VARIETY OF SEARCH AND INNOVATION: A COMPARATIVE STUDY OF US MANUFACTURING AND KNOWLEDGE INTENSIVE BUSINESS SERVICES SECTORS

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Abstract

Whilst the variety of search activities promotes innovation, there is a central tension between a firm's potential benefits from wide and diverse search activities and its ability to reap these potential benefits. In this paper, we argue that the potential and realised benefits from a firm' search activities are influenced not only by its resources and capabilities, but also by the nature of innovation activities at sector level. Drawing upon a statistical analysis of a large scale survey conducted in the US, we examine the impact of a firm's external search strategy along two dimensions (search intensity and direction) on its innovative performance. Our findings suggest that manufacturing firms tend to benefit from wide and diversified search activities whereas knowledge intensive business services (KIBS) firms tend to benefit from narrow and specialised search activities. Furthermore, when taking account of firm size and absorptive capacity, a more nuanced picture emerges. Implications and contributions to the innovation search literature are discussed.

JEL Codes: L25, O14, O32

Keywords: variety of search, open innovation, SME, manufacturing, Knowledge intensive business services, US survey

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1. Introduction

Outside sources of knowledge often accelerate innovation (von Hippel, 1988; Powell et al., 1996; Chesbrough, 2003); and hence firms' external search strategies have become important in explaining the heterogeneity in their innovative performance. While scholars seem to agree that the variety of search activities promotes innovation (Nelson & Winter, 1982; March, 1991), there is a central tension between a firm's potential benefits from wide and diverse search activities and its ability to reap these potential benefits. Indeed, research has shown that 'over-search' has a negative impact on a firm's innovation (Katila & Ahuja, 2002; Laursen & Salter, 2006).

The key proposition of this paper is that, although firm's internal resources and capabilities play a key role in turning external search activities into realised innovation (Cohen & Levinthal, 1990), the potential and realised benefits from a firm's external search activities are also influenced by the nature of innovation activities at sector level. For instance, a car manufacturer needs to search for new ideas across technological and non-technological information and knowledge sources including technology and science-driven R&D centres, suppliers, customers, regulatory bodies and others. This is because whilst technological advances play a key role in car manufacturer's product innovation (e.g. electronic car), market and regulatory knowledge are also important for innovations such as new ways of distributing and selling cars (e.g. car loan and rental share scheme), and appropriating from technological leadership (e.g. winning the standards wars). Whereas, for a law firm a service innovation, which tends to occur in the form of incremental changes adapting to individual client needs such as providing corporate law advices to a new client, often requires searching for demand-side or market knowledge. This is because not only services are often intangible and involve high levels of interaction between service providers and clients from idea generation to implementation, but also technology tends to have 'hidden' or indirect impacts on innovation, such as the means to increase operational efficiencies. This suggests that, while there may be great variations in innovation activities within manufacturing and services sectors (Hughes & Wood, 1999), there are some general 'particularities' between the two sectors (Miles, 2005; Tether, 2005). And we argue that these general 'particularities' affect the potential and realised benefits from the variety of search activities, and hence innovation. However, the extant search literature favours manufacturing sectors. As a result, we know very little about how search activities impact on firms' innovative performance in service sectors despite the growing importance of service sectors in our economy (Miles, 2005).

Over the last five decades, most industrialised countries have become primarily service-based economies. As early as the 1970s, services constituted more than half of the value added in EU countries and by the new century they contributed over two-thirds (Miles, 2005). In the US, in 2000, 75% of the US labour forces was employed in services (Drejer, 2004); and the largest contributors to productivity growth since 2000 have been services sectors (Baily et al., 2006). In the UK, more than 75% of the economy is now based on services sectors (Abreu et al., 2008). Research has shown that, not only have services firms accounted for a significant proportion of GDP and productivity growth, but also they have become major innovators in industrial world, although some of this may be 'hidden' (Tether et al, 2001; Miles, 2005). However, this growing importance of service sectors is not matched by systematic research on the topic. In this paper, we aim to contribute to our understanding of the differing nature and management of innovation activities in manufacturing and services sectors. In particular, we focus on manufacturing and knowledge intensive business services (KIBS), exploring the following two questions.

RQ1: How does the impact of firm' search activities on its innovative performance differ in manufacturing and knowledge intensive business services (KIBS) sectors?

RQ2: How does firm's internal resources and capabilities mediate this relationship in both sectors?

In this paper, drawing upon a statistical analysis of a large scale survey conducted in the US manufacturing and business services sectors in 2004 (through a collaboration between Cambridge University in the UK and MIT in the US), we examine the impact of a firm's external search strategy along two dimensions (search intensity and direction) on its innovative performance. Consistent with previous studies, we find search intensity as measured by search breadth is beneficial to innovation although 'over-search' has negative impact on performance in both sectors. More interestingly, we show that US manufacturing firms tend to benefit from wide and diversified search activities whereas KIBS firms tend to benefit from narrow and specialised search activities. Furthermore, we show that when taking account of firm size, a more nuanced picture emerges.

Our research contributes to the search literature by emphasising that potential and realised benefits of firm's variety of search activities are shaped by both sectoral and firm level factors. Our research also contributes to the growing literature on innovation in services. Furthermore, it contributes to the innovation search literature by adding the US experience, as most studies in this stream utilise the Community Innovation Survey data in the UK and other European countries. The paper is structured as follows. We first review the literature on the relationship between firm search strategy and innovative performance; we then develop hypothesis with regard to how the relationship may be affected by sectoral differences as well as firm's resource base. We describe our data and method followed by our empirical findings. We discuss the implications and contributions to theory and practice.

2. Theoretical Background and Hypothesis

Potential and Realised Benefits from the Variety of Search

An innovation can be seen as a new combination of previously, or newly, available knowledge with a commercial application (Schumpeter, 1934; Nelson & Winter, 1982; Kogut & Zander, 1992). Hence, to achieve successful innovation, including product, process and organizational innovation, a firm's search for knowledge inputs from both technological and non-technological domains is critical. Search can be conceptualised as problem solving and learning activities in organizations (March & Simon, 1958; Cyert & March, 1963); Nelson and Winter, 1982). More specifically, a firm's search activity entails that 'an organization draws from a pool of alternative routines, adopting better ones when they are discovered…And the rate of discovery is a function of both the richness of the pool and of the intensity and direction of search' (Levitt and March, 1988: 321).

Whilst literature has suggested that the variety of knowledge inputs enriches the pool of opportunities and hence promotes innovation, there is a central tension between a firm's potential benefits from wide and diverse search activities and its ability to reap these potential benefits. On the one hand, scholars have suggested that firm's search behaviour tends to be 'locally' bounded in the neighbourhood of firm's current knowledge base, due to path-dependence in organizational learning as well as increasing knowledge integration cost (Nelson et al., 1982; Helfat, 1994; Stuart & Podolny, 1996). On the other hand, scholars have noted that excessively local search may decrease productivity because cognitive frameworks and opportunity becomes stale and exhausted, the so-called 'myopia of learning' (March, 1991; Levinthal & March, 1993; Fleming, 2001). Therefore, to achieve continuous innovations, firms also need to search further afield and make 'a conscious effort to move away from current organizational routines and knowledge bases' (Katila and Ahuja, 2002:1184). However, to reap the potential benefits from distant search is risky, since not only the external environment such as technological trajectory and competition are highly uncertain, but also firm specific resources and capabilities such as 'bounded' managerial rationality and attention as well as absorptive capacity may lead to negative impact on extreme high level of variety of search. Indeed, research has shown that search activities may be subject to diminishing returns in their impact on a firm's innovative performance (Katila & Ahuja, 2002; Laursen & Salter, 2006).

In this paper, we focus on a firm's search for external knowledge (as opposed to internal knowledge); and we look at two dimensions of the variety of search activities-- search intensity and search direction, as suggested by Levitt and March (1988). Following Laursen and Salter (2006), we gauge search intensity by search breadth, i.e. the total number of information or knowledge sources, including suppliers, customers, competitors and etc, used for innovation. Laursen and Salter emphasise that, by focusing on the variety of search channels that firms use in their search for innovative opportunities, this indicator emphasises the benefits and costs of dealing with different types of organizations whose institutional norms, habits and rules vary. However, it does not necessarily capture the different types of knowledge content that is being conveyed in various search channels. For instance, searching among customers, competitors and trade fairs and exhibitions tends to convey market knowledge; searching among public and private research institutions tends to convey technological knowledge; and searching among standard setting bodies and regulations may convey regulatory/institutional knowledge. Hence, we examine search direction by grouping these search channels according to which type of knowledge, i.e. market, technological and regulatory knowledge, tends to be conveyed through search activities. Search direction has rarely been examined in empirical studies with a few exceptions. Two recent studies have shown that a firm's search direction affects innovative performance depending on technology intensity at the sectoral level as well as the firm's absorptive capacities (Grimpe & Sofka, 2009; Sofka & Grimpe, 2010); but it should be noted that our categorization is different. While building upon the existing literature, our approach differs in two respects. Firstly, we argue that, apart from the aforementioned factors, the potential and realised benefits from a firm's search activities are also shaped by the differing nature of innovation activities in manufacturing and KIBS sectors. Since research in this stream has largely focused on the impact of search on firm's innovation in manufacturing sector, we know very little about how this effect might differ in services sectors. Secondly, we look at two dimensions of variety of search at the same time while previous studies tend to examine them separately. Thirdly, we compare manufacturing and KIBS sectors in the US, whereas the existing studies are largely focus on manufacturing firms in the UK and Europe.

