 1998). Firms that focus more on exploitative search follow a path of knowledge deployment and generation that is closely related to their existing knowledge bases and current organizational routines (Helfat, 1994; March, 1991). On the other hand, explorative search behaviors involve a conscious effort to move away from the existing knowledge base and routines (Greve, 2007; March, 1991; Miner, Bassoff, & Moorman, 2001).

To the extent that exploitation and exploration compete for limited organizational resources, there is a tradeoff between these two, and organizations make explicit and implicit choices between exploitation and exploration (March, 1991). Different implications can be drawn from previous perspectives regarding whether a firm should place greater emphasis on exploitation or on exploration. According to the resource- and knowledge-based views of the firm (Barney, 1991; Kogut & Zander, 1992; Wernerfelt, 1984), a source of firms' competitive advantage is firm-specific resources that result from internal accumulation of strategic knowledge and asset stocks (Dierickx & Cool, 1989), which is a key feature of exploitative search. This perspective suggests that exploitative search is generally more desirable than explorative search. On the other hand, some scholars argue that sustainable competitive advantage relies more heavily on a firm's ability to move beyond exploitation and on how it reconfigures its knowledge base through exploration (Rosenkopf & Nerkar, 2001; Teece, Pisano, & Shuen, 1997). In terms of this view, moving toward more exploration should be a more desirable search behavior.

In an attempt to examine which emphasis is more desirable for firms, however, few studies have explicitly considered the role of each firm's unique internal and external conditions. In fact, it might be reasonable to believe that because of the heterogeneity across firms in terms of their internal knowledge resources and asset conditions as well as differences in their operational environments, the appropriate search strategy for different firms may vary greatly. If this were the case, it would not be meaningful to draw any conclusion about which type of search is more desirable for a firm if there is failure to consider the determinants of search behavior. The first aim of this study, therefore, is to establish a baseline argument that firms' choice of search behavior is endogenous to unique firm and industry conditions and thus what is considered optimal or appropriate search behavior also varies across firms.

The argument above suggests that there should be a fit between a firm's unique firm and industry conditions and its knowledge search strategy. Nevertheless, firms are not expected to always emphasize the type of search that has the best fit with their unique conditions. For example, a firm's managers may not choose a knowledge search strategy with the intention of improving firm performance because, for example, there are agency conflicts between the managers and the shareholders of the firm (Jensen & Meckling, 1976). Even if managers attempt to choose their search behaviors in a performance-enhancing manner, the firm's actual search behavior may still deviate from what is desirable because of other types of managerial biases or mistakes (e.g., March & Shapira, 1987; Weinstein, 1980). Considering these premises, we argue that search deviation, or the extent to which a firm's search behavior deviates from its optimal level, has a negative impact on organizational performance. This fills a gap in the knowledge search literature, because to our best knowledge the current study is the first to examine the performance implications of actual knowledge search deviation from an optimal level.

The idea of an optimal level of search implies that a firm's exploitative and explorative search behaviors may be best regarded as two ends of a continuum instead of orthogonal choices.[1] It is reasonable to assume that firms' knowledge search capability is subject to the scarcity of resources and thus firms must face a choice of putting greater emphasis on exploration versus exploitation. This argument is consistent with March's (1991) original idea and some more recent work (e.g., Lavie & Rosenkopf, 2006; Levinthal & March, 1993; Miller, Zhao, & Calatone, 2006; Mitchell & Singh, 1993; Perretti & Negro, 2006; Wadhwa & Kotha, 2006) that also treated exploitation and exploration as a continuum.

We further analyze the role of environmental dynamism in either mitigating or exacerbating the negative effect of search deviation on organizational performance. We argue that the detrimental effect of overexploration and overexploitation varies under different levels of environmental dynamism. Specifically, overexploitation is expected to become more harmful, whereas overexploration becomes less so with an increase in environmental dynamism. In addition to contributing directly to research, the argument and empirical support found in this study provide important practical implications: Managers can be guided to minimize potential damage in the case of committing mistakes in knowledge search, when it is difficult to engage in the exact "appropriate" level of search.

We examine these arguments in the context of patented innovations. Some previous studies examined exploitative and explorative search in the context of innovations either in terms of patents (Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996) or in terms of journal publications (Greve, 2007; Henderson & Cockburn, 1994). None of these studies, however, applied innovation data to examine directly the relationship between search deviation and organizational performance, as we do here. In the following sections, we first develop the baseline argument that a firm's optimal knowledge search strategy is determined by various firm and industry conditions and then move on to the hypotheses linking knowledge search deviation to organizational performance.

Hypotheses Development

Endogenous Knowledge Search

Drawing on several streams of theoretical framework and recent studies on the antecedents of search (Chen & Miller, 2007; Greve, 2007), we argue that a set of firm- and industry-level factors could affect a firm's search strategy. First, the organization theory (e.g., Hannan & Freeman, 1984; Hofer & Schendel, 1978) and literature on industrial organization economics (Bain, 1956; Caves, Porter, & Spence, 1980) suggest that external environmental forces can affect a firm's tendency toward either exploitation or exploration. For instance, a firm's search may be influenced by institutional pressures such as the search behavior of its competitors or of those in its social network (DiMaggio & Powell, 1983; Hannan & Freeman, 1984). Market dynamism may also stimulate innovative exploration. In a constantly changing industry environment, firms need to update their knowledge base continuously to adapt more effectively to the changing environment (Andrews, 1980; Hofer & Schendel, 1978; Teece et al., 1997). Furthermore, in the face of intensive industry competition, explorative search may become less rewarding because competition may invoke imitation by rivals that rips away any potential rents from exploration (Bain, 1956; Caves et al., 1980; Mueller, 1986).

Second, the evolutionary theory of the firm and organizational learning perspectives suggest that interfirm differences in knowledge search strategies exist even when the environmental challenges facing firms are similar (Siggelkow & Levinthal, 2003; Sorenson & Sorensen, 2001). As a result of heterogeneous organizational evolution process, different firms possess their own unique routines or capabilities (Dierickx & Cool, 1989; Nelson & Winter, 1982), which in turn lead to important differences in firms' ability to understand signals about the opportunities available in their environment and to form responses to them. Because firms' routines and response strategies are developed in a path-dependent manner (Nelson & Winter, 1982), their existing knowledge structure, such as their technological scope and previous knowledge search behavior, should influence their current search strategy.

Third, some arguments in the literature on the behavioral theory of the firm suggest that several organizational characteristics may influence a firm's search behavior. In a decision-making context where complete assessment of all the possibilities and payoffs associated with each possibility is impossible, managers may use the satisficing principle as a guide for decision making (Simon, 1955). For example, firms with a low satisficing point may end the search process early, resulting in a lower likelihood for exploration (Winter, 2000). On the other hand, as a firm's actual performance increases relative to its satisfying point or aspiration level, it may be more likely to engage in explorative innovations (Cyert & March, 1963; Greve, 2007; Levinthal & March, 1981). Firms are also found to take on more risks by engaging in greater exploration when they face the threat of bankruptcy or experience financial distress (Ketchen & Palmer, 1999; March & Shapira, 1987). Furthermore, because exploration involves more technological and market risks and lower fit to the existing knowledge, organizational slack has a greater effect on explorative search than on exploitative search (Cyert & March, 1963; Greve, 2007).

