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Absorptive capacity and the search for innovation

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ABSTRACT

This paper examines the link between a firm's absorptive capacity-building activities and the search process for innovation. We propose that the enhanced access to university research enjoyed by firms that engage in basic research and collaborate with university scientists leads to superior search for new inventions and provides advantage in terms of both the timing and quality of search outcomes. Results based on a panel data of pharmaceutical and biotechnology firms support these contentions and suggest that the two research activities are mutually beneficial, but also uncover intriguing differences that suggest differing roles of internally and externally developed knowledge.

1. Introduction

It is now well accepted that establishing and sustaining competitive advantage depends upon effectively developing internal knowledge, utilizing external knowledge, and exploiting knowledge to generate innovations (Kogut and Zander, 1992; Teece, 1996). Firms' ability to assimilate and exploit external knowledge is necessarily related to the firms' use of knowledge in the search for innovation. This paper examines the role of two firm research activities, internal basic research and collaborations with external scientists, in identifying, assimilating, and exploiting external knowledge and considers the role of this external knowledge in the search for new inventions. In doing so, this work both contributes to and tests theory related to the "absorptive capacity" of the firm and extends this literature to consider the impact of firm absorptive capacity on the effectiveness of external collaborations. In addition, it adds to the recent literature on the search for innovation, which has largely examined invention importance, by also considering the implications of external knowledge exploitation for the pace of search for new inventions.

The conceptualization of absorptive capacity put forth by Cohen and Levinthal (1989, 1990) highlights the fact that external knowledge does not equally benefit all firms, and that the benefits enjoyed by the firm are determined in part by the firm's own actions and resources. This has led to a vast and growing body of research, much of which has obscured the concept's original meaning or glossed over important assumptions (Lane et al., 2006). The value and appropriateness of various reconceptualization is a matter of current debate in the literature (for example, see Zahra and George, 2002 and Todorova and Dursin, 2007). However, in all renditions, the fundamental argument remains the same: by investing in certain (research or other capability-building) activities, firms can improve their ability to identify, value, assimilate, and apply (or exploit) knowledge that is developed outside of the firm.

The considerable literature addressing the absorptive capacity of the firm has uncovered a multitude of performance benefits associated with a variety of firm activities. Cohen and Levinthal (1989) discuss the role of the firm's own R&D in developing the necessary expertise and ability to make use of external knowledge. Other literature has identified the importance of in-house *basic* research to develop this capability, particularly when the external science from which the firm draws is of a basic nature (Rosenberg, 1990; Lane and Lubatkin, 1998; Dyer and Singh, 1998). Recent work has considered the nature of research and similarity between knowledge sets (Dyer and Singh, 1998; Lane and Lubatkin, 1998), the routines of the firm

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(Zahra and George, 2002), and employee skills (Vinding, 2006) as sources of absorptive capacity.

The development of the firm's ability to access external knowledge sources is not limited to activities that take place strictly within the firm. As emphasized by Cockburn and Henderson (1998) and Zucker et al. (1994, 1998), "connectedness" to outside knowledge sources (particularly scientists) provides benefits in terms of accessing and exploiting external knowledge. Other work has focused on the ability of firms to use connections and collaborations with university and other public sector scientists to gain advantage in accessing and developing public sector science (Zucker et al., 2002). This is consistent with literature examining the effect of a firm's "network" of connections to potential knowledge sources on inventive performance outcomes (Powell et al., 1996; Owen-Smith and Powell, 2004; Stuart, 2000), although network studies most often examine connections to other firms rather than university scientists.

While existing work emphasizes the advantages of accessing external knowledge, it does not provide or test theory regarding how such knowledge benefits firms' search for new inventions. Recent work regarding the role of knowledge in the innovation search process suggests specific mechanisms by which an improved knowledge base contributes to innovative outcomes. Knowledge provides researchers with an understanding of the fundamental principals underlying a system, which may allow researchers to better anticipate the result of various possible experiments without actually proceeding with the experiment (Nelson, 1982; Fleming and Sorenson, 2004). This allows researchers to prioritize potential research avenues and avoid costly and time consuming research trials that end is failure or low-valued outcomes. The limited empirical research in this vein confirms that a better knowledge base, and in particular scientific knowledge, generates more impactful inventions, especially when the search process is complex (Fleming and Sorenson, 2004).

This paper draws on the literatures describing absorptive capacity, network connections, and the search theories of innovation and makes two contributions to the literature. First, combining these literatures suggests a previously unexplored benefit of absorptive capacity and network connections related to the efficiency of search for new invention. Both the absorptive capacity/networks literatures and the search for innovation literature have been restricted to looking at quantities or importance of firm inventive output, usually with a count of patents or citation-weighted patents. This is consistent with search that leads to superior search outcomes with the guidance of scientific knowledge. However, better access to knowledge inputs useful in the search for new inventions is also expected to lead researches more directly to the better outcomes and help them avoid areas of less valuable outcomes. This suggests a focus on the pace or speed of innovation that is currently absent from these literatures. This paper proposes a novel measure of the pace of innovation, based on the time between establishment of existing knowledge and utilization in a new innovation. Results presented here demonstrate that firm research activities typically associated with building absorptive capacity and network connections do result in a faster pace of innovation, even controlling for the importance of the inventive outcomes.

Second, few studies of firm's collaborative networks consider the effect of variation in the network nodes (Owen-Smith and Powell, 2004). Those that do are interested in the variation across the potential knowledge sources, rather than the focal firms that are accessing the knowledge (Owen-Smith and Powell, 2004; Stuart, 2000). We suggest that the absorptive capacity generated by the firm's internal research influences the ability of the firm to make use of connections to external knowledge sources. Firms with superior internal research knowledge are expected to benefit more from connections to external scientists. Empirical results support this expected complementarity.

The paper proceeds as follows. Section 2 presents theory related to the role of knowledge in the search for innovation and the concept of absorptive capacity, and presents hypotheses related to the relationship between firm research activities and inventive performance. Section 3 describes the sample, data, and key measures employed in the analysis. The empirical methodology and result are discussed in Section 4, and limitations are discussed in Section 5. Section 6 provides a discussion of the implications of this study for the relevant literatures and suggests further research.