Sectoral Differences and Search Activities

While scholars have reached consensus that both manufacturing and services firms can be innovators, the nature and management of a firm's innovation activities is subject to debate. Although there may be great variation in innovation activities within manufacturing and KIBS sectors (Hughes & Wood, 1999), we focus on the general 'particularities' or common features in innovation activities differentiating services from manufacturing firms (Tether, 2005; Miles, 2005). And we argue that these sectoral level general 'particularities' affect the potential and realised benefits of firm's search activities.

We argue that, the potential benefits from the variety of search activities tend to be high among manufacturing firms in comparison with KIBS for the following reasons. Firstly, the role of technological knowledge in innovation differs in these two sectors. For **manufacturing firms**, science and technology often has a direct and significant impact on innovation since product innovation in manufacturing tends to be strongly influenced by technology trajectory (Dosi, 1982). Thus, manufacturing firms tend to have high incentives to search widely to increases the pool of opportunities in combining and recombining technological knowledge (Levinthal & March 1981; Nelson & Winter, 1982; Winter 1984; Klevorick et al, 1995). For **KIBS firms**, technology often has a 'hidden' or indirect impact on innovation (Rhind et al., July 2009). For instance, technology is often the medium for a new service (as when a new form of insurance is stored on informatics) or the means to increase operational efficiencies as often documented in innovation activities among financial and business services sectors (Barras, 1990; Sundbo, 1997). In other words, the role of technological knowledge is not as critical as it is for manufacturing firms. Indeed, research has shown that in comparison with manufacturing firms, innovation in KIBS is often 'soft', rather than primarily technological (Tether & Tajar, 2008).

Secondly, in terms of non-technological knowledge, searching among various sources for both market and regulatory knowledge is critical for manufacturing firms' innovation; whereas focusing for market knowledge seems to be more advantageous for KIBS firms' innovation. Manufacturing firms not only need to engage in jointly exploiting new technology and manufacturing assets to develop new products and 'scale-up' (Galbraith, 1982), but also to understanding how well the product design meets customer needs in order to achieve the commercial success of a new product (Dougherty, 1992). That is, market knowledge is also essential in innovation in manufacturing sectors. Further, the strategy literature has argued that technological superiority does not guarantee superior firm performance as emerging technological standards play a key role in competition as in the case of Matsushita's VHS format triumph over Sony's Betamax format (Shapiro & Varian, 1999). Hence, knowledge about technical standards and industry regulation are also critical in signalling the potential benefits of firm search direction.

On the other hand, 'knowledge intensity' indicates that KIBS firms rely on a substantial body of complex knowledge which are often specialised and person-centric (Starbuck, 1992; Winch & Schneider, 1993; Von Nordenflycht, 2010). Services are often intangible and service innovation tends to involve small incremental changes adapting to different customer needs. Also, innovation activities in KIBS are often highly interactive, i.e. involve high levels of contact between service providers and client in the design, production, delivery, consumption and other phases of service activities; and services are often produced and consumed simultaneously during this interaction process, so called 'co-terminality' (Miles, 2005). Given these features of services, research has shown that the search for demand-side or market knowledge is critical to firm's innovation (Bessant & Davies, 2007). Further, due to the intangible nature of services and asymmetry of expertise, KIBS firms often face 'opaque quality' issues; and one way to overcome these issues is specialization, which has been argued to be a signal of competence (Starbuck, 1992; Greenwood et al., 2005; Von Nordenflycht, 2010).

The above reasoning suggests that manufacturing firms tend to have high potential benefits from wide and diversified search activities, whereas KIBS firms tend to have high potential benefits from narrow and specialised search. In the meantime, manufacturing firms may also be more able to reap the benefits from wide and diversified search in comparison with KIBS for the following two reasons.

Firstly, as Miles (2005:435) noted, the intangible nature of services 'makes it harder to store, transport, and export them than is true of manufacturing products'. 'Co-terminality' of services implies that idea generation and implementation can hardly be separated in the service innovation process. Asymmetry of expertise and 'opaque quality' of services further indicate the complexity of knowledge and information needs to be exchanged during the innovation process. Together these features of services seem to suggest that, in comparison with manufacturing firms, KIBS firm's ability to benefit from wide and diverse search may be constrained by the increasing coordination costs of information and knowledge exchange during the course of creating, implementing and delivering innovative services.

Secondly, a firm's ability to appropriate from its search activities is also a function of the IP regime. Manufacturing firms tend to enjoy strong legal protection of intellectual properties and rights (IPR) such as patents, trademarks, registered design etc. For instance, in the pharmaceutical industry, once a patent is granted on a new drug development, the firm enjoys a period of ‘market exclusivity’ up to twenty years in the US. For KIBS, such a legal mechanism is often unavailable due to the nature of innovation; and the return to innovation is typically subject to swift erosion since many services are often easier and quicker to copy and implement. Thus, the main protection mechanisms tend to be in such strategic forms as ‘first-mover’ advantage, secrecy, and brand and reputation (Tether & Massini, 2007). This issue adds further cost of innovation in KIBS.

In this paper we look at two dimensions of variety of search activities-- search intensity as measured by search breadth; and search direction in different types of knowledge. Put the above together, we hypothesise:

H1: While search breadth is curvilinearly related to firm’s innovation performance in both sectors, the optimal number of search breadth is greater among firms in manufacturing sector compared to those in KIBS.

H2: Technological, market and regulatory knowledge are important for firm’s innovative performance in manufacturing sectors; whereas market knowledge is important for KIBS sectors.

Dual Roles of Firms’ Resources and Capabilities

While both smaller and larger firms face the same kind of competitive pressure to exploit external knowledge sources, their differing resource, capabilities and structural features may shape the potential and realised benefits from their search activities differently.

On the one hand, in comparison with larger firms, smaller firms often lack sufficient financial and human resources and absorptive capacities to innovate. Financial resource is a key constraint among smaller firms due to the lack of slack resources as well as difficulties in obtaining external funding to finance innovation (Katila & Shane, 2005). At the same time, smaller firms tend to have a relatively smaller pool of human capital in terms of the number of employees as well as the number of employees with higher educations. These factors may result in lower absorptive capacities. At one level, smaller firms may lack the ability to identify and transfer potentially valuable external ideas and technologies, since rarely are ideas fully formed at the discovery stage and it often requires visions and expertise to turn novel ideas into commercially viable products. At another level, they may lack the ability to absorb external ideas and technologies once they are identified, since many smaller firms do not have personnel with the required expertise to understand, absorb and exploit externally developed ideas and technologies. For instance, exploiting and transferring knowledge from universities or research institutes often requires dedicated personnel and frequent interactions from both sides. Furthermore, another key aspect of human resource is managerial attention (Simon, 1947); and such resources tend to be more scarce in smaller firms than in larger firms since the top management team of smaller firms often need to be more hands-on, i.e. directly involved in both formulating and implementing strategies; as well as multi-tasking, i.e. a single manager take charge of multiple functions (Lubatkin et al., 2006; Zahra et al., 2006).

In addition, larger firms tend to organize themselves through a more hierarchical administrative structure, which enables them to stabilize organizational routines and to adopt a more systematic approach in managing resources. Put another way, larger firms tend to benefit more from exploiting external knowledge systematically. On the other hand, smaller firms tend to have a more flexible structure, which facilitates a non-systematic, bricolage, or improvisation approach in mobilising resources (Burns & Stalker, 1961; Miner et al., 2001; Garud & Karnøe, 2003), which may limit their ability to systemically exploring the potential benefits from external search activities. All these resource and structure constraints imply that smaller firms do not have sufficient resources and abilities either to scan, or to draw knowledge heavily from, a wide range of external knowledge sources to the same extent as larger firms. Thus, we propose

H3a: Larger firms benefit more from wide and diverse search strategy than smaller firms in both sectors.