Although identification of the above industry and firm attributes may not always explicitly rely on efficiency-based considerations and, moreover, the role of these attributes in a firm's search decision is not always fully agreed on, these attributes provide useful clues about what is considered appropriate search behavior. For example, frequent changes in the environment provide a strong signal for the need to explore new solutions and implement organizational change (e.g., Hofer & Schendel, 1978). As a result, exploration should be desirable search behavior. As another example, when a firm is approaching bankruptcy, it is generally desirable to take on more risks from the perspective of shareholders, although such risk taking is often against the welfare of other stakeholders such as the creditors (D'Aveni, 1989). In sum, we expect that firms' optimal search behavior is influenced by their industry operational environment and unique firm conditions.

Deviation in Search Behavior and Organizational Performance

The argument above suggests that firms should vary in terms of their optimal level of search because of differences across firms in their knowledge asset stock and operational environments. This implies that there should be a fit between firms' unique features and their appropriate search level. However, some firms may inevitably make strategic choices that deviate from those which are considered appropriate (Sampson, 2004). Deviations between the actual and optimal level of knowledge search may originate from two potential sources: managerial misbehavior attributable to the agency conflict between managers and shareholders and managerial mistakes as a result of psychological biases.

First, according to the agency theory (Jensen & Meckling, 1976), managers may make decisions that depart from shareholder value maximization. Thus, managerial misbehavior may be one of the key reasons for deviations between some firms' actual search behavior and the optimal one. Search deviation in such context, in the form of either overexploitation or overexploration, is often associated with the manager's risk attitude and behavior. Wiseman and Gomez-Mejia (1998) suggested that managers may exhibit risk-seeking as well as risk-averse behaviors. For example, managers who are greatly concerned about their employment risk are likely to be more risk averse than the firm shareholders desire (Amihud & Lev, 1981; Holmstrom, 1979; Holmstrom & Milgrom, 1987) and thus may engage in excessive exploitation. On the other hand, managers whose preference for achievement is stronger than their desire to avoid failure may enjoy the challenge that risks entail and thus are more likely to undertake overly risky search strategies biased toward exploration (McClelland, 1961).

Second, some psychological studies (March & Shapira, 1987; Weinstein, 1980) suggest that individuals may engage in biased decision making. Managers tend to be more optimistic about strategy outcomes that they can control and to which they are highly committed, suggesting that managers may be overconfident of the success of their existing projects (Heaton, 2002), leading to escalation of commitment bias and excessive exploitation (Staw, 1981). Leonard-Barton (1995) found evidence that managers may be trapped by their experiences in exploitation and become less sensitive to the need for exploration, even if greater exploration is necessary to deal with changes in the environment. On the other hand, overconfident managers may also overestimate their abilities to explore new areas and fail to fully consider the risk of exploration. For example, Simon and Houghton (2003) examined a sample of high-technology firms and found that overconfidence was positively related to the degree to which product introductions were pioneering or risky when, in fact, these products were less likely to achieve success.

The argument that a firm's search choice may deviate from its optimal level suggests that the performance implications of exploration versus exploitation should hinge on the degree of deviation between a firm's chosen search behavior and the optimal search behavior that would maximize firm value. Search deviation, in the form of either overexploration or overexploitation, involves the inefficient use of valuable corporate resources and thus imposes costs on the firm. For example, firms that engage in excessive exploitation are found to have difficulty in maintaining their leadership positions in the industry (Tushman & O'Reilly, 1997). Similarly, excessive exploration can also be detrimental to firm performance. For example, the unrelated diversification strategy (akin to excessive exploratory behavior) adopted by companies in the 1960s proved to be unsuccessful (Caves et al., 1980; Montgomery, 1982). Therefore, we can expect that the more a firm's search deviates from what is desirable, the higher the cost of search deviation and the worse the firm performance. To the extent that several firm- and industry-level attributes predict optimal search choices, the benefits accruing to a firm should be greater when the firm chooses search behavior based on these attributes than when the search decision is not so chosen.

Hypothesis 1: Firms that deviate from optimal search behavior as predicted by key firm- and industry-level attributes will perform worse than firms whose search behavior does not deviate from what is predicted by these attributes.

Environmental Dynamism and the Performance Effect of Deviation in Search Behavior

Firms may overexploit or overexplore, leading to a negative effect on organizational performance. However, the negative performance effect is not expected to be the same under all conditions, given the same extent of search deviation. In practice, it is difficult to obtain the exact "optimal" level of knowledge search. Understanding the conditions under which a certain type of search deviation (e.g., overexploration or overexploitation) may have relatively less detrimental consequences should thus be helpful. As a result, the negative performance effect of search deviation may be minimized. Because the exploitation of old certainties and the exploration of new possibilities are closely related to and are influenced by a firm's operational environment (Eisenhardt & Martin, 2000), the role of environmental dynamism in influencing the performance effect of search deviation is considered in the study.

Environmental dynamism describes the rate and unpredictability of change in a firm's external environment (Aldrich, 1979; Dess & Beard, 1984). In the absence of environmental demand for change, organizational performance is often simply a reflection of how firms take the best advantage of their existing knowledge assets, routines, and capabilities. Previous studies suggest that a firm can achieve a higher likelihood of successful knowledge accumulation and positive financial outcomes when it engages in exploitation by concentrating in the areas of its established routines and capabilities (Henderson & Cockburn, 1994; Stuart & Podolny, 1996). Even when the extent of exploitation goes beyond the optimal level and thus causes the organization to suffer, the performance decline is generally not very significant because overexploitation in a stable operating environment may reduce the deployment efficiency of the firm's fundamental knowledge assets, routines, and capabilities, but this is unlikely to completely erode the firm's value.

On the other hand, when the firm's operating environment is highly dynamic, excessive exploitation by sticking to existing routines or capabilities reduces the flexibility of the firm to make effective adaptations. In a rapidly changing operating environment, previously developed capabilities may not be able to keep up with the frequent changes in product and technological conditions, leading to a higher probability of misfit between a firm's existing capabilities and the environment where the firm's existing routines or capabilities should be deployed (Anderson & Tushman, 1990, 2001; Sirmon, Hitt, & Ireland, 2007). Moreover, when the decision context changes, a firm that engaged in excessive exploitation develops a stronger inertia and becomes less likely to give up existing routines and operational approaches even when environmental conditions have rendered a particular search direction less attractive (Burgelman, 1994; Stuart & Podolny, 1996). Unlike in a stable environment, in a dynamic environment the damage of overexploitation is more severe because it is likely to be associated with the obsolescence of existing routines and capabilities. These arguments suggest that the negative effect of overexploitation increases with environmental dynamism.

Hypothesis 2a: The negative effect of overexploitation on organizational performance is greater with an increase in the level of environmental dynamism.

The problem of misfit between a firm's existing routines and capabilities and the firm's operational environment under a high level of environmental dynamism may be mitigated if the firm is capable of exploring new areas and building new capabilities. Exploration reduces the risk of value erosion associated with firms' existing capabilities under environmental dynamism by broadening the number of design alternatives available to manage potential environmental changes (Fleming, 2001; Fleming & Sorenson, 2001). Greater flexibility brought about by exploration also helps overcome organizational inertia. Firms engaging in continuous exploration are likely to have technical groups with varied perspectives and are thus better able to reframe problems and overcome familiar thought patterns and competence traps when the environment demands organizational change (Amabile, 1988; Levitt & March, 1988; Kaplan & Simon, 1990; Utterback, 1971). As a result, prior routines and experiences may be better adapted and applied in new situations, and, more important, the likelihood of adopting new approaches increases (Cohen & Levinthal, 1990; Scott & Pascoe, 1987).

