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OPEN FOR INNOVATION: THE ROLE OF OPENNESS IN EXPLAINING INNOVATION PERFORMANCE AMONG U.K. MANUFACTURING FIRMS

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A central part of the innovation process concerns the way firms go about organizing search for new ideas that have commercial potential. New models of innovation have suggested that many innovative firms have changed the way they search for new ideas, adopting open search strategies that involve the use of a wide range of external actors and sources to help them achieve and sustain innovation. Using a large-scale sample of industrial firms, this paper links search strategy to innovative performance, finding that searching widely and deeply is curvilinearly (taking an inverted U-shape) related to performance. Copyright © 2005 John Wiley & Sons, Ltd.

INTRODUCTION

This paper explores the relationship between the openness of firms' external search strategies and their innovative performance. Chesbrough (2003a) suggests that many innovative firms have shifted to an 'open innovation' model, using a wide range of external actors and sources to help them achieve and sustain innovation. A central part of the innovation process involves search for new ideas that have commercial potential. Firms often invest considerable amounts of time, money and other resources in the search for new innovative opportunities. Such investment increases the ability to create, use, and recombine new and existing knowledge. Accordingly, a variety of empirical studies have indicated that the character of a firm's internal search strategy within a technological trajectory can significantly influence its innovative performance (Katila, 2002; Katila and Ahuja, 2002).

However, Chesbrough's work on the 'open innovation' model has not yet been empirically examined using a large-scale dataset and the previous literature on innovative search has not yet investigated the role of search among external actors and sources. In this paper, we follow the work of Cohen and Levinthal, who argue that the ability to exploit external knowledge is a critical component of innovative performance (Cohen and Levinthal, 1990: 128). Extending Cohen and Levinthal, we investigate the influence of search strategies for external knowledge. In doing so, we develop the concepts of *breadth* and *depth* as two components of the openness of individual firms' external search strategies. We link empirically the breadth and depth of external search to innovative performance, exploring how differences in search strategies among firms influence their ability to achieve different levels of novelty in their innovative activities. We find that firms who have open search strategies—those who search widely and deeply—tend to be more innovative. However, we

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find that the benefits to openness are subject to decreasing returns, indicating that there is a point where additional search becomes unproductive. We explore the implications of this finding for theories of managerial attention and for innovative performance.

The research is based on a statistical analysis of the U.K. innovation survey. The survey explores the innovation process inside firms and it contains a sample of 2707 manufacturing firms. The method of analysis is a double-truncated Tobit model where the dependent variable is innovative performance, which is explained by a firm's external search strategies, R&D intensity and a number of control variables, such as market orientation and size. The paper is organized into five sections. The first section explores the literature and examines the influence of external search on innovative performance, describing the hypotheses that drive the analysis. The next two sections outline the database and describe the model. The fourth section reports the results and the final section contains the discussion and conclusions.

CONCEPTUAL BACKGROUND

The role of networks, communities, and linkages has come to the fore in investigations of innovative performance. The early Schumpeterian model of the lone entrepreneur bringing innovations to markets has been superseded by a rich picture of different actors working together in iterative processes of trial and error to bring about the successful commercial exploitation of a new idea (Schumpeter, 1942/87; Rosenberg, 1982; von Hippel, 1988; Freeman and Soete, 1997; Tidd, Bessant, and Pavitt, 2000). These newer models of innovation have highlighted the interactive character of the innovation process, suggesting that innovators rely heavily on their interaction with lead users, suppliers, and with a range of institutions inside the innovation system (von Hippel, 1988; Lundvall, 1992; Brown and Eisenhardt, 1995; Szulanski, 1996). In this respect, innovators rarely innovate alone. They tend to band together in teams and coalitions based on 'swift trust,' nested in communities of practice and embedded in a dense network of interactions (Scott and Brown, 1999; Brown and Duguid, 2000).

A recent example of research regarding the interactive, distributed, and open nature of innovation can be seen in Chesbrough's 'open innovation' model (Chesbrough, 2003a, 2003b). This model suggests that the advantages that firms gain from internal R&D expenditure have declined. Accordingly, many innovative firms now spend little on R&D and yet they are able to successfully innovate by drawing in knowledge and expertise from a wide range of external sources. The erosion in the strategic advantage of internal R&D is related to the increased mobility of knowledge workers, making it difficult for firms to appropriate and control their R&D investments. Chesbrough argues that open innovators commercialize external ideas by deploying outside (as well as in-house) pathways to the market (Chesbrough, 2003b). This process redefines the boundary between the firm and its surrounding environment, making the firm more porous and embedded in loosely coupled networks of different actors, collectively and individually working toward commercializing new knowledge.

At the center of the open innovation model and other similar conceptualizations of innovation is how firms' use ideas and knowledge of external actors in their innovation processes. Chesbrough (2003b) suggests that firms that are 'too focused internally' are 'prone to miss a number of opportunities because many will fall outside the organization's current business or will need to be combined with external technologies to unlock their potential.' An example of this open innovation model can be seen in Proctor & Gamble's (P&G's) approach to R&D. In order to ensure greater exploitation of external ideas and actors, P&G shifted its R&D strategy toward 'connect and develop' rather than focusing on internal R&D. P&G appears to be opening itself up to a wide range of external sources of innovative ideas, explicitly drawing in the ideas of others. The 'connect and develop' model is based on the idea that external sources of ideas may often be more valuable than internal ones (Sakkab, 2002). Accordingly, open innovators are those that integrate these external sources into their innovation processes and competitive strategy (Chesbrough, 2003b).

The focus on openness and interaction in studies of innovation reflects a wider trend in studies of firm behavior that suggest that the network of relationships between the firm and its external environment can play an important role in shaping performance. For instance, Shan, Walker, and Kogut (1994) find an association between cooperation and innovative output in biotechnology start-up firms. Ahuja (2000) finds that indirect and direct ties influence the ability of a firm to innovate, but that the effectiveness of indirect ties is moderated by the number of the firm's direct ties. Rosenkopf and Nerkar (2001) explore the role of boundary-spanning searches for both organizational and technological boundaries and find that search processes that do not span over organizational boundaries generate lower effects on subsequent technological evolution, indicating that the impact of explorative search is greatest when the search spans both organizational and technological boundaries. Powell, Koput, and Smith-Doerr (1996) investigate interorganizational collaboration in biotechnology and assess the contribution of collaboration to learning and performance, showing that firms embedded in benefit-rich networks are likely to have greater innovative performance. In sum, all these studies point to the importance of open behavior by firms in their search for innovative opportunities and they suggest that performance differences between organizations can be ascribed to this behavior.

Research in evolutionary economics also suggests that a firm's openness to its external environment can improve its ability to innovate. Evolutionary economists highlight the role of search in helping organizations to find sources of variety, allowing them to create new combinations of technologies and knowledge (Nelson and Winter, 1982). Such variety provides opportunities for firms to choose among different technological paths (Metcalfe, 1994). Search strategies are also strongly influenced by the richness of technological opportunities available in the environment and by the search activities of other firms (Nelson and Winter, 1982; Levinthal and March, 1993). In industries, with high levels of technological opportunities and extensive investments in search by other firms, a firm will often need to search more widely and deeply in order to gain access to critical knowledge sources. In contrast, in industries where there are low technological opportunities and modest investments in search by other firms, a firm has weaker incentives to draw from external knowledge sources and may instead rely on internal sources (Klevorick *et al.*, 1995).