On the other hand, just as R&D has dual roles in firm's innovation process (Cohen & Levinthal, 1990), lack of resources and capabilities may constrain the smaller firm's ability to exploit the benefits from external search as discussed above, but it may also increase its potential gain from such search activities. Firstly, whilst the lack of resources often means that smaller firms can rarely afford to buy in the full range of expertise to pursue innovation, it may strongly motivate their external search activities for innovation. Take biotech start-ups for example, collaboration at every step of the value creation process has become standard practice; a start-up's ability to manage such partnerships effectively is often key to their survival. Further, smaller firms tend to have more flexible structure and routines, and entrepreneurial drive. As a result, they may be more likely to implement new ideas in comparison to larger firms due to their internal resistance to externally developed ideas (i.e. Not Invented Here syndrome), but also helps them to respond quickly to changes in external environment. Therefore, to leverage their limited resource and capability bases, it seems both necessary and possible for smaller firms to search widely among a diversified range of knowledge sources and reap the benefits.

*H3b: Smaller firms benefit more from wide and diverse search strategy than larger firms in both sectors***.**

3. Methods

Sample

The data for the analysis are drawn from the Innovation Benchmarking Survey conducted in 2004 through a partnership between the Centre of Business Research at the University of Cambridge and the Industrial Performance Centre at the Massachusetts Institute of Technology. The telephone survey gathered information about corporate innovation and performance in the United States at the firm level.

The sampling frame was the Dun & Bradstreet US database. The sample was stratified by industry and firm size. The sectors covered by the surveys were the whole of manufacturing, and the KIBS sectors. The latter include: post and telecommunications, computer and related activities, research and development, and other business activities excluding legal activities. We used Butchart's (1987) definition for high-tech industries to further split the sample into high-tech and conventional sectors. The sample was stratified by sector (high-tech manufacturing; conventional manufacturing; high-tech KIBS; and conventional KIBS) and employment size (10-19; 20-49; 50-99; 100-499; 500-999; 1,000-2,999; and 3,000+), with larger proportions in the smaller size bands. The survey instruments were to cover questions on the following topics: general characteristics of the company; innovation and new technology; principal products and competition; and finance and capital expenditure.

The data were collected between March and November of 2004. An advance letter was sent to prospective respondents prior to the telephone interview. Phone numbers that required multiple attempts were tried at various times and days of the business week as well as times appointed by the respondent or other office personnel. Respondents were managers or directors who were best placed to discuss innovation in the company. The interviews were conducted under the management of a supervisor and, when required, a data retrieval callback was made to the respondent by the original interviewer or supervisor. The interviewers were trained prior to data collection and monitored to ensure quality control.The survey instruments were to cover questions on the following topics: general characteristics of the company; innovation and new technology; principal products and competition; and finance and capital expenditure.

In total, 1,540 US firms provided in-scope answers, resulting in a response rate of 18 percent. There is no evidence of non-response bias by region, firm size, and industry. The sample used for our analysis was restricted to those firms that had reported carrying out an innovation within the previous three years and for which the data were available for the dependent and explanatory variables; and this yielded a sample of 811 US companies.

Alternative data sources such as the Eurostat Community Innovation Survey (e.g. Mairesse & Mohnen, 2002; Laursen & Salter, 2006), which have enabled analyses at the firm level, is currently unavailable for the United States. The lack of the Community Innovation Survey, or similar data sources, for the United States makes it difficult to estimate innovation practices in US firms. Thus, our survey constitutes a novel data source, providing valuable information concerning performance and innovation in US firms.

Dependent Variable

Firm's innovative performance. The variable (**INNOVSAL)** used in this paper is drawn from a question asking about the commercialization of innovation that is found in both this survey and the Community Innovation Survey. It asks the company what percentage of its total sales in the last year can be attributed to products or services that were newly introduced, or significantly improved, over the last three years. This variable is bounded by 0% (61 cases) and 100% (52 cases) and is used in its logarithmic form (**lnINNOVSAL**) following Laursen and Salter (2006).

Explanatory Variables

Search intensity is gauged by search breadth, which is measured in an identical fashion to that used by Laursen and Salter (2006) and others and is drawn from a question about the use of sixteen different sources of knowledge or information for the company's innovation activity. For every source used the company's **breadth** measure gains a score of 1; and so the minimum score for a company is 0 (none used, only six cases) and the maximum score is 16 (all used, seventeen cases). Following Laursen and Salter's work, we also include 'search depth' measure in our analysis for robustness check; it is drawn from the same question, but scores 1 only if the source is not only used but also regarded as being of high importance by the company. It is theoretically possibly for the depth measure to also take values up to 16, but we find the range is from 0 (none of high importance, 139 cases) to 13 (five cases). To explore whether the company could 'over-search' and suffer decreasing returns, the quadratics of breadth and depth are included in our models. By definition, companies can search deeply only for those sources that have been included in the breadth measure and this means that low breadth scores must necessarily imply low depth scores. For this reason when we wish to include both breadth and depth in a model we have used as the depth measure the ratio of depth to breadth (**dptobr**).

Search direction

As mentioned earlier, the breadth and depth measures described above take no account of the direction pursued by the company in its search activities and implicitly give equal weight to each source of knowledge or information. Here, we distinguish the direction of search among different types of knowledge, including technological, market and regulatory knowledge by looking at different types of knowledge sources; and our categorization were also supported by factor analysis. Technological knowledge may be gained through public and private science base (SCI), includes five sources (commercial lads/r&d enterprises; universities/HEIs; government research organizations; other public sector organizations; and private research institutes) (Cronbach alpha = 0.76). In the meantime, technological knowledge may also flow from suppliers (SUPP). Market knowledge may be gained from user/clients (CUST), competitors (COMP) as well as trade associations and conferences (CONF). CONF includes four sources (conferences; trade associations; trade press and databases; and fairs/exhibitions) (Cronbach alpha = 0.68). Regulatory knowledge may be gained through various standard setting bodies, REG, includes three sources (standard setting bodies; health and safety regulations; and environmental regulations) (Cronbach alpha = 0.77).

Consultant as a separate knowledge source is referred to as CONS. Breadth and depth variables were then calculated as described above for the three groups and for the four separate sources. (**SUPPb**, **CUSTb**, **COMPb**, **CONSb**, **SCIb**, **REGb** and **CONFb** for breadth; and the equivalent for depth).

Moderating variables

We argue above that the ability for a company to benefit from search activity will depend on its resources and capabilities. One aspect of this is its ability to absorb knowledge and information and transform it into innovative sales. The analysis presented in this paper focuses on one measure of this ability which is the percentage of the workforce that is engaged in R&D (**rdstaf**). Since this variable takes the value zero for one fifth of our sample and is log-normally distributed for the others, we replace it with two variables: first, a dummy variable with the value 1 if the firm has r&d staff (**dumrdsta**); and second, an interaction variable between this dummy and the natural logarithm of rdstaf (**dxlnrdst**). These variables are included both as contributions to innovative sales and, interacted with breadth (**drdstaxb** and **dlrdstxb**) and depth (**drdstaxd** and **dlrdstxd**), to assess whether they enhance the contributions of these variables.

We experimented with other measures of the company's ability to assimilate external knowledge and information and convert it to innovative sales. R&D intensity, the ratio of r&d expenditure to sales, gave similar results in replacement of the proportion of r&d staff. However, we had no success in using the qualifications of the CEO, or the whole workforce, as measures of absorptive capacity.

Control variables

The novelty of innovations by the company in the previous three years is likely to have a positive influence on the proportion of innovative sales and so we included dummy variables for the introduction of a novel product or service (**novprod**) and for the introduction of a novel process or logistics (**novproc**). The size measured by the number of employees (**lnavemp**) and age of the firm (**lnage**)are included in logarithmic form in the models, as is the age term squared (**lnagesq**) in order to examine both the liability of newness and sclerosis. Finally, we include two dummy variables, one that measures whether the company's principal market is regional/local as opposed to national or international (**markreg**); and the other measures whether the firm has entered into collaborative or partnership arrangements for their innovative activities (**partarr**). We also include some self-reported barriers to innovation measured on a scale from 1 = insignificant barrier to 5 = crucial barrier for three types of constraint: finance (**barfin**); lack of innovation potential (**barpot**); and lack of technological opportunities (**bartec**).

Statistical methodologies

We use a Tobit censored regression model in order to examine the impact of search activity on innovative performance because our dependent variable is both left and right censored. We examine the marginal effects of our variables on innovative sales; the implied optimum levels of the variables included as quadratics; and predicted values of innovative sales for different values of our explanatory variables (whilst holding all other variables at their mean levels).

Three models are tested when making comparisons between manufacturing and KIBS sectors, but only two are used when comparing large (100 or more employees) and small (up to 99 employees) firms within manufacturing and KIBS. The models presented, which explore different combinations of search breadth, depth and direction, are a subset of those tested. In particular, following Laursen and Salter (2005), we tested models including both breadth and depth and their squared terms. When breadth was included without depth, breadth and breadth squared were statistically significant. Equally, when depth was included without breadth, depth and depth squared were significant. However, when all four variables were included together, the breadth variables remained significant, but the depth variables did not, unlike Laursen and Salter's findings. This may in part be due to the correlation (0.5) between depth and breadth and we attempt to tackle this in Model 1 by including the ratio of depth to breadth (which has a much lower correlation with breadth, 0.1) and its squared term. These variables were not statistically significant and so this model is reported only in Table 2.