2. Theory development and hypotheses

The strategy literature that explores variation in firm performance has highlighted the role of the resources or capabilities of the firm as sources of firm competitive advantage, especially when these capabilities are difficult to imitate and are not available through a market transaction. How firms create, maintain, and enhance these capabilities is a fundamental question in the strategy field and the subject of considerable recent literature (Cockburn et al., 2000; Teece et al., 1997). The initial conditions, past activities and experience, and strategic adaptation by the firm over time determine the current set of capabilities held by a firm (Cockburn et al., 2000; Helfat and Peteraf, 2003). By studying the differences among firm-specific characteristics such as experience, knowledge stock, network position, or organizational focus, this research has demonstrated the influence of these differences on firms' innovative performance.[1] This paper adds to this literature by examining differences in firms' research-related activities and the implications of these activities for a firm's absorptive capacity, access to external knowledge, and resulting inventive performance. The following sections review and build upon existing literature regarding absorptive capacity and search for innovation to develop empirically testable hypotheses.

2.1. Scientific knowledge and the search for inventions

Following Nelson (1982), others have focused on the role of scientific knowledge in the search process for new inventions. Inventions are novel combinations of existing and/or new components (Schumpeter, 1934; Kogut and Zander, 1992; Fleming, 2001; Fleming and Sorenson, 2001). The search for a new invention is an uncertain process across a multi-dimensional space of possible new combinations, conditioned by the bounded rationality and preexisting familiarity of the researcher with respect to the research space (Fleming, 2001). A search generates a new invention when the new combination provides an outcome above some threshold level of usefulness or value.

What is particularly interesting about this process is the role played by knowledge. Because innovation is cumulative, accumulated knowledge provides a guide to the search process (Helfat, 1994; Nelson, 1982). Scientific knowledge, however, is different from knowledge developed through prior experimentation because scientific knowledge provides an understanding of the underlying fundamental properties generating the observed outcome–knowledge of *why* rather than simply *what* happened (Fleming and Sorenson, 2004). In this way, scientific knowledge provides an understanding of the area being searched and allows researchers to place feedback from experimentation in the overall context of scientific knowledge, providing additional opportunities for extrapolation and learning.

[1] For example, see Gulati et al. (2000), McGahan and Porter (2002), Gambardella (1992), Henderson and Cockburn (1994), Cockburn et al. (2000).

This understanding benefits the search for innovation by allowing researchers to reason through experiments and form an expectation of the outcome without actually running the trial (Fleming and Sorenson, 2004). Such knowledge facilitates the search for new innovations by suggesting possible solutions and allowing researchers to focus their search in the most likely areas of opportunity and eliminate areas of search that would have proved fruitless (Nelson, 1982; Kortum, 1997; David et al., 1992a,b; Fleming and Sorenson, 2004). Fleming and Sorenson (2004) predict that "[Science] should allow inventors to move quite directly toward the highest peak–the most useful configurations–on the landscape" (p. 914). Those authors demonstrate empirically that utilization of scientific knowledge in patented inventions is associated with inventions of greater importance, especially for complex inventions expected to benefit from science-guided search. This is consistent with science guiding search to better search opportunities. They do not make or test specific predictions regarding the pace of search, although this follows from their discussion of scientific knowledge and search. Search guided by more scientific knowledge should arrive at inventive outcomes more quickly.

One important external (to the firm) source of knowledge relevant for industrial innovation, especially in the biopharmaceutical industry studied here, is university-generated science. Universities are a valuable source of research results for firms in many industries, and this importance has been growing over time (Narin et al., 1997). Several researchers have described industry use of university-based basic scientific research in the development of new products and processes (Cohen et al., 2002; Mansfield, 1991, 1995; Mansfield and Lee, 1996; Mansfield, 1998; Grossman et al., 2001; McMillan et al., 2000; Narin and Olivastro, 1992; Cockburn and Henderson, 2001). Public science is particularly important as an input to innovation in the biotechnology and pharmaceutical industries (McMillan et al., 2000). Firms in the "drugs and medical products" industry report that their innovations draw heavily from academic research and that new products and processes would have been delayed without access to this research (Mansfield, 1991, 1998; Collins and Wyatt, 1998). Patents in the drugs and medicine category cite significantly more scientific publications than patents in other fields (Narin et al., 1997), and these patents more heavily cite basic research journals (Narin and Olivastro, 1992). Firms rely on basic science developments in biology and biochemistry, and many new drugs and delivery systems have their origins in discoveries at universities or government labs.[2]

Based on the expected role of scientific knowledge in the search process and the importance of university-generated scientific knowledge, it follows that firms enjoying enhanced access to university-generated scientific knowledge will demonstrate superior search for new inventions. We test two dimensions of search: the speed with which firms arrive at the new invention, and the quality or importance of the inventive outcome.

2.2. *Developing absorptive capacity*

If university-generated scientific knowledge is useful for search, then it is important to consider how firms can improve their ability to access and utilize such knowledge. The concept of absorptive capacity focuses attention on the fact that knowledge outside the boundaries of the firm is not freely and effortlessly absorbed by the firm, even if it is in the public domain, and it is thus not equally absorbed and exploited by all firms. Instead, effort, expertise, and purposeful action on the part of firm researchers are required to identify, assimilate, and exploit this external knowledge (Cohen and Levinthal, 1989).[3]

Existing absorptive capacity literature has considered a multitude of firm activities that may contribute to the firm's absorptive capacity, including investments in R&D (Cohen and Levinthal, 1989), the firm's basic research activities (Rosenberg, 1990; Lane and Lubatkin, 1998; Dyer and Singh, 1998), the routines of the firm (Zahra and George, 2002), technological overlap or relatedness of research (Mowery et al., 1996; Prager and Omenn, 1980), trust and cultural compatibility across acquiring firm and source of knowledge (Lane et al., 2001), employee skills (Vinding, 2006), and collaborations with external (especially university) scientists scientists (Cockburn and Henderson, 1998; Zucker et al., 1994, 1998, 2002; Gambardella, 1992). Here I will consider separately absorptive capacity developed via the firm's own basic research and the access to knowledge via connections between firm researchers and university scientists.

Some commonality between the firm's internal research and the external research is necessary for successful knowledge transfer (Lane and Lubatkin, 1998; Prager and Omenn, 1980). Basic research performed internally by the firm creates a bridge of familiarity between firm and university researchers and provides a common vocabulary that facilitates communication. This common knowledge base assists firm researchers in identifying and exploiting university science and also allows for more effective communication, understanding, and, consequently, knowledge transfer between the university and firm researchers.