Investigating search has also become a key element in efforts to explain innovative performance. Using patent evidence from the robotics and chemical sectors, Katila (2002) and Katila and Ahuja (2002) investigate the link between search strategy and innovative performance. These studies demonstrate that the age of knowledge and the depth and scope of search processes can influence the potential for innovation. Together these studies shift attention toward the role of search strategies in explaining innovative performance and suggest that the conventional explanatory variables of innovation performance, such as size and R&D expenditure, need to be complemented by investigation into how differences in search strategy give rise to performance heterogeneity.

Our approach builds on and extends previous literature in three ways. First, whereas Katila (2002) and Katila and Ahuja (2002) focus on search inside the firm and along a technological trajectory (as reflected in patent citations), we focus on the firm's external innovative search efforts. We seek to examine how different strategies for using external sources of knowledge influence innovative performance. Our approach focuses on the search channels, such as suppliers, users, and universities, that firms use in their search for innovative opportunities. The concept of search channels shifts attention toward the type and number of pathways of exchange between a firm and its environment rather than toward the degree of its interaction within each of these search channels. In doing so, it focuses attention on the variety of channels used by the firm in its search activities. Following Scott and Brown (1999) and Brown and Duguid (2000), our approach sees each of these channels as a separate search space, encompassing different institutional norms, habits, and rules, often requiring different organizational practices in order to render the search processes effective within the particular knowledge domain. For example, working with a private research laboratory often involves a very different process of exchange than working with a university, including different contractual rules, norms of disclosure and cultural attitudes (Dasgupta and David, 1994). Our approach provides a mechanism to explore the relationship between openness of firms to different knowledge domains and its innovative performance. A limitation of the approach is that it does not allow for the analysis of the importance of breadth and depth of external search to innovative performance within each channel or knowledge domain.

Second, the preceding studies of search and innovation say relatively little about the way in which firms draw external ideas into their innovation processes. These studies are largely based on analysis of patent citation data and patents have several serious shortcomings as indicators of innovation and innovative search. Patents can reflect inventive activities, but may at the same time be the outcome of the appropriability strategy of the firm (Teece, 1986; Chesbrough, 2003a). In addition, most patents are not commercialized and they are widely acknowledged to be a partial indicator of the innovation process only, since many innovations are only partly covered by patent protection—or not patented at all (Levin *et al.*, 1987; Klevorick *et al.*, 1995). Patents citations may also reflect technological similarities in technological profiles of different firms, rather than search activities (Patel and Pavitt, 1997). Moreover, many of the citations in patents are added by the Patent Office, rather than by the patentee, and in those cases the citations in patents itself says little about the importance of different sources of innovation (Alcacer and Gittelman, 2004). Like the Yale survey (Cohen and Levinthal, 1990), our study is based on a questionnaire survey of managers in manufacturing firms, asking them directly about what sources of knowledge they rely upon in their innovation activities. This approach allows us to examine the nature of external search strategy, highlighting the range of choices firms make about how best to exploit external sources of knowledge.

Third, by using the U.K. innovation survey, it is possible to investigate the impact of search on different types of innovation. The U.K. innovation survey provides estimates of the degree of novelty of innovation achieved by the firm and therefore it is possible to analyze whether search affects different types of innovative activity. By exploring the relationship between search and the degree of novelty in innovation, it is possible to investigate the influence of the product life cycle on the relationship between search and performance.

HYPOTHESES

External search breadth and depth

A central component in the movement toward open or interactive innovation models is a change in the way firms go about searching for new ideas and technologies for innovation. Product search can be defined as an '[o]rganization's problem-solving activities that involve the creation and recombination of technological ideas' (Katila and Ahuja, 2002: 1184). The product development process is itself a form of problem-solving activity and associated search processes involve investments in building and sustaining links with users, suppliers, and a wide range of different institutions inside the innovation system (von Hippel, 1988).

The use of different knowledge sources by an individual firm is partly shaped by the external environment, including the availability of technological opportunities, the degree of turbulence in the environment, and the search activities of other firms in the industry (Cohen and Levinthal, 1990; Klevorick *et al.*, 1995). Despite the importance of the external environment in shaping the search behavior, the search activities of different firms in an industry are subject to considerable variety and this variety is a product of different (past and present) managerial choices about how best to organize the search for, and the development of, new products. In this respect, an organization's search processes are rooted in its previous experience as past success conditions future behavior. According to Levinthal and March (1993), organizations build 'inventories' or 'storehouses of information and experience both within the organization and outside it ... They stockpile knowledge about products, technologies, markets and political contexts. They develop networks of contacts with consultants and colleagues' (Levinthal and March, 1993: 103). Moreover, future expectations as perceived by managers may differ when facing the same opportunity set (Shane, 2003). Since search strategies are rooted in the past experiences and future expectations of managers, it is difficult for many organizations to determine the 'optimal' search strategy in terms of being 'broader and deeper', especially in situations where there is turbulence in the knowledge base of the firm (Levinthal and March, 1993: 103).

Those organizations that invest in broader and deeper search may have a greater ability to adapt to change and therefore to innovate. In order to examine the influence of broader and deeper external search on performance, we develop two concepts. The first concept refers to external search breadth, which is defined as the number of external sources or search channels that firms rely upon in their innovative activities. The second concept refers to external search depth and it is defined in terms of the extent to which firms draw deeply from the different external sources or search channels. Together the two variables represent the openness of firms' external search processes.

Two previous studies are especially pertinent to our approach. First, Katila (2002) explores how the age of technological knowledge from within and outside the industry shapes product search and innovative performance in the robotics industry. The study finds that differences in innovative performance are based on differences in how firms deploy knowledge from different industries and over time. Second, Katila and Ahuja (2002) examine how search depth, i.e., how the firm reuses its existing knowledge, and search scope, i.e., how widely the firm explores new knowledge, influence innovative performance. They suggest that these concepts provide an extension of March's (1991) distinction between exploration and exploitation, contrasting the differences between local and distant search processes. In their study, search depth is measured by the 'number of times a firm repeatedly used the citations in the patents it applied for' and search scope is measured as 'share of citations found in a focal year's citations that could not be found in the previous five years' list of patents and citations by the firm' (Katila and Ahuja, 2002). They find that a firm's innovative performance is in part a function of its search behavior and that there is a curvilinear relationship—taking an inverted U-shape—between depth and scope on the one hand and innovative performance on the other, indicating that some firms have a tendency to 'over-search' (Katila and Ahuja, 2002).

The first of our key concepts is external search breadth. Extending on Katila and Ahuja, we hypothesize that external search breadth influences innovative performance. Recall that external search breath is defined as the number of different search channels that a firm draws upon in its innovative activities. Accordingly, organizations often have to go through a period of trial and error to learn how to gain knowledge from an external source. It requires extensive effort and time to build up an understanding of the norms, habits, and routines of different external knowledge channels. This process of learning to absorb external knowledge is subject to considerable uncertainty in the sense that *ex ante* it is difficult for managers to know which external source will be the most rewarding before engaging in the relationship. Accordingly, in some organizations, past unrewarding experiences may create a myopia toward the potential of using different external sources (Levinthal and March, 1993: 103), and in turn this experience may lead them to turn inward, relying on their own resources and capabilities to develop new products.