The variable definitions, their descriptives and the correlation matrix for the whole sample are provided in Tables A1, A2 and A3 in the Appendix.

4. Findings

Manufacturing vs. KIBS sectors

Before turning to the regression findings it is worth making some univariate comparisons of the variables across our samples as shown in table 1. The first two columns of Table 1 show a comparison of the mean values between manufacturing and KIBS. It is worth noting that there are few significant differences between these the means of these sectors in terms of our dependent variable and explanatory variables. The only cases of difference are for the more frequent use of consultants by services and the greater use of regulatory knowledge by manufacturing. There is no difference in innovative sales, breadth, or depth on average across the sectors. In terms of the other variables manufacturing firms tend to be larger and older, more likely to have r&d staff and to serve national and international markets. On the other hand, business service firms are more likely to have novel process and logistic innovations and to have partnership arrangements in place.

The regression findings for the comparison of manufacturing and KIBS are presented in Table 2. Three models are presented. The first includes breadth and the ratio of depth to breadth and their squared terms for the reasons discussed in the previous section. The second includes breadth and breadth squared along with measures of the direction of depth search activity. The third model introduces depth and depth squared, but also includes measures for the direction of search breadth and some interaction terms between r&d activity and search breadth and depth,

The models support Laursen and Salter's finding that there are diminishing returns to search breadth for both manufacturing and KIBS sectors in the US. The optimal levels are 13.6 for model 1 and 15.3 for model 2 for manufacturing compared with 10.5 and 11.4 respectively for KIBS. This finding supports H1 in terms of search breadth. It should be noted that Laursen and Salter found an optimum breadth of 11 for UK manufacturing firms, so our optima are somewhat higher for US manufacturing.

The implications of these results for innovative sales are modelled in Figure 1 keeping all other variables at their mean levels. This figure shows that the effect is not only statistically significant, but also important quantitatively. If we take the optimal level for manufacturing to be a breadth of 13-15, then 10.5% of our sample is at this level, but 87.5% of manufacturing firms are below this optimum breadth. For services, where the optimal level is 10-12, we have 25.6% of the sample at this level and 63.4% below it. On their own, these findings suggest that firms' search activity is often sub-optimal. Of course, the cost of search is not included in our model and so the optimal search level in terms of financial return may possibly be lower than these levels. We note that the depth to breadth ratio in model 1 is not significant for either sector and depth and depth squared in model 3 are statistically significant only for services. The optimal level implied by this model is 5, somewhat higher than found by Laursen and Salter for UK manufacturing. Only 8.4% of the KIBS firms are at this level and 81.1% have a depth score below 5.

Models 2 and 3 enable us to examine our hypotheses in relation to search direction for search depth and breadth respectively. The findings are summarised in Table 3 that shows their implied association with innovative performance, keeping all other variables at their mean levels. It can be seen that manufacturing benefits significantly from a far wider range of search activity than do KIBS. In each of the four areas (and in five of our seven search directions) manufacturing has statistically significant and quantitatively important implied impacts on innovative sales from its search breadth direction. On the other hand it is only market knowledge in terms of conferences etc, and consultants that are significant for KIBS. Therefore H2 find strong support in these findings.

The results from model 2 in relation to the direction of search depth are more patchy. They are generally not statistically significant, but where they are the implied impact is negative. This is the case for competitors in manufacturing and could possibly be due to reverse causation – suggesting that deeply seeking knowledge for innovation from competitors is associated with a company that is doing poorly in terms of its innovative sales. It is not easy to explain why a strong association with the science base should have negative consequences for innovative sales amongst KIBS firms.

Turning to the moderating variables we find that r&d staff are important for innovative sales. The two variables taken together suggest that raising the proportion of r&d staff from 0% to 40% would be associated with a rise in innovative sales from 24% to 45% for manufacturing and from 18% to 35% for KIBS. The interaction of these variables with breadth and depth, shown in model 3, do not yield significant results.

Finally, it is worth noting the impact of our control variables. Size has a negative, but weak, impact on innovative sales. The impact of age is greatest at about two years after founding and negative thereafter, but is significant only for manufacturing firms. As we would expect, novel products have a far greater impact on innovative sales than novel processes and logistics. The barrier of lack of technological opportunities has a highly significant negative effect on innovative sales in KIBS, but not in manufacturing.

Table 1	Differences in Sample Means								
	All Sizes			Manufacturing			Services		
Mean values	Manufact	Services		Small	Large		Small	Large	
lnINNOVSAL	3.31	3.32		3.30	3.32		3.40	3.13	*
breadth	8.33	8.15		7.75	9.44	***	7.84	8.94	***
SUPPb	0.89	0.86		0.88	0.92		0.84	0.90	
CUSTb	0.78	0.76		0.76	0.81		0.75	0.78	
COMPb	0.57	0.57		0.53	0.65	***	0.56	0.60	
CONSb	0.48	0.58	***	0.43	0.57	***	0.54	0.69	***
SCIb	1.17	1.23		0.99	1.53	***	1.20	1.30	
REGb	1.77	1.36	***	1.67	1.98	***	1.23	1.68	***
CONFb	2.66	2.79		2.50	2.99	***	2.72	2.99	*
depth	2.94	2.67		2.85	3.10		2.67	2.69	
SUPPd	0.44	0.43		0.45	0.41		0.41	0.47	
CUSTd	0.43	0.42		0.41	0.46		0.38	0.53	**
COMPd	0.12	0.13		0.11	0.12		0.13	0.14	
CONSd	0.13	0.15		0.12	0.14		0.16	0.11	
SCId	0.36	0.32		0.34	0.41		0.36	0.22	
REGd	0.86	0.53		0.81	0.94		0.48	0.67	
CONFd	0.61	0.69		0.60	0.62		0.75	0.56	*
dptobr	0.34	0.32		0.36	0.32		0.33	0.31	
lnavemp	4.21	3.93	***	3.34	5.90	***	3.24	5.67	***
lnage	3.13	2.77	***	3.01	3.35	***	2.64	3.08	***
novprod	0.55	0.59		0.51	0.63	***	0.59	0.60	
novproc	0.43	0.51	**	0.39	0.49	**	0.50	0.54	
dumrdsta	0.85	0.72	***	0.81	0.93	***	0.71	0.74	
lnrdstaf	1.51	1.44		1.72	1.11	***	1.67	0.84	***
markreg	0.26	0.44	***	0.33	0.12	***	0.47	0.36	*
partarr	0.52	0.75	***	0.46	0.62	***	0.73	0.80	
barfin	2.71	2.92	*	2.82	2.51	**	3.02	2.67	*
barpot	2.25	2.08	**	2.20	2.33		2.02	2.25	
bartec	2.02	1.96		2.04	1.99		1.92	2.06	

***, **, * indicates the means in the two columns to the the left are significantly different at the 1%, 5%, 10% level respectively.
Binary variables were tested using the binomial approximation to normality, the log transformed variables were tested using t-tests, and the rest were tested using the non-parametric Mann-Whitney test.

Table 2 **The determinants of innovative sales - manufacturing vs business services in the US**

Dependent variable: log of percentage os sales due to new or improved goods or services