Even if exploration becomes excessive and the firm becomes overly flexible such that its financial outcome is negatively affected, it is still unlikely that the firm loses all the benefits from its increased flexibility in making organizational changes that are necessary in dealing with environmental dynamism. To the extent that a high level of exploration enables the firm to adapt to the changing environment, environmental dynamism mitigates the negative effect of overexploration on firm performance. In contrast, overexploration is expected to be more detrimental to organizational performance in a stable environment because it not only brings unnecessary risk but also exhausts valuable firm resources and capabilities that are necessary for efficient exploitation.

Hypothesis 2b: The negative effect of overexploration on organizational performance is weaker with an increase in the level of environmental dynamism.

Methods

Data and Sample

Three main data sources were enlisted in this study: Standard & Poor's Compustat, U.S. patent data, and the U.S. Census of Manufacturers. The original sample is drawn from U.S. manufacturing companies listed in the Standard & Poor's Compustat series. The focus on manufacturing firms enabled us to construct a sample with a large group of firms that shared some common characteristics in terms of their knowledge search processes but, at the same time, provided variations in terms of the level of knowledge search and patenting activities across firms. These companies were then merged with patent citation data from the National Bureau of Economic Research (NBER) using CUSIP numbers. Because the NBER data are matched with Compustat data for 1989 (Hall, Jaffe, & Trajtenberg, 2001), we used the 5 years closest to 1989 (1987-1991) as the time period for this study. This minimized problems such as the effect of name changes and the entry and exit of sample firms, which increase as the sample is further away from the matching year. Patent data are used to construct measures of our key independent variables, explorative and exploitative search, as well as one of the dependent variables, innovative performance.

Additional industry-level data were obtained from the U.S. Census of Manufacturers. After we deleted observations with missing values in the Compustat series or the Census of Manufacturers and also eliminated firms that had patents issued in only one of the five sample years, the final panel included 570 firms that had patents issued in at least 2 years in the 5-year period between 1987 and 1991. The sample of firms was distributed over 17 two-digit and 58 three-digit SIC codes. The final sample consisted of 2,006 firm-year observations. The total number of patents included was 54,362, averaging about 27 patents per firm per year.

Model Specification

To test for the argument that knowledge search is endogenously determined by various firm and industry factors, we applied two interrelated approaches. The first was to regress the knowledge search on the series of firm- and industry-factors that are expected to affect search. If significant coefficients were found for many of these predicting variables, we expected that there was a high likelihood that search behavior was endogenous. The second approach was to conduct a Hausman's endogeneity test. In the Hausman's test, in addition to the regression of knowledge search on the series of variables, we calculated the residuals from this equation and included them as an additional regressor in the equation with financial performance as the dependent variable. If the coefficient on this additional regressor (the residuals) was significantly different from zero, then we could conclude that search behavior was endogenous.

We included two instrumental variables in the Hausman's test: lagged firm-level search variable and industry-level search.[2] The first is a lagged endogenous variable, which is one of the most commonly used approaches to the choice of instruments in time series or panel data (Greene, 2000; Kennedy, 2003). The second instrumental variable, industry-level search, is the average level of knowledge search among firms in an industry where a focal firm resides. DiMaggio and Powell (1983) argued that organizations tend to become more similar over time by adopting similar organizational practices through institutional isomorphism. According to this logic, it is reasonable to expect that the search behavior of industry peers has a positive influence on a focal firm's search behavior. On the other hand, it is unlikely that how other firms in the same industry search directly affects the focal firm's subsequent performance.

Some of our models that estimate the relationship between search deviation and organizational performance involve innovation performance as the dependent variable, which is measured as a nonnegative count variable. To estimate such models, Poisson or negative binomial regressions are often applied (e.g., Ahuja & Katila, 2004; Rosenkopf & Nerkar, 2001). Poisson models were not appropriate here because there was overdispersion in the data. Thus negative binomial regressions were applied in estimating these models.

Measures

Organizational performance. We adopted two measures of organizational performance in this study: innovation performance in terms of patent citations and Tobin's *q* as a market-based financial performance measure. Following previous research that has used patents as a measure of knowledge (Ahuja, 2000; Ahuja & Katila, 2001; Rosenkopf & Nerkar, 2001), we measured the innovation performance of each firm in terms of citation-based patent count, or the total number of citations received by a firm's patents in a given year. Self-citations were excluded, thus limiting this measure to the number of subsequent citations by other firms. Citations received also captured the degree to which knowledge generated by a firm is assimilated by other firms, which has been described in the literature as the impact of the firm's patents on subsequent technological evolution (Rosenkopf & Nerkar, 2001) or the usefulness of the patents (Fleming, 2001). In particular, we tracked all patents that cited the focal patents after they were granted. For each firm in a given year, we took all its patents in this year as the base and counted the number of citations to these focal patents by all subsequent patents by other firms up to 1999, which is the last year covered by the NBER patent citation data. Because large firms may have more patents than small firms, we used firm size, as measured by the logged number of employees, to scale the total patent citations received to assess a firm's innovation performance.

Tobin's *q*, a market-based performance measure, was adopted as the financial performance measure in this study. In the context of this paper, Tobin's *q* is superior to other accounting-based measures such as return on assets (ROA) because it is forward looking and thus can avoid the potential concern of a time lag between firm search behavior and accounting-based performance. Tobin's *q* was approximated as the firm's market-to-book ratio, because this measure explains more than 96% of the variance in a more sophisticated Tobin's *q* (e.g., Lindenberg & Ross 1981). The market value numerator was the year-end market value of the firm's common stock plus the book value of preferred stock and debt, and the book value denominator was year-end total assets.

Explorative/exploitative search. Exploitative search refers to search efforts in the neighborhood of a firm's current expertise or knowledge base. Explorative search refers to search efforts that attend to more distant fields beyond the firm or its existing technological fields. To capture the tradeoff between exploitation and exploration (March, 1991), we use the proportion of explorative search—defined as the ratio between the effort a firm puts into explorative search and the total search effort—to measure the firm's search behavior. More specifically, we examine two dimensions of search: organizational and technological (Rosenkopf & Nerkar, 2001). Exploitative (explorative) search can be done organizationally within (outside) a firm's own past innovations or technologically within (outside) its existing technological fields (Cohen & Levinthal, 1989; Nelson & Winter, 1982; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996). In the technological dimension, we followed previous studies (e.g., Hall et al., 2001; Jaffe, Trajtenberg, & Henderson, 1993; Rosenkopf & Nerkar, 2001) to use the three-digit primary patent class developed by the U.S. Patent Office to define a firm's technical domain.

We constructed two continuous measures of the *proportion of explorative search*: explorative search (beyond the firm), measured by the count of prior article citations made in patent applications that originated outside of the focal firm's previous patents, divided by total patent citations made, and explorative search (out of domain), measured by the count of prior citations made in patent applications that originated from different technological domains. Because the search variables are bounded between zero and one, a logarithmic transformation was applied to convert the variable into an unbounded one (e.g., Demsetz & Lehn, 1985). These measures of search were simply lagged by 1 year to obtain the lagged search variables.