Although we hypothesize that external search breadth is associated with innovative performance, we also argue that firms may 'over-search' and that this will have negative consequences for their innovation performance. Given that search strategies are rooted in the past experiences and future expectations of managers, such experience and expectations may lead firms to over-search the external environment with a detrimental outcome as the result. Koput (1997) provides three related reasons why over-searching may have a negative influence on performance. First, there may be too many ideas for the firm to manage and choose between ('the absorptive capacity problem'). Second, many innovative ideas may come at the wrong time and in the wrong place to be fully exploited ('the timing problem'). Third, since there are so many ideas, few of these ideas are taken seriously or given the required level of attention or effort to bring them into implementation ('the attention allocation problem').

As implied by the name, the attention allocation problem is the key element in attention-based theories of the firm (Simon, 1947; Ocasio, 1997). This theory suggests that managerial attention is the most precious resource inside the organization and that the decision to allocate attention to particular activities is a key factor in explaining why some firms are able to both adapt to changes in their external environment and to introduce new products and processes. Central to this approach is to highlight the pool of attention inside the firm and how this attention is allocated. According to the theory, decision-makers need to 'concentrate their energy, effort and mindfulness on a limited number of issues' in order to achieve sustained strategic performance (Ocasio, 1997: 203). Consequently, the theory suggests that a poor allocation of managerial attention can lead to firms engaging in too many (or too few) external and internal communication channels.

Both Koput's model of innovative search and the attention-based theory of the firm suggest that there is a point at which external search breadth becomes disadvantageous. In sum, the hypothesis can be stated as:

Hypothesis 1: External search breadth is curvilinearly (taking an inverted U-shape) related to innovative performance.

Search for new ideas is not just about scanning a wide number of sources; it also involves drawing knowledge heavily from these sources. Innovative firms often draw deeply from a small number of external sources. Key sources for innovators are often lead users, suppliers, or universities (von Hippel, 1988). For each of these sources, firms need to sustain a pattern of interaction over time, building up a shared understanding and common ways of working together. Assessing the depth of a firm's contacts with different external sources provides a mechanism for understanding the way firms search deeply within the innovation system and how these external sources are integrated into internal innovative efforts.

Recall that our concept of external search depth is defined as the extent to which firms draw intensively from different search channels or sources of innovative ideas. Hence, it reflects the importance of deep use of key sources to the internal innovation process. We expect firms that draw deeply from external sources to be more innovative, because they are able to build and sustain virtuous exchanges and collaborations with external actors. However—as in the case of search breadth—we expect to find that some firms can become too deeply reliant on external sources for innovation. Maintaining deep links with external resources requires resources and attention. Therefore, we expect to find that if a firm relies on too many deep relationships with many external sources, it will exhibit lower innovative performance. Accordingly, the hypothesis can be stated as:

Hypothesis 2. External search depth is curvilinearly (taking an inverted U-shape) related to innovative performance.

Novelty of innovation

It is common in studies of innovation to explore the differences in the innovation process for innovations associated with different degrees of novelty (Freeman and Soete, 1997). A variety of empirical studies have shown that the level of novelty of an innovation strongly influences the factors that shape innovative performance (Garcia and Calantone, 2002). Taxonomies of novelty of innovation span from radical and truly revolutionary, such as the microchip, to the incremental, such as changing packaging on existing products (Henderson and Clark, 1990; Freeman and Soete, 1997; Tidd *et al.*, 2000). Radical innovations seem to offer the greatest opportunity for performance differences (Marsili and Salter, 2005). Tushman and Anderson classify radical innovation in terms of 'competence-enhancing' or 'competence-destroying', reflecting the different ways novel innovations alter patterns of industrial competition among firms working within the industry (Tushman and Anderson, 1986; Anderson and Tushman, 1990). To achieve radical innovation, firms often need to make a considerable investment in R&D and the chances of success are lower as the rewards are great. As Schumpeter stated, radical innovation offers 'the carrot of spectacular reward or the stick of destitution' (Schumpeter, 1942/87). In contrast, incremental innovation is more common and the reward is smaller. It requires less effort and its performance implications appear to be more modest (Marsili and Salter, 2005).

To our knowledge little work has been carried out on the relationship between the degree of novelty of the innovation and the breadth and depth of firms' innovative search strategies, let alone firms' external innovative search strategies. Radical innovation may involve a higher degree of discontinuity in the sources of innovation, since knowledge sources previously used may be obsolete in the new context (Abernathy and Utterback, 1975; Christensen, 1997). Accordingly, we expect the use of a few new sources of innovation—used intensively—to be important in the case of radical innovations. Empirical research has shown that in the early phase of the product life-cycle innovations come from a narrow range of sources—in many cases only one—in particular from users, suppliers, and from universities (Rothwell *et al.*, 1974; Urban and von Hippel, 1988; von Hippel, 1988). A recent example of a single source being of utmost importance in the context of radical innovation is biotechnology, where universities are arguably the key source to innovation (Zucker, Darby, and Brewer, 1998). Another example is scientific instruments, where lead users played the key role to the extent that close to 50 percent of the innovations came from such users (Riggs and von Hippel, 1996).

For more incremental innovations, however, after a dominant design has emerged (Abernathy and Utterback, 1975; Utterback, 1994), we expect that a broad variety of sources may be important. After a dominant design has emerged, firms focus on 'fine-tuning' the product by means of incremental improvements which are inspired by many different sources of innovation. As the product matures and the market expands, the number of actors with specific knowledge of various aspects of the technology increases. In these diverse knowledge environments, firms need to be able to work with many different actors in the innovation system (Pavitt, 1998). In other words, radical innovators are likely to draw more deeply from external sources of innovation than firms that are not radical innovators, while incremental innovators are likely to draw more broadly (but less intensively) than non-innovators. These arguments can be stated in the following two hypotheses:

Hypothesis 3: The more radical the innovation, the less effective external search breadth will be in influencing innovative performance.

Hypothesis 4. The more radical the innovation, the more effective external search depth will be in influencing innovative performance.

Openness and absorptive capacity

The Not Invented Here (NIH) syndrome suggests that greater attention to external sources may confront internal resistance from at least some of the company's technical staff. The NIH syndrome can be defined as 'the tendency of a project group of stable composition to believe that it possesses a monopoly of knowledge in its field, which leads it to reject new ideas from outsiders to the detriment of its performance' (Katz and Allen, 1982: 7). Accordingly, the NIH syndrome is a behavioral response that will induce a substitution relationship between the use of external sources and internal R&D activities.[1] In contrast, Cohen and Levinthal (1989, 1990) argue that R&D has two faces: not only does R&D generate genuinely new knowledge; it also enhances the firm's ability to assimilate and exploit existing knowledge from the external environment, both in terms of the firm's ability to imitate new processes or product innovations, and in terms of the firm's ability to exploit knowledge of a more intermediate sort that provides the basis for subsequent applied research and development. Since absorptive capacity and R&D spending are closely linked according to Cohen and Levinthal, we expect—while noting the countervailing NIH syndrome—that firms with high levels of R&D intensity are better able to exploit a host of search channels in terms of breadth and depth. In sum, we hypothesize:

Hypothesis 5. The R&D intensity of the firm is complementary to external search breadth and depth in shaping innovative performance

DATA AND METHODS

Sample

The data for the analysis are drawn from the U.K. innovation survey. The survey was implemented in 2001 and is based on the core Eurostat Community Innovation Survey (CIS) of innovation (Stockdale, 2002; DTI, 2003b). The method and types of questions used in innovation surveys are described in the Organization for Economic Co-operation and Development's (OECD) Olso Manual (OECD, 1997). CIS data have been used in over 60 recent academic articles, mainly in economics (for recent prominent contributions using CIS data; see Cassiman and Veugelers, 2002; Mairesse and Mohnen, 2002). CIS surveys of innovation are often described as 'subject-oriented' because they ask individual firms directly whether they were able to produce an innovation. The interpretability, reliability, and validity of the survey were established by extensive piloting and pre-testing before implementation within different European countries and across firms from a variety of industrial sectors, including services, construction and manufacturing.