	MAN ALL	MAN ALL	MAN ALL	SERV ALL	SERV ALL	SERV ALL
VARIABLES	model 1	model 2	model 3	model 1	model 2	model 3
lnavemp	0.0853*	0.0776*	0.0726	-0.00634	-0.0395	-0.0379
	(0.0447)	(0.0450)	(0.0444)	(0.0711)	(0.0734)	(0.0689)
lnage	0.494	0.416	0.511*	0.206	0.297	0.244
	(0.304)	(0.307)	(0.303)	(0.459)	(0.455)	(0.442)
lnagesq	-0.113**	-0.0982*	-0.116**	-0.0620	-0.0762	-0.0698
	(0.0504)	(0.0510)	(0.0503)	(0.0830)	(0.0822)	(0.0805)
new26	0.445***	0.440***	0.439***	0.281	0.324*	0.328*
	(0.115)	(0.115)	(0.114)	(0.176)	(0.175)	(0.170)
novproc	0.166	0.167	0.217**	0.182	0.150	0.172
	(0.108)	(0.109)	(0.108)	(0.164)	(0.166)	(0.158)
markreg	0.220	0.271*	0.231*	-0.0976	-0.0535	-0.0161
	(0.138)	(0.139)	(0.138)	(0.171)	(0.171)	(0.169)
bar02	0.0602*	0.0509	0.0543	0.0417	0.0576	0.0666
	(0.0358)	(0.0361)	(0.0356)	(0.0560)	(0.0555)	(0.0526)
bar05	-0.0312	-0.0186	-0.00217	-0.0223	-0.0266	-0.00366
	(0.0462)	(0.0459)	(0.0454)	(0.0665)	(0.0658)	(0.0633)
bar13	-0.0475	-0.0523	-0.0661	-0.196***	-0.203***	-0.199***
	(0.0509)	(0.0512)	(0.0503)	(0.0744)	(0.0735)	(0.0699)
dumrdsta	-0.174	-0.137	0.493	0.149	0.100	0.661
	(0.188)	(0.187)	(0.436)	(0.256)	(0.253)	(0.568)
dxlnrdst	0.217***	0.234***	0.470***	0.186**	0.177**	0.343**
	(0.0560)	(0.0565)	(0.121)	(0.0825)	(0.0819)	(0.173)
partarr	-0.0550	-0.0596	-0.0944	-0.216	-0.252	-0.337*
	(0.110)	(0.112)	(0.110)	(0.195)	(0.195)	(0.192)
CUSTb			0.340**			0.188
			(0.139)			(0.191)
COMPb			0.0295			0.0953
			(0.121)			(0.176)
CONSb			0.421***			0.373**
			(0.120)			(0.170)
SCIb			0.169**			-0.00328
			(0.0679)			(0.0825)
CONFb			0.189***			0.388***
			(0.0690)			(0.0822)
REGb			0.214***			-0.0711
			(0.0717)			(0.0880)
SUPPb			0.188			0.283
			(0.177)			(0.228)
depth			0.0555			0.207*
			(0.0823)			(0.109)
depthsq			-0.00129			-0.0206**
			(0.00548)			(0.00866)
breadth	0.216***	0.182***		0.338***	0.284***	
	(0.0644)	(0.0605)		(0.104)	(0.0879)	
breadsq	-0.00797**	-0.00596*		-0.0161***	-0.0125**	
	(0.00371)	(0.00352)		(0.00581)	(0.00516)	
dptobr	-0.471			0.944		
	(0.616)			(0.995)		
dptobrsq	0.358			-1.000		
	(0.687)			(1.144)		

Table 2 (cont'd)

The determinants of innovative sales - manufacturing vs business services in the US

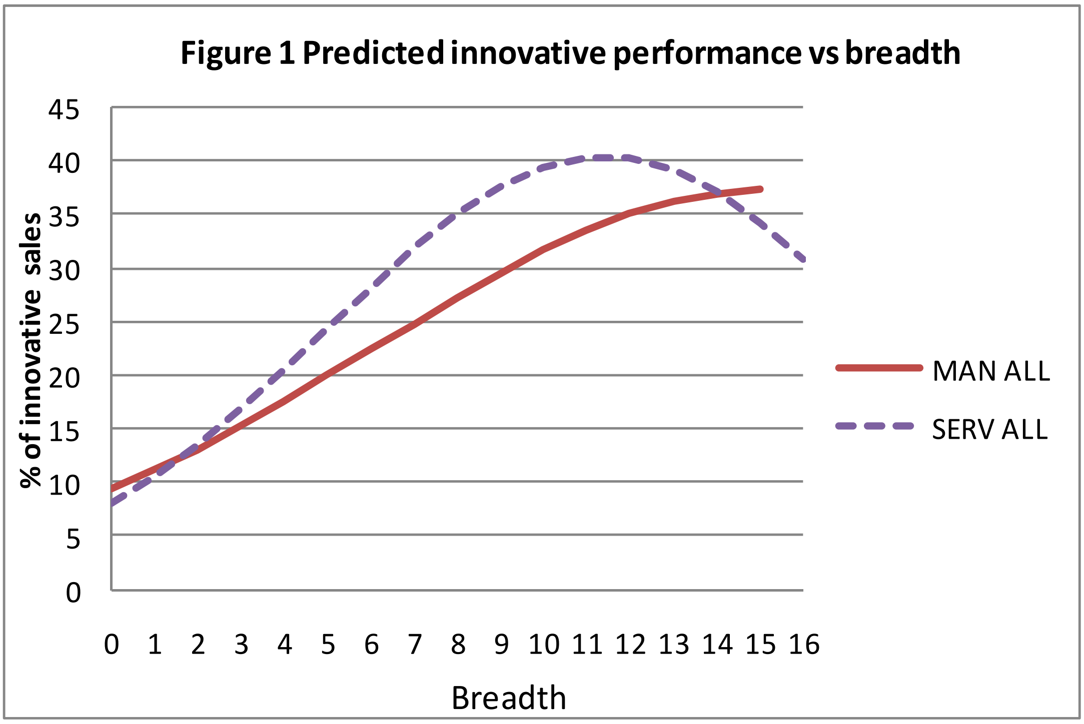
VARIABLES	MAN ALL model 1	MAN ALL model 2	MAN ALL model 3	SERV ALL model 1	SERV ALL model 2	SERV ALL model 3
CUSTd		0.179			0.289	
		(0.112)			(0.177)	
COMPd		-0.320*			0.0348	
		(0.170)			(0.249)	
CONSd		0.0887			-0.0557	
		(0.158)			(0.224)	
SCId		-0.0410			-0.256*	
		(0.0816)			(0.131)	
CONFd		-0.0854			0.111	
		(0.0640)			(0.0860)	
REGd		0.0460			-0.100	
		(0.0565)			(0.103)	
SUPPd		-0.0543			0.0438	
		(0.112)			(0.163)	
drdstaxb			-0.0600			-0.0376
			(0.0605)			(0.0725)
drdstaxd			-0.0867			-0.0643
			(0.0759)			(0.121)
dlrdstxb			-0.0336**			-0.0234
			(0.0148)			(0.0190)
dlrdstxd			0.00915			0.0168
			(0.0179)			(0.0302)
Constant	1.014	1.082*	0.358	1.514*	1.798**	1.239
	(0.628)	(0.623)	(0.658)	(0.863)	(0.810)	(0.804)
Sigma	1.135***	1.137***	1.123***	1.257***	1.241***	1.187***
	(0.0390)	(0.0390)	(0.0385)	(0.0605)	(0.0593)	(0.0567)
Observations	523	526	526	282	285	285
Log likelihood	-791.4	-795.3	-788.3	-442.1	-443.8	-431.8
DF	31	36	40	19	24	28
chi2	126.8	135.7	149.7	76.21	81.87	105.9
r2_p	0.0742	0.0786	0.0867	0.0794	0.0845	0.109

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Modeled using STATA Tobit censored regression.

The models included 15 sector dummies for manufactiuring and three for services.

Table 3	Impact on innovative sales of search direction				
	Manufacturing			**Business Services**	
	Breadth	**Depth**		**Breadth**	**Depth**
Technological knowledge					
SUPP = 0	28.82	30.25		23.62	30.79
SUPP = 1	34.78	28.65		31.35	32.16
SCI = 0	**23.67**	29.95		30.61	**33.93**
SCI = 2	**33.19**	27.59		30.41	**20.33**
SCI = 4	**46.54**	25.42		30.21	**12.19**
Regulatory knowledge					
REG = 0	**21.22**	28.31		34.67	33.10
REG = 2	**32.56**	31.04		30.07	27.10
REG = 4	**49.95**	34.03		26.09	22.19
Market knowledge					
CUST = 0	**25.50**	26.99		25.80	27.18
CUST = 1	**35.82**	32.28		31.14	36.28
COMP = 0	33.61	**31.23**		28.33	31.11
COMP = 1	34.61	**22.68**		31.16	32.21
CONF = 0	**19.51**	30.99		**9.38**	29.20
CONF = 2	**28.47**	26.12		**20.38**	36.45
CONF = 4	**41.55**	22.02		**44.28**	45.51
Consultants					
CONS = 0	**26.55**	29.33		**23.68**	31.55
CONS = 1	**40.45**	32.05		**34.39**	29.84
Notes:					
The above inferneces are drawn from models 2 and3 by setting					
all variables other than those above at their mean levels.					
Statistically significant findings are shown in bold.					



Larger vs. Smaller Firms

The final four columns of table 1 compare larger companies with smaller companies within each of the sectors. Within manufacturing we find no difference in the average proportion of innovative sales between large and small firms. However we do find that the search breadth is higher on average amongst the larger firms. Larger firms make significantly more use of competitors, consultants, regulatory bodies, the science base and conferences and trade fairs. In view of this it is notable that the average level for breadth amongst smaller firms is 7.75, not that far short of the 9.44 for larger firms. We find no difference in the average depth level between large and small firms. Most of the other variables have expected differences: large firms are older; do more novel innovation; have higher r&d staffing levels; are more likely to have international, or national markets, as their principal market and to be engaged in partnership arrangements.

The percentage of innovative sales is somewhat higher amongst smaller firms in KIBS. Again we find that the average breadth is higher for large firms, but again the difference is small, 8.94 for large and 7.84 for small. The only search areas used significantly more by large firms were consultants and regulatory bodies. There is no difference in the average depth, with large firms more likely to use clients and customers and small firms making greater use of conferences, trade fairs etc. Unlike the findings for manufacturing, there were few differences amongst the other variables between large and small firms in KIBS, but the latter are clearly younger.