Search deviation. The degree of search deviation captures the extent to which a firm's search behavior deviates from what is predicted by unique firm and industry conditions. In developing this measure, we estimated the predicted value for explorative search by regressing the proportion of explorative search as a function of these firm- and industry-level attributes. The degree of search deviation was then defined as the absolute value of the firm's actual degree of exploration minus the predicted degree of exploration. The predicted level of exploration is a reasonable proxy for the optimal level of search because the use of this proxy is rather consistent with our theoretical argument. One of our key arguments is that firms vary in their levels of optimal search because of their unique firm- and industry-level features. The optimal search, therefore, should be determined by these unique firm and industry features. When the actual search value is greater than the predicted value, there is an overexploration; and when the actual search value is smaller than the predicted value, there is an overexploitation.

Firm-level variables predicting optimal search level. The following firm-level attributes were expected to affect search behavior: performance relative to aspirations, slack, financial distress, and technological scope. Aspiration is often modeled as a function of own-firm past performance (Bromiley, 1991; Cyert & March, 1963; Wiseman & Bromiley, 1996). Thus, in this study, aspiration was operationalized as the focal firm's performance 1 year prior to its past performance (t-2). Performance relative to the aspiration level, then, was the difference between a firm's performance at t-1 and its performance at t-2. As in previous studies (Bromiley, 1991; Wiseman & Bromiley, 1996), ROA was used as the performance measure. Following the methods of Bourgeois (1981) and Singh (1986), we used each firm's current ratios (current assets divided by current liabilities) to represent available firm slack. The slack variables were lagged 1 year relative to the dependent variables. Also following previous research (e.g., Deephouse & Wiseman, 2000; Miller & Reuer, 1996), we used Altman's *Z* score (Altman, 1968) as a measure of financial distress or distance from bankruptcy. A negative sign was added in front of this variable purely for ease of interpretation, so that the measure's sign corresponded to the construct of the degree of financial distress and bankruptcy risk. We measured a firm's technological scope by calculating the Blau index of the firm's patenting across patent three-digit technology classes (e.g., Ahuja & Katila, 2004). Last, firm size may affect firm search behavior and was thus included in the equation as a control variable.

Industry-level variables predicting optimal search level. We included two measures at the industry-level in the model: industry levels of competition and environmental dynamism. We measured industry-level competition by the four-firm concentration ratio. Both industry-level variables were obtained from the Census of Manufacturers. As in previous studies, we used industry-level shipment, or volatility in customer demand for certain products, to derive a measure of *environmental dynamism* (e.g., Boyd, 1995; Simerly & Li, 2000). Such a measure of dynamism reflects the need for frequent development of new products and for frequent technological advances that give rise to the new products. For a firm facing frequent changes in product conditions, overexploitation of previously developed innovative knowledge (compared with overexploration) would be most harmful to the firm, leading to a higher likelihood of misfit between its existing innovations and the product market where the innovations are deployed (Anderson & Tushman, 1990, 2001; Sirmon et al., 2007). In particular, we regressed the value of industry shipments over 5 years against time and used the standard error of the regression coefficient related to a time dummy variable divided by the average value of the industry's shipment to produce a standardized index of environmental uncertainty. Because patenting activities may vary significantly across industries (e.g., Levin, Klevorick, Nelson, & Winter, 1987), in addition to the above industry-level explanatory variables, we also controlled for industry and time effects by adding industry (at the two-digit SIC level) and year dummy variables.

Instrumental variables. We included two instrumental variables in our analysis: lagged search and industry-level search. Lagged search is simply measured by the level of explorative search that is lagged by 1 year. Industry-level search is calculated as the average level of explorative/exploitative search of firms in the same industry (with the focal firm excluded). Note that the firms included to calculate the industry average were taken from the originally matched Patent-Compustat data in order to obtain a larger number of representative firms in each industry.

Other control variables in the performance equation. In addition to search deviation, the key variable that was hypothesized to affect organizational performance, several other variables that were also expected to influence performance were included as controls. First, because a firm's total number of patents to some extent represents its technological capability and a key element of the firm's stock of knowledge resource, it was hypothesized to have a positive effect on both measures of organizational performance (e.g., Jaffe et al., 1993). This variable is measured as the count of the number of patents applied during each year by each firm. Second, a firm's technological scope is an important feature of the firm's knowledge base: The broader is a firm's innovative scope, the more likely it is to patent in many different classes and possibly the more likely it is be cited more (Ahuja & Katila, 2004). Greater innovation and patent citations will in turn possibly affect the firm's market value.

In addition, several of other variables in the search equation, including financial distress, organizational slack, and performance aspiration, are obviously associated with firm financial performance and were thus also included in the performance equations. Firm size was also included in the performance equations because there is some evidence that size negatively influences firm profitability (Cubbin & Leech, 1986). This negative relationship could be attributable to the diminishing returns to scale as a result of increasing complexity of the operations in big firms or could be attributable to the excessive rigidity of big firms while coping with change and uncertainty (Ling, Zhao, & Baron, 2007). Size as a control variable is not shown in the models with innovation performance as the dependent variable, because it served as an offset variable[3] and thus was omitted in the negative binomial regressions. Moreover, because industry factors are often expected to affect organizational performance, we also included industry concentration and the industry dummy variables, in addition to including environmental dynamism as a moderator, as controls in the performance models.

Results

Table 1 provides a summary and zero-order correlation statistics for the main variables. The descriptive statistics indicate that the firms were characterized by significant diversity in their search behavior, innovation performance, financial performance, and other firm- and industry-level attributes. As expected, both measures of firm-level searches had significant correlations among each other, with measures of industry-level search, and with lagged search variables. Also consistent with our expectation, industry-level search was not significantly related with the performance measures. Although lagged explorative search beyond firm was significantly related to the performance measures, significant correlations were not found for explorative search beyond domain. The correlations between number of patents and both search measures were negative and significant (–.27 and –.22, respectively), suggesting that a firm with a larger patent stock is less likely to explore through citing other firms' patents or patents beyond its existing domain.

Determinants of Knowledge Search

Table 2 presents the results of the models with the level of search as the dependent variable. The dependent variable in Model 1 was explorative search beyond the organizational boundary; the dependent variable in Model 2 was explorative search beyond the technological domain.

Models 1 and 2 demonstrate consistent patterns of results for a number of key firm- and industry-level variables. As predicted, both lagged search and industry-level search (either beyond firm or beyond domain) had positive and significant effects on the current search behavior. The industry concentration ratio, which is a proxy for industry-level competition, was also found to have a significant negative effect on the degree of explorative search for both models, supporting the argument that lack of competition reduces firms' incentives to explore. Also consistent with our predictions, there was a positive association between environmental dynamism (as indicated by variations in industry sales) and explorative search, supporting the argument that market uncertainty tends to stimulate exploration (Andrews, 1980; Hofer & Schendel, 1978; Teece et al., 1997). In both models, technological scope, or the diversity in patent classes, had a significantly negative effect on explorative search, indicating that firms in broader technology areas allocate more of their efforts to exploitative search, both within the firm and within their technology domains. But we did not find a significant effect of performance aspirations on search behavior.