Collaborations between firm and external researchers aid in identifying and incorporating external science. This has been described in the considerable body of research addressing learning and knowledge transfer in firm-to-firm strategic alliances (see for example example Mowery et al. (1996), Stuart (2000) and Grant and Baden-Fuller (2004)) and is the focus of much of the literature on knowledge flows within interorganizational networks (for example Powell et al., 1996 and Owen-Smith and Powell, 2004). Recent work in the "open innovation" paradigm draws attention to the fact that firms benefit from an active awareness and focus on external research and innovation (Chesbrough, 2003; Laursen and Salter, 2006). Consistent with the logic put forth by Cockburn and Henderson (1998), a firm that operates under a particularly insular research culture will have difficulty keeping up with recent scientific developments, while a firm that maintains connections to the larger research community will enjoy superior access to the knowledge within that community.

Although many of the studies concerned with collaborations, networks, and access to knowledge focus on firm-to-firm linkages, the same knowledge-sourcing logic applies to collaborations between firm researchers and university scientists. Collaborations with university scientists not only help to identify relevant scientific research, which may or may not be published, but also provide the firm with access to the tacit knowledge complementary to published research results. In many cases, reading the published or otherwise codified research results may not provide a researcher with enough knowledge to utilize the results in the absence of the related tacit knowledge that remains uncodified (Dasgupta and David, 1994; David et al., 1992a,b). As described by von Hippel (1994), research-related knowledge often resides with

[2] Cockburn and Henderson (1998) summarize case studies of many important drug developments with their origins in public sector science.

[3] Factors affecting the use of knowledge external to the firm in the innovation and development process have been discussed in the context of the monitoring role of R&D (Kline and Rosenberg, 1986; Rosenberg, 1990), the necessity of investment in absorptive capacity (Cohen and Levinthal, 1990; Pavitt and Patel, 1995), the scope, depth, and breadth of search (Katila and Ahuja, 2002; Laursen and Salter, 2006), and the market for intellectual property (Arrow, 1971; Williamson, 1975, 1985; Teece, 1981, 1989, 1996; Lamoreaux and Sokoloff, 1999; Nelson, 1959, 1982).

the researcher, and is “sticky” and difficult to transfer. Knowledge transfer among individuals with an on-going pattern of collaborations is more fine-grained, tacit, and cooperative than otherwise possible (Uzzi, 1996, 1997).

In several empirical studies, internal basic research and collaboration with university scientists have been shown to be significantly and positively related to the number of pharmaceutical firm patents (Cockburn and Henderson, 1998; Gambardella, 1992) and the number and importance of biotechnology firm patents (Zucker et al., 2002; Baum et al., 2000), providing some evidence of the expected innovative performance benefits of absorptive capacity. In a survey of firms in the information technology, scientific instruments, and new materials sectors, industry researchers report that linkages to universities provide substantial advantage in terms of keeping abreast of university research, gaining access to the expertise of university researchers, and receiving general assistant with problem solving (Rappert et al., 1999). Similarly, Thursby and Thursby (2000) find that personal contacts of firm researchers are often the source of information about technologies available from university research. Both studies highlight the importance of interpersonal linkages and interactions for research knowledge transfer.

This paper considers that a firm’s research and collaborations not only provides access to external knowledge that would otherwise be missed, which in itself in expected to produce more efficient search, but also allows firm researchers to identify and absorb external knowledge more quickly. The president of Centocor, a biotechnology company, claims that by providing their scientists the freedom to develop scientific expertise, keep up with recent scientific discoveries, and maintain a social network within the scientific community, “Centocor should know about major research at least a year before it’s published” (Gibson, 1985). Both faster identification and assimilation and more efficient search improve the innovative performance of a firm.

Finally, there is reason to expect that the firm’s internal research and external collaborations are complementary activities (Powell et al., 1996; Arora and Gambardella, 1994). The firm’s internally developed research capability allows it to better evaluate, understand, and assimilate new knowledge to which it is exposed via external collaborations. Hence, collaborations with university scientists should be more beneficial, in terms of accessing knowledge, to firms with more internally developed research capabilities. Likewise, the internal research of firms is of more value to firms that also engage in external collaborations because these firms exploit the absorptive capacity provided by their internal research more extensively.

Firms have pursued differing strategies along these dimensions. For example, Merck focused on building internal research expertise. Merck’s early internal research regarding the formation of cholesterol allowed it to take advantage of (Nobel Prize winning) published research by two University of Texas researchers regarding a key step in the production of cholesterol. This research led Merck scientists to the discovery of cholesterol inhibitors and the development of the blockbuster drug Mevacor. Other firms did not exploit this published science as effectively (Gambardella, 1992). In contrast, Novartis has focused more on building connections to university scientists as avenues for identifying and exploiting public science. The company sponsors weekly seminars on site, where university scientists discuss cutting edge work.

2.3. Absorptive capacity & search for innovation

Combining the absorptive capacity literature with the recent theory regarding the role of scientific knowledge in the search for new inventions leads to straightforward predictions. Absorptive capacity-enhancing research activities provide benefits in terms of the level of external scientific knowledge available and/or the timeliness with which it is available, which will help guide the uncertain search for new inventions. As a result, firms investing in more absorptive capacity-generating research activities will enjoy superior search, in terms of pace of search and the importance of inventive outcomes.

Hypothesis 1. Firms that perform more in-house basic research will exhibit superior search for new inventions.

In addition, the collaborations between firm researchers and university scientists provide a firm with earlier, richer, and more comprehensive access to important university-based science. Controlling for the amount of basic research done by the firm, firms that do more of this research in collaboration with university research are expected to enjoy search benefits.

Hypothesis 2. Firms with a greater degree of connectedness to university scientists will exhibit superior search for new inventions

Finally, internal research and external collaborations are complementary activities that together allow greater access to knowledge, and as a result promote superior search outcomes. Specifically, we expect that collaborations provide more benefit when a firm also possesses greater internal research, and the benefits resulting from internal research are greater when the firm also engages in external collaborations. Note that these possibilities are not inseparable: each refers to the difference in marginal effects of one activity on search outcomes at different values of the other activity.