The regression results for the comparison of larger and smaller firms are presented in table 4. While in KIBS sector, we find that there are diminishing returns to search breadth for both larger and smaller firms; such effect does not exist in small firms in manufacturing sector. The optimal number of search breadth for manufacturing large firms, services large and smaller firms are 10.4, 11.4 and 11.3 respectively. This suggests that US manufacturing large firms has an optimal number of search breadth lower than their sectoral average 13-15 as mentioned earlier. At the same time, there is little difference in optimal search breadth between large and small firms in US services sectors. We model the predicted relationship between innovative performance and search breadth in figure 2 keeping all other variables at their mean levels. In terms of search depth, we only find diminishing returns in manufacturing large firms and services small firms, and their optimal numbers are 13.8 and 4.7 respectively. Table 5 shows the implied association between diversity of search direction in breadth and innovative performance keeping all other variables at their mean level. The inferences are drawn from model 2 and 3 by setting all variables other than those above at their mean levels. In manufacturing sector, in each of the four search directions, i.e. technological, market and regulatory knowledge and consultants (and five of the seven sources) smaller firms has statistically significant and quantitatively important implied impact on innovative sales from its search breadth. While only search for regulatory knowledge is significant for larger firms. In KIBS sectors, three out of the four directions, i.e. technological and market knowledge and consultants, (and three out of the seven sources) are significant and quantitatively important. And only market knowledge is significant for larger firms.

It is also worth noting that, while search in technological and market knowledge are important for smaller firms in both manufacturing and KIBS sectors, their knowledge sources differ. For instance, it seems that manufacturing smaller firms tend to gain technological knowledge from private and public scientific base (SCI), whilst service smaller firms tend to gain such knowledge from suppliers. Also, both manufacturing smaller firms and service larger firms tend to search for market knowledge through user/customers (CUST) and trade association and conferences (CONF), whilst smaller service firms tend to search in the latter source only. Further, regulatory knowledge seems to be important for both large and small manufacturing firms. Also, consultants are important for smaller firms in both sectors but not for larger firms.

Last but not the least, we find support for H3a only in KIBS sectors.; while breadth is significant and positively associated with innovative performance across all models, the parameter for larger firms is greater than for smaller firms. This seems to suggest that the impact of search breadth on innovative performance is greater among larger firms than smaller firms in KIBS sectors. Whereas in manufacturing sector, there is a cross-over point before which larger firms seem to reap more benefit from broad search; and after this point smaller firms seem to gain more.

Table 4	The determinants of innovative sales - large vs small compabies in the US							
Dependent variable: log of percentage os sales due to new or improved goods or services								
	MAN L	MAN L	MAN S	MAN S	SERV L	SERV L	SERV S	SERV S
VARIABLES	model 2	model 3	model 2	model 3	model 2	model 3	model 2	model 3
lnavemp	0.144**	0.148**	0.0971	0.0726	-0.119	-0.148	0.107	0.221
	(0.0631)	(0.0658)	(0.115)	(0.112)	(0.128)	(0.120)	(0.155)	(0.151)
lnage	0.371	0.522	0.393	0.511	-0.856	-0.882	1.206**	1.170**
	(0.325)	(0.334)	(0.511)	(0.492)	(0.954)	(0.865)	(0.575)	(0.558)
lnagesq	-0.101*	-0.119**	-0.0926	-0.116	0.119	0.140	-0.270**	-0.266**
	(0.0537)	(0.0553)	(0.0857)	(0.0824)	(0.156)	(0.142)	(0.112)	(0.109)
new26	0.0303	-0.00492	0.615***	0.664***	0.0774	0.0737	0.383*	0.459**
	(0.161)	(0.168)	(0.155)	(0.150)	(0.263)	(0.234)	(0.214)	(0.211)
novproc	0.421***	0.444***	0.151	0.155	-0.228	-0.171	0.250	0.213
	(0.152)	(0.163)	(0.151)	(0.146)	(0.274)	(0.234)	(0.197)	(0.190)
markreg	0.545**	0.500*	0.185	0.131	0.0221	-0.314	-0.158	-0.137
	(0.254)	(0.256)	(0.178)	(0.173)	(0.275)	(0.269)	(0.206)	(0.205)
bar02	0.128**	0.111*	0.0384	0.0368	-0.103	-0.0458	0.114*	0.127**
	(0.0561)	(0.0575)	(0.0475)	(0.0455)	(0.0955)	(0.0744)	(0.0659)	(0.0630)
bar05	-0.0401	0.00253	-0.0148	0.000186	-0.233**	-0.199**	0.0416	0.0956
	(0.0670)	(0.0682)	(0.0653)	(0.0633)	(0.109)	(0.0974)	(0.0789)	(0.0767)
bar13	-0.0149	-0.0552	-0.0582	-0.0748	-0.327***	-0.247**	-0.166*	-0.181**
	(0.0734)	(0.0759)	(0.0683)	(0.0653)	(0.109)	(0.103)	(0.0893)	(0.0858)
dumrdsta	0.264	0.844	-0.360	-0.228	-0.0267	0.335	-0.119	-0.378
	(0.297)	(0.924)	(0.282)	(0.685)	(0.316)	(0.764)	(0.387)	(0.893)
dxlnrdst	0.262***	0.397**	0.279***	0.888***	0.211**	0.548**	0.175	0.649**
	(0.0667)	(0.154)	(0.0935)	(0.227)	(0.0963)	(0.232)	(0.127)	(0.297)
partarr	-0.0500	-0.122	-6.99e-05	-0.0495	0.329	-0.239	-0.463**	-0.671***
	(0.156)	(0.158)	(0.150)	(0.144)	(0.331)	(0.322)	(0.228)	(0.232)
CUSTb		0.178		0.451**		0.541*		0.216
		(0.213)		(0.184)		(0.295)		(0.231)
COMPb		0.0416		0.0660		0.0672		0.122
		(0.197)		(0.156)		(0.296)		(0.208)
CONSb		0.179		0.557***		0.339		0.335*
		(0.179)		(0.156)		(0.271)		(0.196)
SCIb		0.00920		0.339***		-0.0902		0.126
		(0.0972)		(0.0948)		(0.109)		(0.108)
CONFb		0.00128		0.316***		0.693***		0.225**
		(0.119)		(0.0885)		(0.146)		(0.0971)
REGb		0.200*		0.241***		-0.127		-0.0631
		(0.113)		(0.0922)		(0.140)		(0.106)
SUPPb		-0.157		0.337		0.228		0.578**
		(0.280)		(0.227)		(0.390)		(0.263)
depth		0.346**		-0.0710		0.0878		0.302**
		(0.144)		(0.113)		(0.187)		(0.123)
depthsq		-0.0125*		0.00242		-0.00980		-0.0324***
		(0.00728)		(0.00793)		(0.0153)		(0.0101)
breadth	0.314***		0.147*		0.353**		0.255**	
	(0.0919)		(0.0800)		(0.156)		(0.100)	
breadsq	-0.0151***		-0.00244		-0.0155*		-0.0113*	
	(0.00504)		(0.00488)		(0.00860)		(0.00617)	

Table 4 (cont'd)

The determinants of innovative sales - large vs small compabies in the US

VARIABLES	MAN L model 2	MAN L model 3	MAN S model 2	MAN S model 3	SERV L model 2	SERV L model 3	SERV S model 2	SERV S model 3
CUSTd	0.332**		0.156		0.772***		0.191	
	(0.152)		(0.154)		(0.271)		(0.215)	
COMPd	-0.00135		-0.417*		-0.0722		0.107	
	(0.238)		(0.231)		(0.453)		(0.292)	
CONSd	0.0457		0.0216		0.128		0.151	
	(0.221)		(0.217)		(0.407)		(0.261)	
SCId	0.0492		-0.116		-0.101		-0.311**	
	(0.105)		(0.117)		(0.258)		(0.150)	
CONFd	-0.100		-0.116		0.0761		0.140	
	(0.0823)		(0.0891)		(0.132)		(0.103)	
REGd	0.150**		0.0215		0.0633		-0.199	
	(0.0732)		(0.0808)		(0.148)		(0.129)	
SUPPd	-0.110		-0.0407		-0.304		0.171	
	(0.154)		(0.151)		(0.255)		(0.197)	
drdstaxb		0.0134		-0.00310		-0.0380		0.0770
		(0.0914)		(0.0991)		(0.0853)		(0.134)
drdstaxd		-0.212		-0.0874		0.0550		-0.169
		(0.136)		(0.120)		(0.184)		(0.206)
dlrdstxb		-0.0200		-0.0948***		-0.0298		-0.0694*
		(0.0168)		(0.0300)		(0.0219)		(0.0402)
dlrdstxd		0.0125		0.0358		0.00478		0.0526
		(0.0191)		(0.0356)		(0.0488)		(0.0574)
Constant	0.00661	0.0592	1.186	0.0882	4.946**	4.020**	0.191	-0.878
	(0.827)	(1.135)	(0.955)	(0.962)	(1.879)	(1.796)	(0.986)	(0.992)
Sigma	0.853***	0.860***	1.234***	1.188***	0.944***	0.825***	1.229***	1.175***
	(0.0480)	(0.0484)	(0.0533)	(0.0512)	(0.0812)	(0.0708)	(0.0705)	(0.0672)
Observations	178	178	348	348	81	81	204	204
Log likelihood	-224.9	-226.3	-544.6	-531.3	-107.9	-97.55	-311.7	-302.3
DF	36	40	36	40	24	28	24	28
chi2	86.95	84.10	88.74	115.3	56.03	76.76	70.22	89.15
r2_p	0.162	0.157	0.0753	0.0979	0.206	0.282	0.101	0.129