Table 1
Descriptive Statistics and Correlation Matrix

Variables	Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Financial performance (Tobin's *q*)	1.67	1.14	0.46	9.77															
2. Innovation performance	188	547	0	7,314	.21*														
Continuous search variables (firm-level)																			
3. Explorative search (firm)[a]	3.02	1.37	–4.51	4.60	.14*	.25*													
4. Explorative search (domain)[a]	2.31	1.28	–4.63	4.25	–.07*	–.03	.50*												
Continuous search variables (industry–level)																			
5. Explorative search (firm)[a]	2.88	1.16	–3.67	3.86	–.02	.04	.47*	.35*											
6. Explorative search (domain)[a]	2.37	1.13	–3.55	3.38	.04	–.00	.51*	.31*	.69*										
7. No. of patents ($\times10^{-2}$)	0.27	0.83	1	6.39	.09*	.23*	–.27*	–.22*	–.17*	–.15*									
8. Technology scope	1.60	1.04	0	4.67	.12*	.11*	–.29*	.07*	–.17*	.09*	.41*								
9. Firm size[a]	5.90	1.92	0.49	12.12	–.14*	–.25*	–.14*	–.12*	–.05*	–.11*	.43*	.57*							
10. Financial distress	–1.98	2.04	–7.34	60.70	–.18*	–.04	–.04	–.01	–.03	–.02	–.00	–.04	–.14*						
11. Performance aspiration	0.06	0.34	0	13.9	.16*	.15*	–.00	.00	–.01	–.00	–.03	.08*	–.14*	.23*					
12. Organizational slack	2.87	2.65	0.22	44.6	.21*	.20*	.05*	–.01	.03	.05*	–.13*	–.22*	–.32*	.07*	.12*				
13. Environmental dynamism	0.02	0.01	0	0.09	.01	.10*	.05*	.03	.02	.01	–.02	–.10*	–.11*	.10*	.05*	.24*			
14. Industry concentration ($\times10^{-2}$)	0.37	0.17	0	0.90	–.01	–.02	.00	–.04	–.00	–.06*	.22*	.14*	.20*	–.07*	.05*	.00	.23*		
15. Search deviation (firm)	1.03	0.74	0	8.17	–.16*	–.06*	–.18*	–.15*	–.11*	–.17*	.10*	–.24*	–.21*	.04	.02	.06*	–.00	–.05*	
16. Search deviation (domain)	0.92	0.68	0	8.33	–.12*	–.04	–.20*	–.22*	–.15*	–.22*	–.08*	–.18*	–.26*	.05*	–.02	.09*	–.01	–.09*	.65*

Note: $N = 2{,}006$.
a. Logarithm transformation
$*p < .05$

Table 2
Determinants of Explorative Search: Results From First-Stage Two-Stage Least Squares Regressions

Variables	Search Beyond Firm, Model 1	Search Beyond Domain, Model 2
Intercept	2.31*** (0.35)	3.02*** (0.38)
Firm size	0.08** (0.03)	–0.06* (0.03)
Technology scope	–0.42*** (0.04)	–0.59*** (0.04)
Financial distress	–0.04* (0.02)	–0.04† (0.02)
Organizational slack	0.02* (0.01)	–0.01 (0.02)
Performance aspiration	–0.08 (0.08)	0.07 (0.09)
Environmental dynamism	4.55* (2.23)	4.01† (2.30)
Industry concentration (×10^2)	–0.44* (0.21)	–0.40* (0.19)
Lagged search variable	0.63*** (0.09)	0.67*** (0.11)
Industry-level search	0.07*** (0.01)	0.12*** (0.02)
R^2	.81	.77
Hausman's test for endogeneity	***	**
No. of observations	2,006	2,006

Note: Values are percentages. Standard errors are shown in parentheses. Year dummies and industry dummies are included but are not shown.
†$p < .10$
*$p < .05$
**$p < .01$
***$p < .001$

Different from our predictions that firms tend to engage in more explorative search when they approach bankruptcy (Ketchen & Palmer, 1999; March & Shapira, 1987), financial distress was found to be negatively associated with explorative search beyond both firm boundaries and technological domains. This finding suggests that instead of taking on more risks, firms tend to behave conservatively under financial distress by engaging in more exploitation (D'Aveni, 1989). Somewhat different findings for the two types of explorative search were found for organizational slack and firm size. Both of these two variables had positive effects on explorative search beyond firm boundaries but negative (or insignificant) effects on explorative search beyond technological domains. This may indicate that firms with greater resources are likely to engage in more exploration beyond firm boundaries but constrain themselves to exploitation within their exiting technological domains.

The significant coefficients found for most of these predicting variables (with the exception of performance aspiration) support our argument that firm search behavior is endogenously determined by various firm and industry factors. Further support for this argument can be found from the Hausman's test of endogeneity. As shown in Table 2, the Hausman's test statistics indicate strong endogeneity in both of the search variables (all significant to at least the .01 level).[4]

Effect of Search Deviation on Organizational Performance

The results presented in Tables 3 and 4 demonstrate the effect on firm performances of the degree of deviation between a firm's actual search behavior and optimal search behavior. Table 3 has innovation performance as the dependent variable, and Table 4 has Tobin's *q* as the dependent variable. The results from the full sample models indicate that overall search deviation had a significantly negative impact on both firm innovation performance and financial performance as indicated by Tobin's *q*. These consistent results suggest that the degree of deviation between actual search and optimal search predicted by firm and industry attributes did affect firm performance. This provides strong support for Hypothesis 1.

Although the specifications presented in the full sample models contribute to our understanding of the effect of search deviation on innovation performance, this contribution is limited to the extent that the estimated coefficients on knowledge search deviation are restricted to be equivalent across the two types of deviation from predicted search, overexploration (or exploration above predicted level) and overexploitation (or exploration below the predicted level). We then relaxed this constraint by separately estimating models using subgroups of the sample for overexploration and overexploitation, respectively. The results are largely consistent with those from the full sample, except for the overexploitation sample when explorative search beyond technological domain was used to define firm search behavior and when Tobin's *q* was used as the dependent variable (the last two equations in Table 4).

Next, we examined the interactions effects of search deviation and environmental dynamism. In the full sample, although the coefficients on the interaction terms were significant for some of the models, the results were not consistent and have different signs for the two performance measures. The lack of clear pattern in these results is not surprising given that the full sample included both firms that overexplore and those that overexploit and that we predicted opposite moderating effect of environmental dynamism for these two types of firms. The results became more revealing when we examined the two subsamples (overexploration and overexploration) separately. In particular, we found positive and significant interaction effects for all models in the sample of firms that overexplored. In contrast, when the sample of firms that overexploit was examined, the interaction effects became negative for most of these models (three of four models) and two of the models also showed significant signs. Thus, we found some support for Hypothesis 2a, that is, that the negative effect of overexploitation on organizational performance is greater with a high level of environmental dynamism. On the other hand, we found very strong support for Hypothesis 2b, which states that the negative effect of overexploration on organizational performance is mitigated with an increase in environmental dynamism.