Hypothesis 3a. The relationship between the firm’s internal basic research and search for inventions is more pronounced when the firm also collaborates more with university scientists.

Hypothesis 3b. The relationship between the firm’s collaborations with university scientists and search for inventions is more pronounced when the firm also does more basic research.

3. Methodology

In order to test these hypotheses, I examine the relationship between firm research activities and the effectiveness of search for new inventions with two outcome measures: (1) the pace of innovation, measured as the speed with which the firm is able to exploit existing knowledge in new patented inventions and (2) importance of the new inventions developed. These measures correspond to the efficiency or pace of the search for inventions and the quality of the search outcome. The following sections describe the sample and data used in the empirical analysis, and each of the variables used in the analysis. The variables and data sources are summarized in Table 1.

3.1. Sample and data

I construct a panel data set of 83 firms in the biotechnology and pharmaceutical industries during the 1976–1999 period. The sample of firms is composed of companies listed as major pharmaceutical firms and those listed as biotechnology firms in Standard & Poor’s Industry Surveys for the years 1979, 1985, 1990, 1995 and 2003.[4] For each company, I collect firm-specific data covering the 1976–1999 period from several sources. In order to compare similar technologies, my sample of patents is limited to the fifteen 4-digit international patent classes most closely associated with pharmaceutical and biotechnology firms.[5]

[4] These industries were not surveyed in the 1980 edition.

[5] The international patent classes that I include are A01N, A61B, A61F, A61K, A61M, C07C, C07D, C07F, C07H, C07K, C08F, C08G, C12N, C12P, and G01N. These classes account for 80% of all patents associated with the sample companies.

Table 1
Description of variables, data and sources.

Construct	Variable name	Description	Data source
Pace of knowledge exploitation	$MeanCiteLag_{f,k,t}$	Natural log of mean number of years between grant date of cited patent prior art and application date of focal patent, excluding self-citations	NBER Patent Database
Invention importance	$\#ForwardCites_{f,k,t}$	Natural log of average number of citations received by firm's patents in class and year	NBER Patent Database, MicroPatent database
Firm basic research	$\#Pubs/R\&D_{f,t}$	Ratio of number of publications by firm researchers in given year to R&D spending	Science Citation Index, Compustat
Firm collaboration w/university scientists	$\%UnivCo–AuthorP\ ubs_{f,t}$	Percentage of firm publications co-authored with university scientists in given year	Science Citation Index
Firm Research Intensity	$R\&D/Employee_{f,t-1}$	R&D expenses per employee in thousands of dollars, in prior year	Compustat and Datastream
Firm size	$\#Employees_{f,t-1}$	Natural log of the # Employees in prior year	Compustat and Datastream
Firm age	$Firmage_{f,t}$	Number of years since firm founding	Corptech, Mergent, Lexis Nexis
Foreign firm indicator	$ForeignFirmID_f$	Equal to 1 for non-U.S. firms, 0 for U.S. firms	Corptech, Mergent, Lexis Nexis
Biotechnology firm indicator	$BiotechID_f$	Equal to 1 for biotechnology firms, 0 for pharmaceutical firms	Standard & Poor's Industry Surveys
Avg. number of citations	$\#Citations_{f,k,t}$	Natural log of the average number of citations to patent prior art in firm, class, year, excluding self citations	NBER Patent Database
Avg. number of claims	$\#Claims_{f,k,t}$	Natural log of average number of claims in firm, class, year patents	NBER Patent Database
% Self citations	$\%SelfCites_{f,k,t}$	Average percent of self-citations (to same assignee) contained in patents in firm-class-year	NBER Patent Database
Patent class size	$\#Patents_k$	#Patents in technology class-year observation	NBER Patent Database
Growth in patent class	$GrowthOfPatent_k$	#Patents in technology class in current year – #patents in technology class 10 years prior	NBER Patent Database

Subscripts *t* (time), *f* (firm), *k* (patent class).

Corptech, Hoovers Online, Mergent, Lexis-Nexis article searches, and the Capital Changes Reports provide corporate structure information detailing the founding date, geographic location, and mergers and acquisitions for each firm.[6] I was able to locate the required firm level data for 83 companies.[7] Note that use of public data restricts the sample of firms to those that went public, indicating at least some level of success (although some went on to fail or be acquired). Drawing the sample from Standard & Poor's Industry Surveys also introducing a large-company bias. Therefore, all results should be interpreted as conditional on at least achieving public status.[8]

I rely on information found on the front page of each of the sample firms' patent to develop measures of the pace of knowledge exploitation and importance of inventions. The dependent variables based on firms' patents are described in the following sections.

3.2. *Pace of innovation*

Each patent lists U.S. and foreign patents cited as prior art in the "References Cited" section. The dependent variables measuring the pace of innovation are calculated based on each patent's prior art citations; that is, the U.S. patents and published articles listed in the "References Cited" section of the patent. These prior art citations indicate the existing knowledge on which the new patent builds.[9] The grant dates of the patents cited as prior art and the publication dates of non-patent prior art references provide an indication of the age or vintage of the knowledge being built upon. The time lag between the cited patents or publications and the new invention therefore represents the speed with which that prior knowledge is utilized in the new invention, with longer lags indicating a slower pace of knowledge exploitation.[10] Other studies, such as Sorenson and Fleming (2004), have used *forward* citation lags similarly to measure the speed of diffusion. I am interested in the *backward* citation lag as a measure of the age of prior art being built upon.

Patents in technology classes experiencing more rapid advance will cite, on average, more recent prior art. Fig. 1 displays the smoothed distribution of backward citation lags for citations made by patents applied for in 1985 in each of four patent classes. Fields characterized by fast follow-on innovation and relatively rapid obsolescence of the knowledge base, medical preparations and semiconductors, are characterized by quickly peaking distributions of backward citation lags with relatively low average backward citation lags. Patents in the other two categories, stone working and hinges, rely on relatively older technology as patented prior art and are characterized by a less peaky distribution with a higher average citation lag. The mean backward citation lag for each patent is calculated, and then averaged at the firm-class-year level for the analysis.[11] The distributions the average citation lag is significantly skewed, and so I use the natural log as the dependent variable in the regression.