The CIS questionnaire draws from a long tradition of research on innovation, including the Yale survey and the SPRU innovation database (for examples, see Levin *et al*., 1987; Pavitt, Robson, and Townsend, 1987, 1989; Cohen and Levinthal, 1990; Klevorick *et al*., 1995). CIS data provide a useful complement to the traditional measures of innovation output, such as patent statistics (Kaiser,

[1] We are grateful to a referee for making this point.

2002; Mairesse and Mohnen, 2002). CIS data offer 'a direct measure of success in commercializing innovations for a broad range of industries ... that more traditional measures may not capture' (Leiponen and Helfat, 2003). The questionnaire asks firms to indicate whether the firm has been able to achieve a product innovation. Product innovation is defined as:

> ... goods and services introduced to the market which are either new or significantly improved with respect to fundamental characteristics. The innovations should be based on the results of new technological developments, new combinations of existing technology or utilization of other knowledge by your firm. (DTI, 2003a)

Firms are then asked to state what share of their sales can be ascribed to different types of innovations, such as innovations new to the world. Alongside these performance questions, there are a number of questions about the sources of knowledge for innovation, the effects of innovation, intellectual property strategies and expenditures on R&D, and other innovative activities.

The U.K. innovation survey is 12 pages long and includes a page of definitions. The sample of respondents was created by the Office of National Statistics (ONS). It was sent to the firm's official representative for filling in information on the firm's activities, such as surveys for calculating the U.K. Gross Domestic Product and R&D expenditures. It was normally completed by the Managing Director, the Chief Financial Officer, or by the R&D manager of the firm. The implementation of the survey was administered by the ONS and to guide respondents a help service was provided (Stockdale, 2002).

The survey was sent to 13,315 business units in the United Kingdom in April 2001 and a supplementary sample of 6287 was posted the survey in November 2001. It received a response rate of 41.7 percent (Stockdale, 2002). The second mail out was designed to top up the number of regional responses to the survey. The responses were voluntary and respondents were promised confidentiality and that the survey would be used to shape government policy. The sample was stratified by 12 Standard Industrial Classification (SIC) classes and includes all main sectors of the U.K. economy, excluding public bodies, retail, and hotels and restaurants. The response rates for different sectors, regions, and size are largely consistent with the overall response pattern (Stockdale, 2002). Our subsample of the survey includes 2707 manufacturing firms and draw from the entire U.K. manufacturing sector.

Descriptive results

Using the U.K. innovation survey, we explore the knowledge sources for innovation in the United Kingdom. Table 1 lists all 16 external sources listed in the U.K. survey. Each firm was asked to indicate on a 0-1-2-3 scale the degree of use for each source. On the survey, the sources are grouped together under four different headings (market, institutional, other, and specialized). Table 1 presents the results for the entire range of sources for U.K. manufacturing firms. Overall, the results indicate that the most important source is suppliers of equipment, materials, and components, followed closely by clients and customers (or 'users'). Alongside customers and suppliers, a range of standards, such as health and safety standards, are among key sources of innovation. As might be expected (see von Hippel, 1988), the results indicate that U.K. firms' innovation activities are strongly determined by relations between themselves and their suppliers and customers.

In Table 2, we examine the level of external search breadth and depth across industrial sectors. We also examine the level of R&D intensity and percentage of radical innovators in each industry. Overall, we find that firms cite seven external sources of knowledge for innovation. Chemicals, electrical and machinery industries exhibit the highest level of external search breath, indicating that firms in industries with medium to high levels of scientific and technological activity search widely. In contrast, firms in low-technology sectors, such as paper and printing, have the lowest levels of external search breadth.

External search depth is by definition less common. On average, firms draw deeply from only one source. Search depth is greatest in the machinery, chemicals, and transport industries. Firms in textiles and wood product industries have little external search depth. Both the level of external search breadth and depth are highest in industries with high levels of R&D intensity and rates of innovation. For example, the chemical and electrical industries exhibit the highest rates of openness, the greatest percentage of radical innovators, and

Table 1. Sources of information and knowledge for innovation activities in U.K. manufacturing firms, year 2000 ($n = 2707$)

Type	Knowledge source	Percentages			
		Not used	Low	Medium	High
Market	Suppliers of equipment, materials, components, or software	32	20	32	15
	Clients or customers	34	22	28	16
	Competitors	46	27	20	6
	Consultants	62	22	13	3
	Commercial laboratories/R&D enterprises	73	18	7	2
Institutional	Universities or other higher education institutes	73	17	8	2
	Government research organizations	82	14	3	1
	Other public sector, e.g., business links, government offices	76	17	6	1
	Private research institutes	82	14	4	1
Other	Professional conferences, meetings	58	27	12	2
	Trade associations	52	28	17	3
	Technical/trade press, computer databases	47	27	22	4
	Fairs, exhibitions	42	28	23	7
Specialized	Technical standards	43	23	23	11
	Health and safety standards and regulations	37	24	27	12
	Environmental standards and regulations	39	26	24	11
Average		55	22	17	6

Table 2. Breadth and depth by industry

	No. of firms	Percentage of firms that introduced a product new to the world	Average R&D intensity	Breadth mean	Depth mean
Food, drink and tobacco	212	12.26	0.13	7.23	0.84
Textiles	157	13.38	0.10	6.12	0.59
Wood	156	11.54	0.10	6.37	0.75
Paper and printing	249	11.25	0.47	5.87	0.94
Chemicals	114	33.33	2.95	9.95	1.23
Plastics	135	21.48	0.63	6.84	1.09
Non-metallic minerals	71	15.49	0.21	6.17	0.96
Basic metals	54	7.41	0.15	7.98	1.07
Fabric. metal products	293	9.90	0.12	5.70	0.72
Machinery	210	21.90	0.68	8.59	1.27
Electrical	444	23.65	1.40	8.86	1.15
Transport	279	15.05	0.36	7.51	1.18
Other	333	11.11	0.33	6.52	0.77
Average		15.98	0.59	7.21	0.97

the largest R&D intensity among all manufacturing industries. However, there is no simple one-to-one relationship between innovativeness and openness at the industry level. This is reflected in the fact that some industries, such as basic metals, exhibit low rates of innovation, and broad and deep search patterns. One explanation for the difference between patterns of search and innovativeness across industries may be related to the complexity of technological knowledge bases in different industries. In industries where there are simple technologies but high levels of innovation, patterns of innovative search may be narrower than in industries where there are complex technologies but low rates of innovation. Accordingly, more research on the sources and determinants of external search at the firm and industry level will be required in the future to better understand the complex relationship among innovativeness, search, and R&D intensity.