To gain further insights into these moderating effects, we plotted the relationships between search deviation (overexploration and overexploitation) and both innovation and financial performances (Figures 1 and 2) to show how environmental dynamism moderates these relationships. Both figures further confirm that the relationship between search deviation and firm performance and the moderating effect of environmental dynamism were largely in the direction predicted in the hypotheses. Both overexploration and overexploitation were negatively associated with firm performance. Furthermore, the figures clearly demonstrate the different moderating effect of environmental dynamism for overexploration and overexploitation: The

Table 3
Effect of Deviation in Search on Innovation Performance (Citation-Weighted Patent Counts)

	Explorative Search—Beyond Firm						Explorative Search—Beyond Domain					
Variables	Full Sample		Overexploration		Overexploitation		Full Sample		Overexploration		Overexploitation	
Intercept	0.37	0.39	0.72*	0.70*	0.25	0.29	0.44	0.37	1.07***	1.13***	1.62***	1.58***
	(0.32)	(0.33)	(0.35)	(0.35)	(0.51)	(0.47)	(0.30)	(0.29)	(0.29)	(0.30)	(0.33)	(0.33)
Financial distress	–0.04**	–0.04**	–0.05***	–0.05***	–0.04**	–0.04**	–0.04**	–0.04**	–0.04**	–0.04**	–0.04**	–0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Organizational slack	0.06**	0.05**	0.05***	0.06***	0.04*	0.04*	0.05***	0.05***	0.05***	0.05***	0.05*	0.04*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Performance aspiration	0.07	0.08	0.03	0.05	0.09	0.13	0.11	0.10	0.10†	0.09†	0.20	0.15
	(0.09)	(0.09)	(0.09)	(0.10)	(0.17)	(0.18)	(0.09)	(0.09)	(0.06)	(0.06)	(0.15)	(0.15)
No. of patents ($\times 10^2$)	0.93***	0.89***	2.43***	2.45***	0.58***	0.55***	0.84***	0.88***	2.51***	2.47***	1.55***	1.49***
	(0.08)	(0.08)	(0.21)	(0.22)	(0.07)	(0.07)	(0.09)	(0.08)	(0.24)	(0.23)	(0.10)	(0.11)
Technology scope	0.39***	0.42***	0.40***	0.42***	0.28***	0.30***	0.40***	0.39***	0.46***	0.41***	0.31***	0.27***
	(0.03)	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
Environmental dynamism	9.31***	9.85***	9.98***	9.95***	9.19***	9.38***	8.99***	9.27***	9.82***	9.95***	8.93***	9.03***
	(2.09)	(2.09)	(2.55)	(2.57)	(2.32)	(2.32)	(2.08)	(2.10)	(2.73)	(2.75)	(2.58)	(2.59)
Industry concentration ($\times 10^2$)	0.02	–0.01	0.39†	0.42†	–0.22	–0.18	–0.11	–0.07	0.18	0.25	0.15	0.07
	(0.33)	(0.25)	(0.24)	(0.25)	(0.27)	(0.28)	(0.23)	(0.25)	(0.22)	(0.23)	(0.30)	(0.29)
Search deviation	–0.52***	–0.51***	–0.48***	–0.47**	–0.34**	–0.30**	–0.49***	–0.42***	–0.59***	–0.66***	–0.21†	–0.19†
	(0.10)	(0.10)	(0.15)	(0.16)	(0.13)	(0.13)	(0.03)	(0.03)	(0.05)	(0.05)	(0.12)	(0.12)
Search Deviation × Environmental Dynamism		3.71		12.33*		–19.08*		4.22†		4.38**		–1.78
		(4.27)		(5.01)		(9.44)		(2.35)		(1.57)		(1.21)
Log likelihood	–1527.5	–1525.1	–1461.6	–1456.9	–1536.3	–1533.1	–1528.6	–1526.4	–1457.9	–1453.4	–1550.3	–1548.6
No. of observations	2,006	2,006	1,216	1,216	790	790	2,006	2,006	869	869	1,137	1,137

Note: Standard errors are shown in parentheses. Year dummies and industry dummies are included, but are not shown. Firm size is treated as an offset variable in all the negative binomial regressions.

†$p < .10$

*$p < .05$

**$p < .01$

***$p < .001$.

Table 4
Effect of Deviation in Search on Financial Performance (Tobin's Q)

	Explorative Search—Beyond Firm						Explorative Search—Beyond Domain					
Variables	Full Sample		Overexploration		Overexploitation		Full Sample		Overexploration		Overexploitation	
Intercept	1.29***	1.38***	2.14***	1.55***	0.33	0.69	1.59***	1.75***	1.51***	1.49***	0.68	0.73
	(0.21)	(0.25)	(0.51)	(0.46)	(0.48)	(0.59)	(0.29)	(0.28)	(0.50)	(0.51)	(0.52)	(0.55)
Financial distress	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***	–0.07***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Organizational slack	0.04**	0.04**	0.05*	0.04*	0.03**	0.03**	0.04**	0.04**	0.03**	0.03**	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Performance aspiration	0.35***	0.33***	0.24**	0.25**	0.29***	0.30***	0.33***	0.32***	0.28**	0.27**	0.32***	0.31***
	(0.07)	(0.07)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)	(0.07)	(0.10)	(0.10)	(0.09)	(0.09)
No. of patents ($\times 10^2$)	0.09*	0.08*	1.93***	1.86***	0.07**	0.07**	0.08*	0.08*	2.01***	1.91***	0.07**	0.07**
	(0.04)	(0.04)	(0.13)	(0.13)	(0.03)	(0.03)	(0.04)	(0.04)	(0.13)	(0.12)	(0.03)	(0.03)
Technology scope	–0.11***	–0.12***	–0.11**	–0.10**	–0.12***	–0.13***	–0.10**	–0.11***	–0.11**	–0.10**	–0.13***	–0.12***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Environmental dynamism	3.01	2.68	2.05	1.59	2.17	2.33	3.01	2.77	1.95	2.01	2.99	3.02
	(2.39)	(2.48)	(3.05)	(3.17)	(2.66)	(2.67)	(2.54)	(2.49)	(3.08)	(3.13)	(2.70)	(2.71)
Industry concentration ($\times 10^2$)	–0.25	–0.29	0.03	0.08	–0.25	–0.19	–0.19	–0.25	0.05	0.11	–0.18	–0.21
	(0.21)	(0.21)	(0.21)	(0.17)	(0.26)	(0.23)	(0.20)	(0.21)	(0.17)	(0.19)	(0.24)	(0.22)
Firm size	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**	–0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Search deviation	–1.02***	–1.03***	–0.90**	–0.82**	–0.81***	–0.76***	–0.85***	–0.88***	–1.93***	–1.89***	–0.35	–0.57
	(0.21)	(0.21)	(0.31)	(0.30)	(0.17)	(0.17)	(0.09)	(0.09)	(0.22)	(0.22)	(0.44)	(0.44)
Search Deviation × Environmental Dynamism		–11.7*		13.02*		6.69		–9.38		21.38**		–3.29†
		(5.09)		(6.54)		(4.57)		(8.72)		(7.53)		(1.90)
Adjusted R^2	.30	.31	.32	.34	.33	.33	.30	.30	.33	.35	.32	.33
No. of observations	2,006	2,006	1,216	1,216	790	790	2,006	2,006	869	869	1,137	1,137

Note: Standard errors are shown in parentheses. Year dummies and industry dummies are included, but are not shown.
†$p < .10$
*$p < .05$
**$p < .01$
***$p < .001$