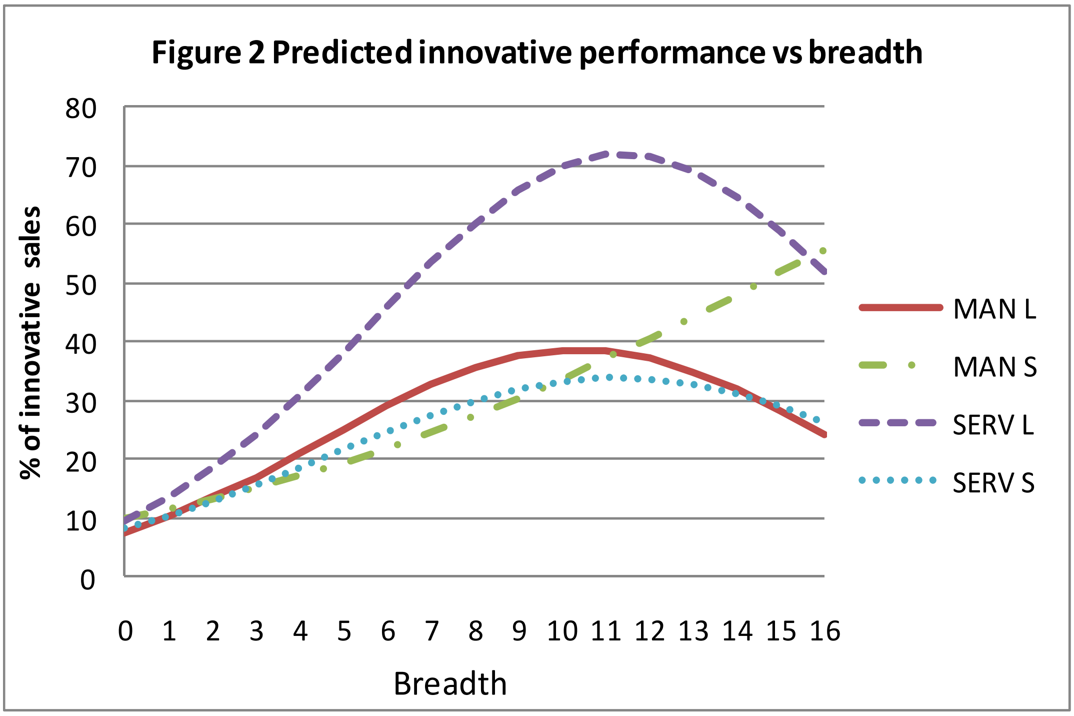
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Modeled using STATA Tobit censored regression.

The models included 15 sector dummies for manufactiuring and three for services.

Table 5	Impact on innovative sales of search direction (breadth)			
	Manufacturing		**Business Services**	
	Larger	**Smaller**	**Larger**	**Smaller**
Technological knowledge				
SUPP = 0	41.49	30.47	34.51	**16.67**
SUPP = 1	35.47	42.68	43.35	**29.71**
SCI = 0	34.96	**20.97**	51.52	21.46
SCI = 2	35.61	**41.32**	43.02	27.61
SCI = 4	36.27	**81.39**	35.92	35.52
Regulatory knowledge				
REG = 0	**22.27**	**24.60**	55.39	30.98
REG = 2	**33.22**	**39.83**	42.97	27.30
REG = 4	**49.55**	**64.50**	33.33	24.07
Market knowledge				
CUST = 0	30.51	**28.20**	**26.47**	22.97
CUST = 1	36.45	**44.27**	**45.47**	28.51
COMP = 0	34.63	39.75	40.44	25.35
COMP = 1	36.11	42.46	43.26	28.64
CONF = 0	35.63	**16.97**	**4.79**	**14.17**
CONF = 2	35.73	**31.92**	**19.15**	**22.22**
CONF = 4	35.82	**60.05**	**76.59**	**34.85**
Consultants				
CONS = 0	31.58	**30.39**	33.36	**22.30**
CONS = 1	37.77	**53.04**	46.82	**31.17**

Notes:
The above inferences are drawn from models 2 and 3 by setting all variables other than those above at their mean levels.
Statistically significant findings are shown in bold.



5. Discussion and Conclusions

The key proposition of this paper is that, the potential and realised benefits from a firm's external search activities are influenced not only by the firm's internal resources and absorptive capacities, but also by the nature of innovation activities at sector level. By comparing US manufacturing and KIBS firms, our findings suggest that both sectoral and firm level differences play a key role in the impact of firm's external search activities on innovative performance. These findings contribute to the literature in the following ways.

Firstly, to further explore the notion of variety of search, we examine both search intensity and search direction among three types of knowledge (i.e. technological knowledge, market knowledge and regulatory knowledge). Our finding suggests that searching widely among a diversified range of sources is associated with better innovative performance in manufacturing firms than in KIBS firms. And while sourcing for technological, market and regulatory knowledge are important for manufacturing firm's performance, only market knowledge is important for KIBS firms. While operationally speaking, paying attention to search direction implies that we should not assign equal weight to each search channel or information source; it is also important theoretically. We suggest that the notion of variety of search also needs to consider the heterogeneity of knowledge sources that are being searched for and utilized. This has implications for managing and mobilising firm resources effective and efficiently. For instance, as managers can pay attention to only a limited number of issues, i.e. the bounded rationality of managers (Simon, 1947), they need to consider which direction or type of knowledge that they need to focus upon in promoting innovation. And our findings highlight that it depends on both their sector and firm size.

Secondly, we also explore when a firm's external search strategy affects its innovative performance when taking firm resources and structural features into account. Our findings suggest that larger firms tend to appropriate more value from the variety of search activities. This poses a challenge as well as presenting opportunities to small firms in developing and implementing their 'open innovation' strategy.

Thirdly, we find support for Laursen and Salter's finding that there is a 'tipping point' beyond which searching more widely appears to have negative consequences for innovative performance in both manufacturing and KIBS sectors; but we do not find such an effect in search depth in the US sample. Our results also suggest that the optimal search breadth in US manufacturing (13-15 sources) is rather high, supporting the view that greater breadth of innovative search is associated with greater innovation success at the firm level (Leiponen & Helfat, 2010). This seems to point to the benefits of exploration or distant search (March, 1991). At the same time, it is worth noting that most firms' actual search activities are sub-optimal, echoing the view that firms tend to search locally although distant search is beneficial to innovation (Nelson & Winter, 1982; Levinthal & March, 1993).

Last but not least, our findings also contribute to the growing yet limited literature on innovation in services. In particular, it supports the view that firm's innovation activities differ in manufacturing and service sectors (Miles, 2000; Tether, 2005). This supports the view that demand-side knowledge is critical to firm performance in service sectors (Bessant & Davis, 2007). At the same time, it is interesting that users and customers do not appear to be an important driver for innovative performance in the KIBS sector in general, whilst conferences etc. are critical. This may due to the fact that conferences and exhibitions are important venues for KIBS firms to meet new clients, catch up on new trends and information regarding emerging standards as well as to reduce search costs. This further highlights the differences of innovation activities in different sectors. Also, the fact that consultants appear to be an important knowledge source for both sectors supports the view that knowledge brokers are key to combining and recombining ideas and knowledge (Hargadon & Sutton, 1997), although the pattern of usage of such brokers differs in manufacturing and service firms (Tether & Tajar, 2008).

To conclude, our study contributes to the innovation search literature by providing support to the view that search breadth benefits innovation, but suffers from diminishing returns. It further shows that a firm's external search strategy or 'openness' can also be manifested in the diversity of search direction in terms of different types of knowledge being conveyed through the search channels. Furthermore, we show that whether 'variety of search' promotes or hinders innovation depends on both sectoral and firm level differences, supporting the view that we need to consider both sectoral and firm level characteristics in gaining a fuller understanding of the linkage between firm's behaviour and innovative performance (Gupta et al., 2007).