Measures

Dependent variable

We use three proxies aimed at reflecting various types of innovative performance by firms. First, we use a variable aimed at indicating the ability of the firm to produce radical innovations. This variable is measured as the fraction of the firm's turnover relating to products new to the world market (INNWORLD). In addition, we add two variables as proxies for incremental innovation. First, we include a variable expressing the fraction of the firm's turnover pertaining to products new to the firm (INNFIRM) and another variable expressing the fraction of the firm's turnover pertaining to products significantly improved (INNIMP). The two latter variables are mutually exclusive since they—together with unchanged or only marginally modified products—add up to 100%.

Independent variables

As determinants of innovative performance, we introduce two new variables reflecting openness in terms of external search strategies of firms.[2] The first new variable is termed BREADTH and is constructed as a combination of the 16 sources of knowledge or information for innovation listed in Table 1 of this paper. As a starting point, each of the 16 sources are coded as a binary variable, 0 being no use and 1 being use of the given knowledge source. Subsequently, the 16 sources are simply added up so that each firm gets a 0 when no knowledge sources are used, while the firm gets the value of 16, when all knowledge sources are used. In other words, it is assumed that firms that use higher numbers of sources are more 'open', with respect to search breadth, than firms that are not. Although our variable is a relatively simple construct, it has a high degree of internal consistency (Cronbach's alpha coefficient = 0.93).

External search depth is defined as the extent to which firms draw intensively from different search channels or sources of innovative ideas. Accordingly, the second variable is named DEPTH and is constructed using the same 16 sources of knowledge as those used in constructing BREADTH. In this case each of the 16 sources are coded with 1 when the firm in question reports that it uses the source to a high degree and 0 in the case of no, low, or medium use of the given source. As in the case of BREADTH, the 16 sources are subsequently added up so that each firm gets a score of 0 when no knowledge sources are used to a high degree, while the firm gets the value of 16 when all knowledge sources are used to a high degree (Cronbach's alpha coefficient = 0.76). Again, it is assumed that firms that use higher numbers of sources are more 'open' with respect to search depth than firms that are not.

As a test of the robustness of the results for the measure of external search depth, we calculate an alternative measure (DEPTH_COLLAB) by looking at whether or not the firm in question has formal innovation collaboration links with different external sources. This variable is based on a subsequent question on the U.K. innovation survey. The survey lists eight different external partners, including: (1) suppliers, (2) clients or customers, (3) competitors, (4) consultants, (5) commercial laboratories/R&D enterprises, (6) universities or other higher education institutes, (7) government research organizations, or (8) private research institutes. As in the case of BREADTH and DEPTH, the eight dummies are subsequently added up so that each firm gets a score of 0 when no partners are used, while the firm gets a value of 8 when the firm is collaborating with all potential collaboration partners (Cronbach's alpha coefficient = 0.83).

Although the list of sources on the questionnaire is not fully comprehensive, it is extensive and the items are not mutually exclusive. It reflects a wide range of sources of innovation, including suppliers, clients, and competitors as well as general institutions operating inside the innovation system, such as regulations and standards. The sources listed in the survey overlap with the resources and institutions that are considered part of the national innovation system (Lundvall, 1992; Nelson, 1993; Spencer, 2001). Although the introduction of any variable into a well-established area of research is always contentious, the introduction of the two new variables to reflect the openness of innovative search does enable researchers to better explore the link between innovative search and innovative performance.

[2] However, a very similar variable to that of the variable measuring search breadth has been used by Laursen and Salter (2003) as a predictor of the propensity of firms to use knowledge developed at universities. Also Leiponen and Helfat (2003) use a similar search breadth variable.

Control variables

We include a measure of R&D intensity (RDINT), measured as firm R&D expenditure divided by firm sales, in order both to control the effect on R&D on innovative performance and in order to test Hypothesis 5. The numerator is taken from the U.K. innovation survey, while the denominator firm turnover or sales is based on Office of National Statistics register data, supplied with the survey data.

Given that many studies of innovation have found that a key source for innovations are lead users, we include a variable reflecting the use of lead users in innovation (Rothwell *et al.*, 1974; Urban and von Hippel, 1988; von Hippel, 1988). The variable (USER) is constructed based on the 'clients or customers' source of knowledge for innovation listed in Table 1. Simply the variable takes the value of 1 when the firm indicates that it uses clients or customers to a high degree as sources of information and knowledge for innovation activities, and 0 otherwise. Moreover, we include firm size and whether or not the firm was a recent start-up. Firm size (expressed in logarithms) is measured by the number of employees (LOGEMP). Whether or not the firm was a start-up in the period 1998–2000 (STARTUP) is based on a question on the survey concerning whether or not the firm was established during that period. In addition, we control for the size of the perceived product market (GEOMARKET). The variable measures whether the largest market of the firm is perceived to be local, regional, national, or international. This variable takes the values from 1 to 4, with 1 corresponding to 'local' and 4 corresponding to 'international'. Furthermore—and using a binary variable—we control for whether or not firms engaged in collaboration arrangements on innovation activities (COLLAB), a supplementary question on the survey. Finally, we include 13 industry controls to account for different propensities to innovate across industries.

Statistical method and results

The dependent variable in the regression model is (double) censored, since the variable is the percentage of innovative sales and therefore by definition ranges between 0 and 100. Accordingly, a Tobit analysis is applied (see Greene, 2000: 905–926). However, the assumption of normality of residuals in the standard Tobit model is not satisfied in our case. Under these conditions, the maximum likelihood estimators of the standard Tobit model are not consistent. Alternative specifications of the Tobit model have been formulated that account for departures of the distributions from normality (see Greene, 2000: 916). The variables reflecting the innovative performance of firms are highly skewed and, accordingly, the pattern observed in the empirical distribution is better represented by lognormal distributions. Other studies, facing similar problems in terms of similar characteristics of skewness and departure from normality, have proposed a log-transformation of the Tobit model with a multiplicative exponential error term (Filippucci, Drudi, and Papalia, 1996; Papalia and Di Iorio, 2001). We apply this approach to the study of innovative performance and assume a lognormal distribution for the residuals of the Tobit model.[3] This model introduces a latent variable, INN^*, as a logarithmic transformation of an observed measure of innovative performance, INN: that is, $INN^* = \ln(1 + INN)$. It is then assumed that the latent variable of innovative performance of a firm i is a function of a number of explicative variables.

Descriptive statistics are given in Table 3. From the table it can be seen that on, average, 2.81 percent of firms' turnover can be attributed to products new to the world (INNWORLD), while 4.94 percent of firms' turnover pertain to innovations new to the firm (INNFIRM). 4.72 percent can be attributed to turnover in significantly improved products (INNIMP). Moreover, on average, firms use about seven sources of knowledge for their innovative activities, but they use only about one source deeply. Simple correlations between our explanatory variables can be found in the Appendix.

The results of the Tobit regression analysis can be found in Table 4. We find strong support for the hypothesis asserting that external search breadth is curvilinearly—taking an inverted U-shape—related to innovative performance (Hypothesis 1). First, the parameter for external BREADTH is significant and positive for all degrees of novelty of innovation (INNWORLD,

[3] However, it should be noted that the lognormal transformation neither changes the signs nor the significance of parameters for the key variables in the subsequent estimations. Nor does the transformation change the relative sizes of the parameters for the search variables.