Figure 1
Moderating Effect of Environment Dynamism: Innovation Performance as the Dependent Variable

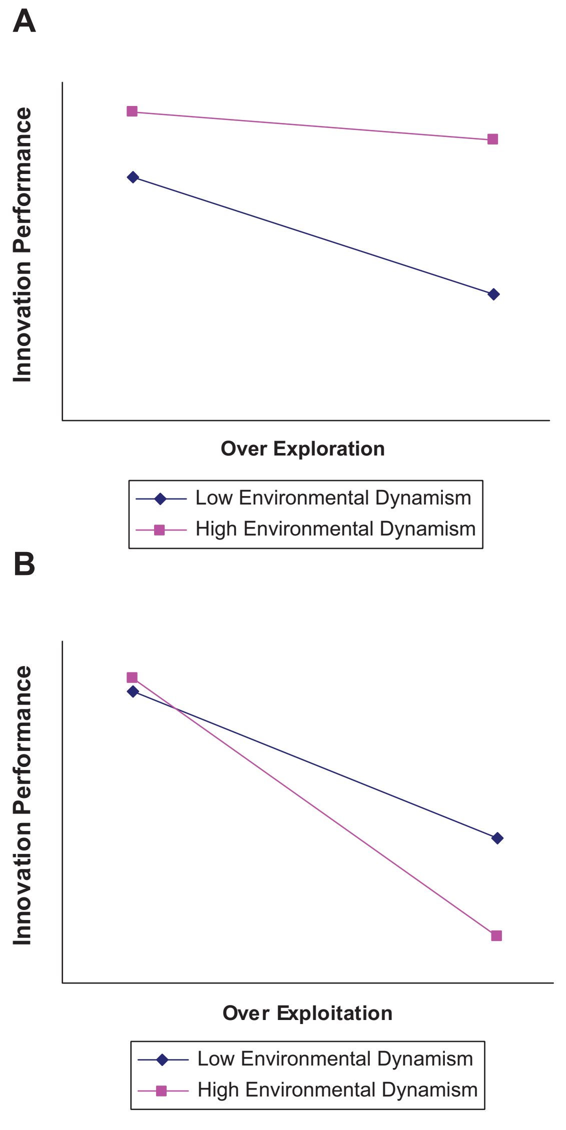
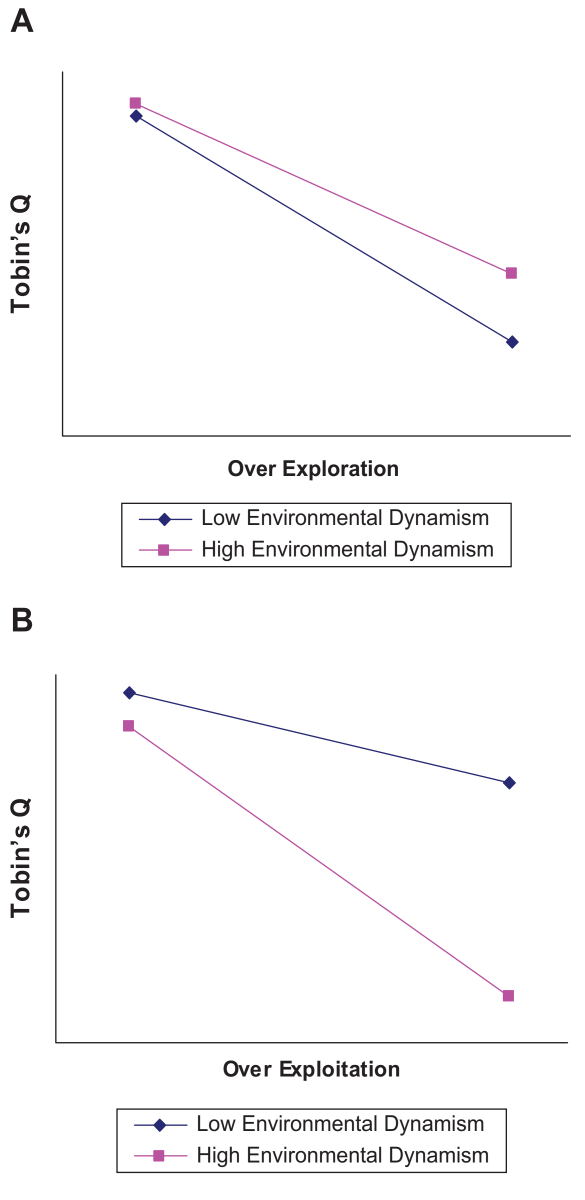


Figure 2
Moderating Effect of Environment Dynamism: Tobin's Q as the Dependent Variable



relationship between overexploration and firm performance was less negative but that between overexploitation and firm performance was more negative at a high level of environmental dynamism.

Discussion

Because of the heterogeneity across firms in terms of their internal knowledge resources and asset conditions as well as differences in their operational environments, firms' appropriate knowledge search strategies in terms of exploitation and exploration should also vary greatly on the need for a fit between their search strategy and their unique firm and industry conditions. However, because of the presence of managerial opportunism, hubris, and psychological biases, some firms may deviate from their optimal level of search that is predicted by firm- and industry-level attributes. Given these situations, the first contribution of this study to the knowledge search literature is an examination of the effect of search deviation on organizational performance. Using patent citations data to construct the proxies for firm search behavior and to derive unique measures of search deviation, we found strong empirical support for the argument that the level of search deviation is negatively associated with organizational performance. This fills a gap in the knowledge search literature because the current study is the first to explore the search deviation–performance relationship. We hope that our efforts will remind researchers of the importance of considering the effect of search deviation, rather than search strategies themselves, on organizational performance.

Drawing on the distinction between two types of search deviation in the analysis presented on overexploitation and overexploration, we have further developed some intriguing arguments that the moderating effect of environmental dynamism differs for the two types of search deviation. In particular, the negative effect of overexploitation on organizational performance is expected to be greater but that of overexploration is weaker with an increase in environmental dynamism. Our empirical analyses largely support these novel predictions. Therefore, although deviation from optimal search still hurts firm performance, the degree of these negative effects varies with the features of the firm's operational environment: Overexploration is still damageable under environmental dynamism, but it is less damageable than a similar level of overexploitation. This finding also provides valuable implications for practitioners and managers: When mistakes are unavoidable because of the difficulty of engaging in the exact "optimal" level of knowledge search, managers may minimize the potential damage by choosing between search decisions—either overexploitation or overexploration—based on the level of environmental dynamism.

The study generates some interesting implications for future research, which stem from several of the study's limitations. First, although we found very strong and consistent support for the hypothesized moderating effect of environmental dynamism on the relationship between overexploration and organizational performance (Hypothesis 2b), we found limited support for the hypothesized moderating effect on the relationship between overexploitation and performance (Hypothesis 2a). In particular, although Hypothesis 2a was supported when search and search deviation were measured in terms of firm boundary, it was not supported when search and search deviation were measured in terms of technological boundary. This finding seems to suggest that a high level of environmental dynamism increases the risk of overexploitation within firm boundary, but overexploitation within technological domain does not become more harmful under environmental dynamism. We hope that future research can explore the rationale behind this finding and, moreover, use more refined data and methods to tease out the complexities raised here.