[6] When a firm merges with or acquires another firm, the surviving firm remains in the sample and publications with either original firms' name are used for the resulting firm in subsequent years.

[7] I could not include companies with no identifiable patents during the sample period, so all results should be interpreted as conditional on having at least one patent.

[8] Many of the firms do not span the entire 24-year window. A firm enters my sample in the first year for which Compustat reports employee data, and exits when this data item is no longer reported. Unfortunately, Datastream provides data only for 1980 and subsequent years, so the six foreign firms in the sample that are not covered by Compustat do not enter until 1980.

[9] The information contained in patent citations has been used to trace the transfer of knowledge across inventors, institutions, geographic locations, and technology classes, and to develop measures of importance, generality, and originality (Trajtenberg et al., 1997; Henderson et al., 1998a,b; Hall et al., 2001). See Narin (1994) for a discussion of the use of patent citations generally.

[10] Similarly, Narin (1994) defines the technology cycle time of an industry as the median age of the patents cited in other patents. As an example, he states that electronics, which is a "relatively fast moving area," has a much shorter cycle time than slower moving areas such as mechanical areas. Deng et al. (1999) use the technology cycle time at the patent level to proxy for how quickly firms are innovating. Trajtenberg et al. (1997) describe the average backward citation lag of a patent as a measure of the remoteness in time of the patent, where a longer lag corresponds to drawing from older sources.

[11] I exclude self-citations, or citations where the assignee of the cited patent is the same as the assignee of the citing patent, following Mowery et al. (2002). Patent citation lags are grant year to application year.

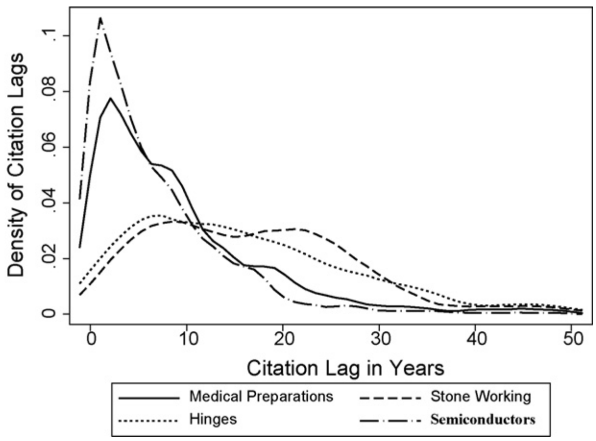

Fig. 1. Distribution of backward citation lags for patents applied for in 1985.

3.3. Invention importance

As in other recent studies, I use a count of the forward citations received by a patent as a measure of the patent's quality or importance (Hall et al., 2001; Trajtenberg, 1990; Fleming and Sorenson, 2004). Conceptually, the number of citations received is an indication of the invention's usefulness to future, follow-on inventions–those follow-on citing patented inventions are referencing the focal patent as relevant prior art relied upon in the new invention. Empirically, the number of forward citations received by a firm's patents has been shown to be positively related to the market value of the firm (Hall et al., 2005) and the social value of a given patented invention (Trajtenberg, 1990). The dependent variable at the firm-class-year level is the average number of forward citations received by patents generated by the focal firm in that technology class and application year.

3.4. Firm research activities

To test the hypotheses described above, I develop proxies for the basic research performed by the firm and the collaborative linkages between the firm and university scientists. The ratio of the number of the annual scientific publications by firm researchers to firm expenditures on R&D is used as a proxy for the internal basic science expertise of the firm, as it was in Cockburn and Henderson (1998).[12] The number of publications appears to reflect the underlying research focus and activity. For example, Merck is well known for a strong focus on internal research rather than external collaborations, as well as an organizational structure that promotes academic norms (Gambardella, 1992). This is reflected in publication counts for Merck scientists that are well above the sample average over the entire period. Genentech, also a company with a focus on internal basic research established by founders from academe, also generates more publications per year than the average firm in the sample.

Although the two companies both pursue internal basic research, Genentech is much more active in developing research collaborations outside of the firm. For example, Genentech's "Find Program" is specifically designed to promote interaction with the scientific community in order to identify new research and build relationships with scientists. Merck, on the other hand, values internal science and innovation development primarily based on in-house research (Economist, 1997). I proxy for the degree of connectedness with university scientists with the percentage of the firm's publications in a year that are co-authored with university scientists.[13] Genentech consistently collaborates with university scientists on a higher share of their publications, while Merck falls at approximately the sample mean, reflecting the difference in research strategies of these firms.

These publication-based measures encompass more than the firm's publication activity. Firms that openly publish research may have a more "academic" organizational structure, promoting interaction, disclosure, and individual inquiry (Henderson and Cockburn, 1994). Firms with more university-coauthored publications, such as Genentech, may also have a significant number of Ph.D. scientists or founders that were university-affiliated. The analysis here does not differentiate between these aspects of firm research strategy, and so the coefficients on the publications and co-authorships variables may partially reflect other unobserved, correlated factors. The variables used here should be interpreted as indicators of the larger underlying strategy and organizational focus of the firm.

3.5. Controls

I control for the firm's research intensity using the ratio of annual R&D expenditures to the number of employees at the firm level, as did Cohen and Levinthal (1989). I control for firm size with the annual number of employees. Mowery et al. (1996) found that large firms did not demonstrate as much absorptive capacity with respect to alliance partners relative to smaller firms. I also include a dummy variable *Biotech* equal to one for companies listed as biotechnology companies in the Standard & Poor's Industry Surveys, a dummy for firms located outside of the United States, *ForeignID*, and the age of the firm, *FirmAge*, equal to the number of years since firm founding.[14]

I control for additional firm-class specific patent-level characteristics that are expected to be significantly related to the backward citation lag. First, I control for the average number of citations to prior art, *#Citations*.[15] In the backward citation lag regression, this controls for the fact that since the distribution of the citation lag has a long right tail (there are very few lags of a very long length) and patent citations come only in whole numbers (i.e. it is not possible to have 0.5 of a citation), the more citations there are, the greater the likelihood of having a citations drawn from the long right tail of the distribution, and thus a higher mean lag. In both the citation lag and the importance regressions, it also controls for the complexity and "size" of the patent, where more complex patents may cite more prior art and may also take longer to develop but be more useful to future inventions. Second, I include a control for the average number of claims contained in the firm's patents, *#Claims*, to adjust for complexity or scope that may be reflected by the number of claims. Finally, in the regressions predicting the average importance of firm patents, I control for the average percentage of backward citations that are to the firm's own patents, *%SelfCite*. Firms building heavily on their own prior art may be developing primarily incremental inventions or lower average importance.[16]

[12] Gambardella (1992), Arora and Gambardella (1994), and Lim (2004) use the count of firm publications similarly. As in Cockburn and Henderson (1998), I use the address field for the researcher to identify the company or university affiliation.