Table 3. Descriptive statistics

	No. of firms	Mean	S.D.	Minimum	Maximum
INNWORLD	2707	2.81	11.43	0	100
INNFIRM	2687	4.94	13.97	0	100
INNIMP	2687	4.72	12.95	0	100
BREADTH	2707	7.22	5.30	0	16
DEPTH	2707	0.96	1.68	0	16
DEPTH_COLLAB	2707	0.38	1.14	0	8
RDINT	2707	0.60	3.82	0	90.6
USER	2707	0.16	0.37	0	1
LOGEMP	2707	4.14	1.42	0	9.0
STARTUP	2707	0.06	0.24	0	1
GEOMARKET	2707	2.78	0.90	1	4
COLLAB	2707	0.16	0.37	0	1

Table 4. Tobit regression, explaining innovative performance across UK manufacturing firms

Model	I		II		III	
Dependent variables	INNWORLD		INNFIRM		INNIMP	
Independent variables	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
BREADTH	0.549***	0.091	0.617***	0.063	0.795***	0.086
BREADTH2	−0.024***	0.005	−0.027***	0.004	−0.033***	0.005
DEPTH	0.370**	0.167	0.203*	0.112	−0.029	0.136
DEPTH2	−0.057**	0.023	−0.031**	0.015	−0.015	0.018
RDINT	0.072***	0.023	0.069***	0.018	0.037***	0.022
USER	0.714**	0.332	0.275	0.236	0.912***	0.291
LOGEMP	0.026	0.093	0.117*	0.065	0.196**	0.081
STARTUP	−0.022	0.518	0.333	0.349	−1.656***	0.519
STARTUP × RDINT	22.497	14.561	15.419	11.537	0.263	7.659
GEOMARKET	0.739***	0.166	0.546***	0.111	0.621***	0.140
COLLAB	1.677***	0.287	1.456***	0.202	1.565***	0.248
Industry dummies	Yes		Yes		Yes	
No. of obs	2707		2687		2687	
No. of left-censored obs	2307		1986		2123	
No. of right-censored obs	16		21		6	
Log likelihood	−1681.2		−2487.3		−2186.2	
Chi-square	324.4***		595.5***		533.5***	
Pseudo R^2	0.09		0.11		0.11	

One-tailed t-test applied. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

INNFIRM, INNIMP), showing that the breadth of openness of firms' innovative search is an important factor in explaining innovative performance. Second, the parameter for BREADTH squared is significant as well, showing that when firms use too many sources in their search for innovation there are decreasing returns. From Figure 1 it can be seen that, in the case of innovations new to the world (INNWORLD), the point where search appears to have negative consequences for performance—what could be called the 'tipping point'—is at 11 sources, so that if firms use more than 11 sources of external knowledge for their innovative activities negative returns set in. However, although the model *predicts* negative returns, we can only conclude that there are decreasing returns from a negative and significant squared term, since the downward bend of the curve may not be statistically significant. In order to investigate this issue, we estimate a model where we replace BREADTH with a set of dummies, where the benchmark dummy is one, when BREADTH

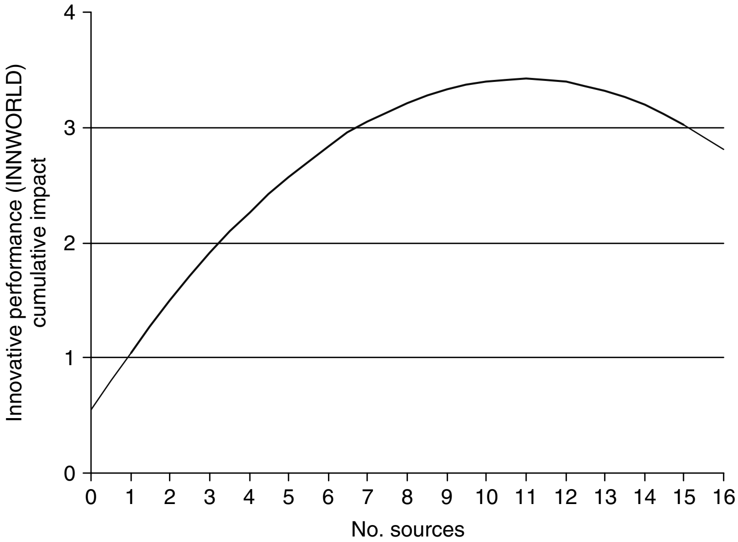

Figure 1. Predicted relationship between innovative performance and the breadth of search through external sources of innovation

takes the values of 9–14 (i.e., a range around the 'tipping point'); 0 otherwise.[4] In a similar fashion, we create dummies for the ranges of 0 sources; 1–4 sources; 5–8 sources; and for 9–16 sources. The results of this exercise are reported in Table 5, Model IV (for reasons of space, the results are reported for INNWORLD only). The results show that the dummies below the benchmark all have a negative sign—as expected—but only the dummy for the value of 0 is significant. The dummy above the benchmark is positive but insignificant. Further experimentation with dummies reveals that if a dummy for the value of 16 sources is created separately (not shown for reasons of space), such a dummy gets a negative sign, but it is not significantly different from the benchmark at a conventional level of significance. The results indicate that while there are decreasing returns in innovation for increased openness in terms of breadth, no negative returns are to be detected.

We find rather strong support for the hypothesis that external search depth—the extent to which firms draw intensively from different sources of innovative ideas—is curvilinearly (taking an inverted U-shape) related to innovative performance (Hypothesis 2), since the variable measuring the DEPTH of openness and the squared term are both significant and have the expected signs for INNWORLD and INNFIRM. However, for INNIMP the parameters are not significant. From Figure 2 it can be seen that in the case of INNWORLD the 'tipping point' is three sources, so that if firms use more than three sources of external knowledge deeply in their innovative activities, decreasing returns are likely to set in. As in the case of BREATH, we cannot be sure that there are statistically significant negative returns, although such returns are predicted by our model. In order to test for negative returns, we again use the dummy variable approach. In the case of DEPTH, we create a benchmark for the values 2–4 sources. The two dummies created for values below the benchmark are for 0 and for 1 source respectively, while the dummies above the benchmark are for 5–8 sources and for 9–16 sources. The results of this analysis are also reported in Table 5, Model IV. The results show that below the benchmark the dummy for 0 sources is negative and significant. The dummies above the benchmark are both negative, but only the dummy for the value of 9–16 sources is significant at the 10 percent level. Accordingly, the results indicate that while there are decreasing returns in innovation for increased openness in terms of external search depth, there are negative returns for 9–16 sources only.

The results using the alternative measure of external search depth DEPTH_COLLAB can be found in Table 5, Model V. As in the

[4] We are grateful to Bronwyn Hall for the suggestion of this econometric approach.