Second, although the focus here was on search beyond organizational and technological boundaries (Rosenkopf & Nerkar, 2001), the framework used in this study can be extended to the analysis of other dimensions of search that have been explored recently. These include search depth and search scope (Katila & Ahuja, 2002), science search and geography or location search (Ahuja & Katila, 2004; Fleming & Sorenson, 2004), and temporal search (Katila, 2002; Nerkar, 2003), among others. Understanding the nature of knowledge formation in greater depth and in higher levels of complexity may require researchers to apply approaches similar to those used in the current study to differentiate among various dimensions of search and investigate their performance implications. Studies can also be designed to explore issues related to changes in search behavior over time. For example, what would be the performance implications if a firm suddenly changed its search strategy from more explorative search to more exploitative search, or vice versa?

Third, we recognize that this study may not be fully generalizable to all knowledge search situations because it used patent data and was limited to manufacturing firms. A key drawback of patent citation data is that patents measure only codified knowledge, but much of firm knowledge cannot be codified. Thus, these results are not likely to be applicable to industries where patents and citations are not important indicators of firms' knowledge assets. Future studies may explore more comprehensive measures of search behavior that encompass broader categories of firm knowledge assets and more diverse industry contexts.

Fourth, although we believe that treating exploitation and exploration as a continuum is appropriate in the context of this article, some recent literature indicated the need to regard them as orthogonal choices (e.g., Baum, Li, & Usher, 2000; Beckman, Haunschild, & Phillips, 2004; Gupta, Smith, & Shalley, 2006; Katila & Ahuja, 2002; Nerkar, 2003). For example, Baum et al. (2000) viewed exploitative learning (learning from a firm's own experience) and explorative learning (learning from others' experience) as orthogonal, based on the idea that both types of learning may be possible without the need to compete with limited resources. Although no universal arguments may be made in favor of either treating exploitation and exploration as continuous or treating them as orthogonal (Gupta et al., 2006), future research may extend this study to examine how the implications may change if exploitation and exploration are treated as orthogonal. For example, it may be reasonable to expect that under the assumption of orthogonality, each search pattern (exploitation or exploration) should have its distinct optimal level that maximizes firm performance. Therefore, each firm would have two different optimal levels of exploitation versus exploration. As a result, although this study considered over(under) exploration the same as under(over) exploitation and thus only examined overexploration and overexploitation, future studies treating exploitation/exploration as orthogonal may be able to examine the performance implications of both over- and underexploitation as well as those of both over- and underexploration.

Furthermore, treating exploitation/exploration as orthogonal enables researchers to examine the interrelationship between the two domains of organizational learning. For example, the performance benefit of a firm's doing well in exploration may be further influenced by how well the firm does in exploitation (Gupta et al., 2006). This is in line with a growing literature that holds the ambidexterity hypothesis (Benner & Tushman, 2002; Burgelman, 1991, 2002; He & Wong, 2004; Katila & Ahuja, 2002; Knott, 2002; Levinthal & March, 1993; Tushman & O'Reilly, 1996), which emphasizes that firms capable of both exploring and exploiting do better than firms rooted in either one (Beckman, 2006; Gibson & Birkinshaw, 2004).

Fifth, although existing theories as well as statistical techniques such as those applied here are valuable in identifying and controlling for underlying firm characteristics that determine firms' optimal search level, we believe it would be promising for future research to further develop and apply appropriate theories that help to predict the level of the optimal search as well as deviation in search. More solid efficiency-based theoretical frameworks that explain firm search behavior will help identify the underlying characteristics more accurately. For example, although we drew on the institutional theory in this study to include an industry-level variable, industry search norm, as an antecedent of firm-level search, additional insights can be gained by examining the legitimacy concerns that lead a firm to mimic the search behavior of the successful firms in the industry. Along with the effort of this study, some other recent works (e.g., Beckman et al., 2004; Chen & Miller, 2007; Greve, 2007) have already headed in that direction by further unraveling the specific factors that underlie firms' search behavior.

Sixth, this study examined the moderating effect of environmental dynamism in terms of volatility in industry demand on the relationship between deviation from optimal search behavior and organizational performance. Nonetheless, environmental dynamism may be multifaceted (e.g., Castrogiovanni, 2002; Dess & Beard, 1984) and there might be other dimensions of environmental dynamism, such as dynamism in employment, in technology, and in the level of competition, that were not taken into consideration in this study. Although demand dynamism has been considered a key aspect of environmental dynamism and was the aspect most frequently used in previous studies (e.g., Boyd, 1995; Keats & Hitt, 1988; Simerly & Li, 2000; Wholey & Brittain, 1989), it would be fruitful to also consider the other aspects of environmental dynamism and examine how they may provide different implications for the arguments developed here. Furthermore, it is reasonable to expect that some other industry- or firm-level factors may also affect this relationship. For example, the resource-based and evolutionary theories of the firm perspective may be integrated into the arguments made in this article to explore how the negative effect of knowledge search deviation may vary with each firm's unique circumstances and other environmental characteristics. Such consideration of other possible moderators may shed light on variations in the relationship between search deviation and performance contingent on industry- and firm-specific features. In addition, although our main interest in this article was the performance effect of search deviation, an equally interesting research potential is to empirically explore the factors that cause search deviation that have been argued in this study, such as agency costs, psychological bias, and other managerial decision-making complexities.

Despite these limitations, this article is the first to examine the performance implications of the degree to which a firm's actual level of knowledge search deviates from the optimal level as predicted by the firm and industry conditions. This report provides further support for the argument that the negative effect of search deviation on organizational performance varies with environmental dynamism. We believe that the study contributes to our understanding of the complexities associated with both the antecedents and consequences of firm knowledge search strategies and their interconnections with the firms' operational environment.

Notes

1. To the extent that both exploitation of existing knowledge and the exploration of new knowledge are essential for organizational learning, they are not always mutually exclusive. In some studies, exploitation and exploration were treated as orthogonal (e.g., Baum et al., 2000; Beckman et al., 2004; Katila & Ahuja, 2002; Nerkar, 2003). This alternative treatment is considered more appropriate in settings where there is little resource constraint and where exploitation and exploration can be categorized into two different domains (Gupta et al., 2006).

2. We have conducted partial F tests for these two instruments as a set and found that the corresponding partial F statistics are at least greater than 98 (for different search measures), which is significantly above the critical value of 11.59 (Stock, Wright, & Yogo, 2002). This indicates that the two variables serve as strong instruments in our analyses.

3. An offset variable is often used in Poisson or negative binomial regression. It is an explanatory variable whose coefficient is fixed at 1.0.

4. We further conducted a two-stage least squared analysis of the search–performance relationship and compared the results with and without taking into consideration of the endogeneity of search. Without controlling for endogeneity, we found that an increase in explorative search expanding organizational boundaries was associated with superior organizational performance; but search expanding technological boundaries was associated with low organizational performance. However, the effect of search behavior on firm performance becomes largely nonsignificant after we controlled for search endogeneity. We conducted additional robustness tests using two alternative models that also account for the endogeneity of search behavior: Heckman's selection models and firm fixed effect models. We found very similar result patterns. Taken together, these analyses suggest that the effect of search behavior on innovation performance becomes much weaker after the endogeneity of search is controlled for. Detailed results for these analyses are available from the authors on request.

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