[13] A similar measure of "connectedness" to university science was used in Cockburn and Henderson (1998), although those authors allow a single publication to count as more than one co-authorship if more than one outside institution is involved.

[14] The number of such biotech companies grows over the sample period, and by the end of the period is approximately equal to the number of pharmaceutical firms.

[15] The count of citations used in the citation lag equations excludes self-citations because the lag is calculated excluding self-citations.

[16] One might expect that the backward citation lag would be shorter for firms building primarily on their own prior inventions. However, the backward citation lag measure excludes self citations, and therefore this control in unnecessary in the back-

Table 2
Summary statistics, 1975–1999.

Variable	Mean	St. Dev.	Min	Max
Firm-year level observations				
$\#Pubs/R\&D_{f,t}$	0.91	2.10	0	37.31
$\%UnivCo\text{–}AuthorPubs_{f,t}$	30.93%	25.22%	0	100%
$R\&D/Employee_{f,t-1}$ (M$)	299.60	2369.53	0	34862
$\#Employees_{f,t-1}$	18.09	29.44	0.005	186.85
$Firmage_{f,t}$	50.13	48.37	2	218
$ForeignFirmID_f$	0.14	0.35	0	1
$BiotechID_f$	0.41	0.49	0	1
Firm-class-year level observations				
$MeanCiteLag_{f,k,t}$	6.75	5.24	0	49
$\#ForwardCites_{f,k,t}$	3.68	6.79	0	104
$\#Pubs/R\&D_{f,t}$	0.77	1.79	0	37.31
$\%UnivCo\text{–}AuthorPubs_{f,t}$	31.22%	20.34%	0	100%
$R\&D/Employee_{f,t-1}$ (M$)	319.76	2511.28	0	34862
$\#Employees_{f,t-1}$	29.51	36.83	0.005	186.85
$Firmage_{f,t}$	68.80	51.28	2	218
$ForeignFirmID_f$	0.20	0.40	0	1
$BiotechID_f$	0.25	0.43	0	1
$\#Citations_{f,k,t}$	6.15	7.63	0	124
$\#Claims_{f,k,t}$	10.74	9.73	0	140
$\%Selfcitations_{f,k,t}$	15.61%	20.59	0	100%
$\#Patents_{k,t}$	1304.85	1233.73	7	7326
$GrowthofPatents_{k,t}$	641.17	833.37	−858	5259

Subscripts t (time), f (firm), k (patent class).
N = 917 at the firm-year level; N = 4723 at the patent level, except for mean lag N = 4647.

While the specification includes technology class level indicator variables to control for time-invariant differences across technology area, there are also two important technology class-year level control variables that control for changes in the technology area over time that are expected to affect the backward citation lag. I control for the total number of patents in the same technology class and application year as the focal patent, *#Patents*, in order to control for the development of the technological area. I control for the recent growth in the number of patents in the technology class, *GrowthOfPatents*, using the change in the number of patents in the class over the previous five years. This controls for "citation inflation," or the fact that backward citation lags are getting shorter due to the increasing number of patents each year, resulting in more recent patents relative to the number of older patents available to cite.

Summary statistics are reported in Table 2.[17] There is considerable variation within the sample for all of the variables of interest. These summary statistics reinforce the strong science base in these fields. Across firm-year observations, the mean ratio of publications to R&D is 0.9 publications for every 1000 R&D dollars, with a range of zero to 37. The mean percentage of publications co-authored with university scientists is 31%, and the range is from zero to 100%. Table 3 reports the simple correlation coefficients for these variables (at the firm-class-year level of observation). The publications to R&D ratio is positively correlated with the percentage of publications that are co-authored with university scientists, suggesting that firms engaged in internal basic science are also more highly focused on external knowledge sources. Both publication intensity and collaborations are negatively correlated with the mean citation lag and positively correlated with the number of citations received, consistent with the predictions.

4. Empirical results

The hypotheses predict that in-house basic science and collaborative linkages to university researchers will be associated with a faster pace of knowledge exploitation and more important inventions. The results for each of these outcome variables are discussed in the following two section.

4.1. Pace of innovation

First, consider the speed or pace of search for new inventions. The firm's pace of knowledge exploitation is related to how long it takes that firm to build upon existing knowledge in new inventions. By comparing the average length of the citation lags across firm, I evaluate whether the firms' pace of knowledge exploitation is related to their research activities. I estimate the following equation for firm f in year t in technology class k:

$$\ln(MeanLag_{fkt}) = \beta_1 Pubs/R\&D_{ft} + \beta_2 \%UnivCoAuthor_{ft} + X'_{1_{ft}}\beta_3 + X'_{2_{kt}}\beta_4 + \sum_t \alpha_t Year_t + \sum_k \theta_k Class_k + \varepsilon_{fkt} \quad (1)$$

where *MeanLag* is the natural log of the mean backward patent citation lag of firm f's patents in class k and year t as described above.

Consistent with the "knowledge production function" empirical methodology (Griliches, 1995; Jaffe, 1986), and because a non-linear relationship is expected (i.e. percentage change matter more than a unit change), number of employees, number of patents, average number of citations, and average number of claims in the patents are all included as natural logs. The year of the patent is the *application year*, more closely approximating the invention date. Publications and publications co-authored with university scientists are dated to the *year of publication* because that is the only date reliably available. The publication-based variables therefore represent research activity of the firm in the recent past. The R&D intensity and the number of employees are included with a lag of one year.[18]

All equations include year and technology class dummy variables to control for average technology class effects, such as the changing nature of technological opportunity in a given technology area, and year effects, including all changes in this industry that are common across firms. Results should therefore be interpreted as within a given technology area, across firms. Robust standard errors, clustered by firm, are reported for all equations to account for the non-independence of the multiple observations for each firm (Bertrand et al., 2004).[19]

Hypotheses 1 and 2 predict that β_1 and β_2, respectively, will be negative. The implicit null hypothesis is that the variation in average citation lag length is not systematically related to the firm's research activities. This would hold, for example, if openly published scientific research were equally available to all industry researchers. This cross-firm analysis is in the spirit of deconstructing the firm fixed effect; it allows evaluation of which firm activities contribute to the heterogeneity observed across firms. As discussed in more detail below, one might be concerned about unobserved heterogeneity at the firm level. Robustness checks using firm level firms effects are reported and discussed in the next section.

ward citation lag regressions. If included, it is insignificant and has no measurable effect on the other variables.