Table 5. Tobit regression, explaining innovative performance (INNWORD) across U.K. manufacturing firms ($n = 2707$)

Model	IV		V		VI		VII	
Independent variables	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
BREADTH			0.591***	0.090	0.386***	0.106	0.536***	0.091
BREADTH2			−0.027***	0.005	−0.016***	0.006	−0.023***	0.005
DEPTH							0.366**	0.166
DEPTH2							−0.052**	0.023
DEPTH_COLLAB			0.878***	0.224				
DEPTH_COLLAB2			−0.072*	0.039				
DEPTH_B (th = 2)					0.392***	0.125		
DEPTH_B2 (th = 2)					−0.030***	0.009		
DUM BREADTH, 0 sources	−3.789***	0.602						
DUM BREADTH, 1–4 sources	−0.604	0.402						
DUM BREADTH, 5–8 sources	−0.088	0.304						
DUM BREADTH, 9–14 sources	Benchmark							
DUM BREADTH, 15–16 sources	0.166	0.347						
DUM DEPTH, 0 sources	−0.699*	0.345						
DUM DEPTH, 1 sources	0.204	0.352						
DUM DEPTH, 2–4 sources	Benchmark							
DUM DEPTH, 5–8 sources	−0.385	0.517						
DUM DEPTH, 9–16 sources	−3.394*	2.054						
RDINT	0.069***	0.024	0.067***	0.023	0.068***	0.023	0.299***	0.098
BREADTH × RDINT							−0.016**	0.008
DEPTH × RDINT							−0.015**	0.009
USER	0.534	0.336	0.873***	0.287	0.812***	0.295	0.717**	0.330
LOGEMP	0.047	0.092	0.022	0.093	0.019	0.093	0.066	0.093
STARTUP	0.060	0.518	0.088	0.515	−0.035	0.519	0.042	0.515
STARTUP × RDINT	21.384	13.704	20.600	13.817	25.607*	14.999	15.310	15.132
GEOMARKET	0.722***	0.165	0.735***	0.166	0.739***	0.166	0.728***	0.165
COLLAB	1.669***	0.283			1.682***	0.286	1.671***	0.285
Industry dummies	Yes		Yes		Yes		Yes	
Log likelihood	−1669.9		−1684.2		−1678.8		−1675.4	
Chi-square	347.1***		318.4***		329.4***		336.0***	
Pseudo R^2	0.09		0.09		0.09		0.09	

One-tailed t-test applied. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

case of the DEPTH variable, we detect a curvilinear relationship with INNWORLD, since the DEPTH_COLLAB variable and the squared term are both significant and have the expected signs. Consequently, this additional analysis gives further support to Hypothesis 2. As an additional robustness check, we examine whether recoding DEPTH, so that it does not only include the importance of a given source being 'high,' but also being 'medium,' will affect the results. In Table 5, Model VI, we find that the results are indeed robust to such a change in specification. Again we find a positive impact, but with decreasing returns.

With respect to our hypothesis stating that the more radical the innovation, the less effective external search breadth will be on innovative performance (Hypothesis 3), we do find some evidence for the hypothesis from Table 4, Models I–III. In particular, the parameter for BREADTH in the case of INNWORLD is the smallest; INNFIRM is higher; and the parameter for INNIMP is the highest. In other words, while the parameter for BREADTH is significant and positive for all degrees of novelty of innovation, the parameter is smaller the more radical the level of innovation.

However, we need to find out whether or not the observed differences in parameter sizes are significantly different. As a starting point, one would like to use an incremental F-test—utilizing the information in the constrained and unconstrained sum of squares—or a Wald test, utilizing the estimated coefficients and the variances/covariances of the estimates from the unconstrained model. The conventional tests are, however, devised to

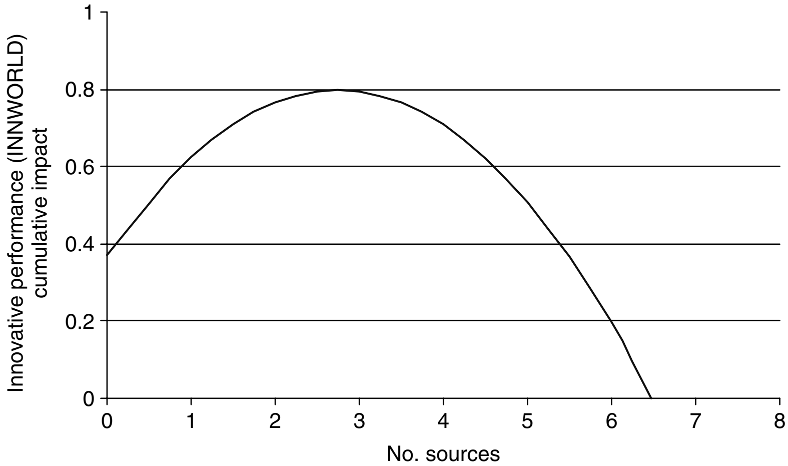

Figure 2. Predicted relationship between innovative performance and the depth of search through external sources of innovation

compare the sizes of parameters within the same regression model. Yet, in this case, we have coefficients for the same independent variables, but we have different dependent variables—and hence three separate regression models. Accordingly, we cannot use a conventional incremental F-test or a Wald test. We solved this potential problem by estimating three models where the dependent variables are the difference between the initial dependent variables (not shown for reasons of space). The outcome of this exercise shows that the size of the parameter in Model I (where the dependent variable is INNWORLD) for BREADTH is significantly smaller than the parameter in Model III (where the dependent variable is INNIMP) at the 1 percent level and that the parameter in Model I is significantly smaller than the parameter in Model II. Although the parameter in Model II is not significantly smaller than the parameter estimated in Model III, it can be concluded overall that the findings are largely consistent with Hypothesis 3 of this paper.

The hypothesis affirming that the more radical the innovation the more effective external search depth will be in shaping innovative performance (Hypothesis 4) finds support as well. The parameter for DEPTH of openness is the highest in the case of INNWORLD, while INNFIRM is lower and the parameter for INNIMP is the smallest to the extent that it is insignificant. Again we examine whether the parameters in the three models are significantly different. The results show that in the case of INNWORLD (Model I) the parameter for DEPTH is significantly larger than for INNIMP (Model III) at the 5 percent level. The parameter for DEPTH in Model II is larger than the corresponding parameter in Model III (5 per cent level), but the parameter in Model I is not significantly larger than the parameter in Model II. Nevertheless, it can be concluded that, overall, the findings are generally consistent with Hypothesis 4.

We do not find support for the hypothesis suggesting that the R&D intensity of the firm is complementary to external search breadth and depth in shaping innovative performance (Hypothesis 5). In fact, from Model VII in Table 5, it can be seen that the interaction effects between R&D intensity and both BREADTH and DEPTH are significant at the 5 percent level, but they have negative signs, indicating a substitution effect between internal R&D and openness. The finding is the same when INNFIRM and INNIMP are included as dependent variables (the results of these estimations are not displayed for reasons of space). One likely interpretation of this result is that it is the product of the NIH syndrome—that greater attention to openness for external sources confronts internal resistance from some of the company's technical staff. Moreover, it may also be the result of an additional attention allocation problem, since ideas are produced both internally and externally.

Of our control variables, the parameters for R&D intensity (RDINT), the scope of the market (GEOMARKET), and collaboration in innovative activities (COLLAB) are consistently positive and significant in explaining the proportion of sales due to novel products no matter the degree of novelty of the product. The parameters for lead users (USER) are significant for radical and well as for incremental innovation, but not for the intermediate category (INNFIRM). The size of the firm only seems to matter for the two incremental types of innovation (INNFIRM and INNIMP), with larger firms having greater sales of new products as compared to smaller firms. For radical innovation, the size of the firm appears to have no bearing on its innovative performance. This finding is consistent with the findings from previous studies (see Cohen, 1995; Laursen and Foss, 2003). Whether or not the firm is a start-up has no positive influence on innovative performance, no matter whether or not this is conditional on the R&D intensity of the firm.