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APPENDIX

Table A1 Variable definitions

INNOVSAL	percentage of its total sales in the last year can be attributed to products or services that were newly introduced, or significantly improved, over the last three years
Breadth	Total no. of the knowledge sources
SUPPb	Breadth measure for sourcing from supplier
CUSTb	Breadth measure for sourcing from user/clients
COMPb	Breadth measure for sourcing from competitors
CONSb	Breadth measure for sourcing from consultants
SCIb	Breadth measure for sourcing from public and private science base inc. 5 sources--commercial lads/r&d enterprises; universities/HEIs; government research organizations; other public sector organizations; and private research institutes
REGb	Breadth measure for sourcing from standard setting bodies; health and safety regulations; and environmental regulations
CONFb	Breadth measure for sourcing from conferences; trade associations; trade press and databases; and fairs/exhibitions
depth	Total no. of the knowledge sources that are regarded as being of high importance
SUPPd	Depth measure for sourcing from supplier
CUSTd	Depth measure for sourcing from user/clients
COMPd	Depth measure for sourcing from competitors
CONSd	Depth measure for sourcing from consultants
SCId	Depth measure for sourcing from public and private science base inc. 5 sources--commercial lads/r&d enterprises; universities/HEIs; government research organizations; other public sector organizations; and private research institutes
REGd	Depth measure for sourcing from standard setting bodies; health and safety regulations; and environmental regulations
CONFd	Depth measure for sourcing from conferences; trade associations; trade press and databases; and fairs/exhibitions
dptobr	the ratio of depth to breadth
lnavemp	the natural logarithm of firm size, i.e. the number of employees
lnage	the natural logarithm of firm age
novprod	dummy variables for the introduction of a novel product or service
novproc	Dummy variable for the introduction of a novel process or logistics
lnrdstaf	the natural logarithm of the proportion of r&d staff
dumrdsta	a dummy variable with the value 1 if the firm has r&d staff
dxlnrdst	an interaction variable between dumrdsta and the natural logarithm of rdstaf
markreg	whether the company's principal market is regional/local as opposed to national or international
partarr	whether the firm has entered into collaborative or partnership arrangements for their innovative activities
barfin	Lack of finance
barpot	lack of innovation potential
bartec	lack of technological opportunities
drdstaxb	an interaction variable between dumrdsta and breadth
drdstaxd	an interaction variable between dumrdst and depth

dlrdstxb	an interaction variable between dxlnrdst and breadth
dlrdstxd	an interaction variable between dxlnrdst and depth

Table A2 Descriptives

	Mean	N	Std. Dev.	Median	Minimum	Maximum
INNOVSAL	40.90	811	29.00	35	0	100
lnINNOVSAL	3.31	811	1.18	3.58	0	4.62
breadth	8.26	811	3.48	8	0	16
SUPPb	0.88	811	0.33	1	0	1
CUSTb	0.77	811	0.42	1	0	1
COMPb	0.57	811	0.50	1	0	1
CONSb	0.51	811	0.50	1	0	1
SCIb	1.19	811	1.38	1	0	5
REGb	1.63	811	1.17	2	0	3
CONFb	2.71	811	1.26	3	0	4
depth	2.84	811	2.60	2	0	13
SUPPd	0.43	811	0.50	0	0	1
CUSTd	0.43	811	0.49	0	0	1
COMPd	0.12	811	0.33	0	0	1
CONSd	0.14	811	0.34	0	0	1
SCId	0.35	811	0.73	0	0	4
REGd	0.74	811	1.03	0	0	3
CONFd	0.64	811	0.98	0	0	4
dptobr	0.34	805	0.26	0.29	0	1
avemp	609.50	811	5739.17	45	6	114000
lnavemp	4.11	811	1.50	3.81	1.79	11.64
age	27.84	811	24.38	20	1	167
lnage	3.00	811	0.83	3.00	0	5.12
novprod	0.56	811	0.50	1	0	1
novproc	0.46	811	0.50	0	0	1
dumrdsta	0.80	811	0.40	1	0	1
rdstaf	13.63	811	19.90	5.83	0	100
lnrdstaf	1.49	811	1.73	1.76	-2.69	4.61
markreg	0.32	811	0.47	0	0	1
partarr	0.60	811	0.49	1	0	1
barfin	2.79	811	1.48	3	1	5
barpot	2.19	811	1.26	2	1	5
bartec	2.00	811	1.12	2	1	5

Table A3 Spearman Rank Correlations

N = 811 observations

ns: indicates that the correlation was not significant at 5% level

1	lnINNOVSAL																													
2	breadth	0.17																												
3	SUPPb	ns	0.27																											
4	CUSTb	0.16	0.37	0.09																										
5	COMPb	ns	0.41	0.08	0.27																									
6	CONSb	0.12	0.41	0.09	0.12	0.08																								
7	SCIb	0.12	0.72	0.08	0.18	0.16	0.26																							
8	REGb	0.08	0.73	0.17	0.15	0.18	0.18	0.37																						
9	CONFb	0.14	0.74	0.17	0.21	0.24	0.22	0.34	0.41																					
10	depth	0.13	0.50	0.20	0.18	0.21	0.13	0.37	0.45	0.32																				
11	SUPPd	ns	0.14	0.32	ns	ns	ns	ns	0.15	0.10	0.47																			
12	CUSTd	0.19	0.25	ns	0.47	0.23	ns	0.16	0.13	0.14	0.44	ns																		
13	COMPd	ns	0.17	ns	0.16	0.32	ns	0.08	0.10	0.09	0.35	0.11	0.21																	
14	CONSd	ns	0.16	ns	ns	ns	0.39	0.10	ns	0.09	0.29	0.07	Ns	0.14																
15	SCId	0.09	0.38	ns	0.08	0.08	ns	0.55	0.20	0.18	0.54	0.14	0.17	0.15	0.18															
16	REGd	0.08	0.41	0.13	0.09	0.09	0.08	0.26	0.59	0.17	0.72	0.23	0.19	0.16	0.12	0.32														
17	CONFd	ns	0.33	0.12	ns	0.14	ns	0.22	0.20	0.37	0.65	0.25	0.17	0.20	0.14	0.29	0.30													
18	dptobr	ns	0.11	0.09	ns	ns	ns	0.10	0.17	ns	0.87	0.49	0.38	0.32	0.25	0.43	0.58	0.58												
19	lnavemp		0.23	ns	0.10	0.10	0.16	0.13	0.18	0.18	ns	ns	0.08	ns	ns	ns	0.07	ns	-0.07											
20	lnage	-0.25	ns	ns	ns	ns	ns	ns	0.07	ns	ns	ns	-0.08	ns	ns	ns	ns	ns	-0.08	0.30										
21	novprod	0.24	0.08	ns	ns	ns	ns	0.11	ns	0.07	ns	ns	0.09	ns	ns	0.09	ns	ns	ns	ns	-0.13									
22	novproc	0.12	ns	ns	ns	ns	ns	ns	ns	ns	0.10	ns	0.07	ns	ns	ns	ns	0.11	0.08	ns	ns	0.24								
23	lnrdstaf	0.34	0.09	ns	0.16	ns	ns	0.11	ns	ns	ns	-0.09	0.15	0.09	ns	0.10	ns	ns	ns	-0.26	-0.28	0.27	ns							
24	dumrdsta	0.18	0.11	ns	0.16	0.09	ns	0.09	ns	ns	ns	ns	0.15	ns	ns	ns	ns	ns	ns	0.14	ns	0.23	ns	0.67						
25	dxlnrdst	0.34	0.07	ns	0.15	ns	ns	0.10	ns	ns	ns	-0.09	0.14	0.07	ns	0.10	ns	ns	ns	-0.31	-0.30	0.27	ns	0.99	0.60					
26	markreg	-0.10	-0.09	ns	-0.18	ns	ns	ns	ns	-0.08	ns	0.15	-0.16	ns	ns	ns	ns	ns	ns	-0.23	ns	-0.14	ns	-0.25	-0.33	-0.23				
27	partarr	ns	0.25	0.09	0.13	0.12	0.19	0.26	ns	0.22	ns	ns	ns	ns	ns	0.14	ns	0.09	ns	0.12	-0.09	0.15	ns	0.16	0.16	0.15	-0.16			
28	barfin	0.08	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	-0.15	-0.17	ns	ns	0.11	ns	0.12	ns	0.13		
29	barpot	-0.14	ns	ns	ns	0.08	ns	ns	0.08	ns	ns	ns	ns	ns	0.08	ns	0.08	ns	ns	ns	0.10	-0.18	ns	-0.16	-0.09	-0.16	0.07	ns	0.08	
30	bartec	-0.15	ns	0.07	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	-0.08	0.07	ns	ns	ns	0.12	-0.15	ns	-0.18	-0.10	-0.19	0.14	-0.08	ns	0.38
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**