[17] Note that there are 76 firm-class-year observations for which it was not possible to calculate the average citation lag because the patents by that firm in that class-year did not contain any backward citations. These observations are not included in the estimates of the mean backward citation lag.

[18] The same timing for publications, patents, and R&D was used by Gambardella (1992). In both the analysis of non-patent citations and the analysis of the backward citation lags that follows, I tested the robustness of the results to lagging the publications variables by one year, two years, or three years, or including the rolling average of the prior three years. The results were very similar to those reported here.

[19] A Wooldridge test for serial correction in panel data failed to reject the null hypothesis of no first order serial correlation (Wooldridge, 2002; Drukker, 2003).

Table 3
Correlation coefficients.

		1	2	3	4	5	6	7	8
1	$\mathit{MeanCiteLag}_{f,k,t}$								
2	$\mathit{AvgForwardCites}_{f,k,t}$	−0.03							
3	$\mathit{\#Pubs/R\&D}_{f,t}$	−0.12	0.10						
4	$\mathit{\%UnivCo{-}AuthorPubs}_{f,t}$	−0.09	0.13	0.20					
5	$\mathit{\#Employees}_{f,t-1}$	0.12	−0.06	−0.15	−0.07				
6	$\mathit{R\&D/Employee}_{f,t-1}$	−0.00	−0.02	−0.03	−0.02	−0.10			
7	$\mathit{\#Citations}_{f,k,t}$	0.21	0.17	−0.06	−0.04	−0.05	−0.04		
8	$\mathit{\#Claims}_{f,k,t}$	0.03	0.23	0.05	0.14	−0.07	−0.05	0.06	
9	$\mathit{\%SelfCite}_{f,k,t}$	0.07	−0.07	−0.01	−0.09	0.04	0.05	0.05	−0.02

Subscripts *t* (time), *f* (firm), *k* (patent class).
Note: Correlations at the firm-class-year level of observation, $N = 4647$.

Table 4
Mean backward patent citation lag as a function of firm research activities.

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathit{\#Pubs/R\&D\$}_{f,t}$	−0.026		−0.024		−0.011	−0.021
	(0.006)**		(0.005)**		(0.004)**	(0.005)**
$\mathit{\%UnivCo{-}AuthorPubs}_{f,t}$		−0.288	−0.249		−0.174	−0.232
		(0.100)**	(0.086)**		(0.077)*	(0.085)**
$\mathit{\#Pubs/R\&D\$}_{f,t}$, *Hi%UnivCo–Author*				−0.022		
				(0.005)**		
$\mathit{\#Pubs/R\&D\$}_{f,t}$, *Lo%UnivCo–Author*				0.001		
				(0.019)		
%UnivCo–Author, $\mathit{Hi\#Pubs/R\&D\$}_{f,t}$				−0.300		
				(0.098)**		
%UnivCo–Author, $\mathit{Lo\#Pubs/R\&D\$}_{f,t}$				−0.150		
				(0.083)		
$\mathit{R\&D/Employee}_{f,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.000)	(0.000)*	(0.000)**	(0.000)*
$\ln(\mathit{\#Employees})_{f,t-1}$	0.024	0.026	0.019	0.030	0.081	0.020
	(0.015)	(0.014)	(0.015)	(0.012)*	(0.039)*	(0.013)
$\mathit{ForeignFirmID}_{f}$	0.024	0.023	0.027	0.038		0.023
	(0.047)	(0.044)	(0.044)	(0.037)		(0.039)
$\mathit{biotech}_{f}$	−0.130	−0.127	−0.124	−0.113		−0.098
	(0.074)	(0.067)	(0.067)	(0.068)		(0.063)
$\mathit{Firmage}_{f,t}$	−0.000	−0.000	−0.000	−0.000		−0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
$\ln(\mathit{\#Citations})_{f,k,t}$	0.204	0.205	0.204	0.208	0.219	0.220
	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.020)**	(0.021)**
$\ln(\mathit{\#Claims})_{f,k,t}$	−0.028	−0.032	−0.030	−0.029		−0.009
	(0.016)	(0.016)*	(0.016)	(0.016)		(0.016)
$\ln(\mathit{\#Patents})_{k,t}$	−0.029	−0.020	−0.028	−0.021	−0.035	−0.047
	(0.041)	(0.043)	(0.042)	(0.042)	(0.038)	(0.041)
$\mathit{GrowthofPatents}_{k,t}$	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)*	(0.000)*	(0.000)*	(0.000)**	(0.000)**	(0.000)*
$\mathit{ZeroLag}_{f,k,t}$	−1.541	−1.531	−1.537	−1.532	−1.498	−1.529
	(0.043)**	(0.044)**	(0.043)**	(0.044)**	(0.044)**	(0.043)**
$\mathit{ZeroPubs}_{f,t}$		−0.110	−0.132	−0.092	−0.225	−0.105
		(0.091)	(0.091)	(0.077)	(0.070)**	(0.087)
$\ln(\mathit{\#Forwardcites})_{f,k,t}$						−0.097
						(0.014)**
Constant	2.086	2.067	2.151	2.039	1.439	2.273
	(0.263)**	(0.269)**	(0.266)**	(0.269)**	(0.208)**	(0.263)**
Observations	4647	4647	4647	4647	4647	4647
R-squared	0.55	0.55	0.55	0.55	0.51	0.56

Subscripts *t* (time), *f* (firm), *k* (patent class).
The dependent variable is the natural log of the mean backward patent citation lag for patents in the firm-class-year.
Robust standard errors (clustered by firm) in parentheses; *significant at 5%; **significant at 1%.
All equations include year and technology class dummy variables.
Equation 5 includes firm fixed effects.