DISCUSSION AND CONCLUSIONS

Firms are increasingly drawing in knowledge from external sources in their innovative activities. Modern innovation processes require firms to master highly specific knowledge about different users, technologies, and markets. To deepen our understanding about how firms draw knowledge from external sources, the present study examined the role of external search strategies in shaping innovative performance. In order to do so, we sought to extend conceptual understanding of innovative search processes. In particular, we introduced two new concepts—*external search breadth* and *external search depth*—to describe the character of a firm's strategies for accessing knowledge from sources outside of the firm. We have argued that firms who are more open to external sources or search channels are more likely to have a higher level of innovative performance. Openness to external sources allows firms to draw in ideas from outsiders to deepen the pool of technological opportunities available to them. As Chesbrough suggests, firms that are too internally focused may miss opportunities, as many knowledge sources necessary to achieve innovation can only be found outside the firm. The lack of openness of firms to their external environment may reflect an organizational myopia, indicating that managers may overemphasize internal sources and under emphasize external sources. Indeed, the results strongly suggest that searching widely and deeply across a variety of search channels can provide ideas and resources that help firms gain and exploit innovative opportunities.

Innovation search is, however, not costless. It can be time consuming, expensive, and laborious. Although we use a different approach, we confirm Katila and Ahuja's finding that 'over-search' may indeed hinder innovation performance. It appears that there are moments or tipping points after which openness—in terms of breadth and depth—can negatively affect innovative performance. The possibility of over-search helps to create a more nuanced view of the role of openness, search, and interaction. The optimistic view of search ascribed great importance to openness of firms to external sources in the development of new innovative opportunities. Our research supports this view, but it suggests that the enthusiasm for openness needs to be tempered by an understanding of the costs of such search efforts. It suggests external sources need to be managed carefully so that search efforts are not dissipated across too many search channels.

To gain further insight into the role of external search on innovative performance, we examined the importance of external search breadth and depth for different types of innovation. We found that external search depth is associated with radical innovation. In early stages of the product life cycle when the state of technology is in flux, innovative firms need to draw deeply from a small number of key sources of innovation, such as lead users, component suppliers, or universities. In these early stages, only a few actors may have knowledge of the key technologies underlying the evolution of the product. Innovators need to cling to these sources, drawing deeply from their knowledge and experience. As the technology and market mature and the network supporting innovation expands, more and more actors inside the innovation system retain specialist knowledge. In order to access the variety of knowledge sources in these networks, innovative firms need to scan across a wide number of search channels. In doing so, they seek to find new combinations of existing technologies to enable them to make significant improvements in their existing products.

To examine the relationship between the openness to external search activities and internal R&D, we interacted the measures of openness with R&D intensity. Our results indicate the existence of a substitution effect between the two activities. Accordingly, we have provided empirical content to the often cited, but seldom-quantified, NIH syndrome (however, see Chesbrough and Tucci, 2004, in a different context).

Limitations and future research

The analysis of large-scale databases (such as the U.K. innovation survey) poses many questions that cannot be investigated without more direct observational research methods. As Katila suggests, much greater knowledge is needed about how firms organize their search for external ideas for innovation. Most of the literature on search is based on indirect data and infers relationships from data and existing theoretical models. Yet the empirical base underlying these models is relatively slight and it would be extremely useful to develop a number of studies of how different organizations organize their search processes. In-depth case studies and observational research may allow for a more full description of how firms become trapped in the position of under- or over-search. New strategies for drawing in external knowledge, such as Proctor & Gamble's connect and develop, appear to provide promising approaches for enhancing innovative performance.

As pointed out earlier in this paper, a limitation of the framework proposed here is that it does not allow for the analysis of the importance of breadth and depth of external search to innovative performance within each individual knowledge channel. Future research should examine this issue by developing several fine-grained items for each of the knowledge sources. A further limitation of the present paper has to do with the fact that we have focused on the distinction between incremental and radical innovations only. For this reason, it remains unclear how the complexity of an innovation shapes the way firms search for new innovation opportunities. Past research suggests that firms producing simple or discrete technologies that are artefactually simple, that is, they involve relatively few components and clear interfaces between modules, or that rely on a small number of knowledge bases, will tend to search more narrowly than firms involved in the design and development of complex technologies (Nelson and Winter, 1982). Complex technologies, such as aeroengines, often require firms to master a wide number of different knowledge bases and to understand the interfaces and integration of a range of different components (Brusoni, Prencipe, and Pavitt, 2001). Also, the literature on architectural innovation suggests that changes in the integration and interfaces between modules may require firms to change their search strategies given that their past search activities are ill suited to understanding the new product architecture (Henderson and Clark, 1990). Future research on the relationship between innovative search and complexity could yield a new understanding of the cognitive and managerial challenges of organizational responses to significant technological change.

Another future research challenge is to understand changes in innovative search over time. Our approach focuses on innovative search and performance in one period and this remains a severe limitation of the study. However, with future innovation surveys, it will be possible to examine whether the search behavior of innovative firms has changed over time as suggested by Chesbrough. It may be too early to determine whether 'open innovation' represents a new model of the innovation process or whether it simply reflects a transitional strategy by a small number of relatively large U.S.-based firms. Indeed, it would be interesting to explore whether changes in the technology base of industries are reflected by changes in the search patterns of individual firms. It is possible to imagine that firms who are able to alter their search strategies to respond to major changes will exhibit better performance than firms who maintain the same search strategy over the same period. It may be that the ability of the firm to reconfigure its search strategies over time as a result of changes in the external environment is the key managerial challenge faced by 'open innovators.' Until greater research is undertaken on the nature of search over time, the full implications of the movement towards 'open innovation' will not be fully understood.

While the present study examined different external search strategies for innovative ideas across different knowledge sources, it did not investigate the role of the type and nature of the technological trajectory that a firm may be exploring (as in the case of Katila and Ahuja) and how its approach to this trajectory may influence its innovative performance. Future studies should relate external search across knowledge sources to internal technological search within different technological trajectories. In this context, Fleming and Sorenson's (2001) attempt to classify patent citations by different sources—such as academic papers—may be a profitable starting point. Such research may allow for the integration of research on the external search strategies among different knowledge sources and search within different technological trajectories.

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APPENDIX: SIMPLE CORRELATIONS AMONG THE INDEPENDENT VARIABLES ($N = 2707$)

		1.	2.	3.	4.	5.	6.	7.	8.
1.	BREADTH								
	p-value								
2.	DEPTH	0.417							
	p-value	*0.000*							
3.	DEPTH_COLLAB	0.294	0.200						
	p-value	*0.000*	*0.000*						
4.	RDINT	0.101	0.099	0.119					
	p-value	*0.000*	*0.000*	*0.000*					
5.	USER	0.294	0.549	0.183	0.063				
	p-value	*0.000*	*0.000*	*0.000*	*0.001*				
6.	LOGEMP	0.358	0.132	0.182	0.056	0.085			
	p-value	*0.000*	*0.000*	*0.000*	*0.004*	*0.000*			
7.	STARTUP	−0.029	−0.012	−0.017	0.007	0.031	−0.077		
	p-value	*0.133*	*0.550*	*0.381*	*0.704*	*0.108*	*0.000*		
8.	GEOMARKET	0.260	0.091	0.162	0.133	0.112	0.349	−0.018	
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.358*	
9.	COLLAB	0.303	0.183	0.773	0.110	0.194	0.215	−0.014	0.192
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.474*	*0.000*