Results are reported in Table 4. As expected, the coefficient on the average number of citations is significant and positive, and the coefficient on the growth in the number of patents in the class is significant and negative. As demonstrated in column (1), the coefficient on the number of firm publications is negative and significant, indicating a faster pace of knowledge exploitation for firms with more internal basic research, in support of Hypothesis 1. As reported in column (2), the coefficient on the percentage of publications that are university co-authored is also significant and negative, in support of Hypotheses 2. The specification reported in column 3 is the preferred specification, and includes both the firm's internal basic research and the collaborations with university scientists. Coefficients on both are negative and significant, consistent with the expected search benefits from these activities. These results suggest that a one standard deviation increase in the number of publications per 1000 R&D dollar by firm researchers is associated with a 4.3% decrease in the average citation lag. For the mean patent, this implies a 3.5-month decrease for the citation lag associated with the standard deviation increase in publication intensity. A one standard deviation increase in the percent of publications that are co-authored with university scientists (equal to 20.34%) is associated with a decrease in the mean patent and non-patent backward citation lag of 5.1%, or a decrease of 4 months for the mean patent.[20] Delays on the order months may sound small, but in an industry where profits are heavily dependent on innovations, and every research project is potentially a patent race, these delays can be quite significant.

In order to evaluate hypotheses 3a and 3b, I generate indicators for "high" and "low" values of firm publications and university collaborations. Low and High are relative to the median for the firms patenting in a given technology class-year observation. Establishing the criteria in this way takes into account that firms active in certain technology areas may be differentially disposed to each research activity. Consistent with the identification strategy, this provides a relative measure across firms within the technology class. I interact the firm publication variable with the high and low indicators for university collaborations, and interact the collaborations variable with the high and low indicator for firm publications. Including these four variables in the regression equation in place of the two variables (firm publications and university collaborations) allows a test for the difference in marginal value of each research activity in the different regions (low versus high) of the other variable.

Results of the specification including these variables are reported in column (4). Hypothesis 3a predicts that the relationship between firm publications and search efficiency is more pronounced at higher levels of collaboration. The coefficient on firm publications at high values of university collaboration is in fact larger in magnitude (and negative) than that on firm publications at low values of university collaborations, consistent with expectations. However, the difference is not statistically significant. Hypothesis 3b predicts that the relationship between university collaborations and search efficiency is more pronounced at higher levels of firm publications. The coefficient on university collaborations at high values of publications is larger in magnitude than that on university collaborations at low values of publications, and this difference is statistically significant.[21] This is consistent with external collaborations providing more benefits to firms with greater internally developed absorptive capacity.

[20] I also estimated these specifications using the minimum lag, i.e. the lag to the most recent cited patent, and the median lag. My qualitative results are robust to either of these alterations, and the magnitude of the coefficients on publications and co-authorships are quite similar.

[21] The difference in the coefficients is significant at the 2% level.

4.2. Invention importance

Second, consider the importance of the results inventive outcomes, as measured using the average number of citations received by the firm's patents. I estimate the following equation for firm *f* in year *t* in technology class *k*:

$$\ln(\#ForCites_{fkt}) = \beta_1 Pubs/R\&D_{ft} + \beta_2 \%UnivCoAuthor_{ft} + X'_{1_{ft}}\beta_3 + X'_{2_{kt}}\beta_4 + \sum_t \alpha_t Year_t + \sum_k \theta_k Class_k + \varepsilon_{fkt} \qquad (2)$$

where ln(#*ForCites*) is the natural log of the average number of forward citations received by firm *f*'s patents in class *k* and year *t*. The specification is analogous to the citation lag equation in terms of the lag structure, use of natural logs, and inclusion of technology class and year indicator variables. Hypotheses 1 and 2 predict that β_1 and β_2, respectively, will be positive.

Results are reported in Table 5. The structure of the table is analogous to the prior table of results, and thus the discussion is kept brief. Column (3) reports the preferred specification, results of which support the prediction that firms with more internal basic research activities generate more importance patents. The coefficient on the collaborations variable is positive, but significant only at the 11% level.

Column (4) reports the results including the interactions with high/low indicators to test for complementarity. Consistent with the overall results, collaborations are not significant over either range of publication activity. However, consistent with hypothesis 3a, the marginal effect of the firm's own publications is greater when the firm also collaborates more with university scientists.[22]

4.3. Robustness checks

There is a potential concern that unobserved heterogeneity across the firms in the sample that may drive these results. For example, firms may be specializing in certain research areas that require different research strategies. Firms specializing in areas that rely more heavily on scientific inputs may elect to engage in more basic research and collaborate more with university scientists. If the patents in these areas of research also tend to have shorter backward citation lags and receive more citations for some reason, it could be that the unobserved heterogeneity is driving the results. The selection of the biotechnology and pharmaceutical sectors for study alleviates this concern somewhat, because public science is known to be an important, omnipresent, critical input to the innovation process. The technology class fixed effects also help alleviate this concern because each patent's citations to public science and citation lags are being compared to other patents in the same technology area, within which the incentives and opportunities are more homogeneous than across the entire sample of innovations. However, the technology areas may not fully capture differences across the research areas in which firms may specialize.

In order to explore the sensitivity of the results to unobserved firm level heterogeneity, the main specification was re-estimated with firm-level fixed effects. This is not the preferred specification because firm's research strategies, as reflected in publication intensity and university collaborations, are expected to be somewhat stable over time. In addition, to the extent that firm research strategies change overtime in a way that affects publications, co-authoring, and the citation lag, the firm fixed effect in insufficient to control for these unobserved changes. Because firm capabilities are often path-dependent, developing slowly and remaining fairly

[22] The difference in coefficients on the publication variables is significant at the 4% level.

Table 5
Average importance as a function of firm research activities.

	(1)	(2)	(3)	(4)	(5)	(6)
*#Pubs/R&D$*$_{f,t}$	0.019 (0.008)*		0.020 (0.008)*		0.012 (0.004)**	0.018 (0.008)*
%UnivCo–Author_Pubs$_{f,t}$		0.216 (0.112)	0.183 (0.116)		0.149 (0.099)	0.134 (0.112)
*#Pubs/R&D$*$_{f,t}$, *Hi%UnivCo–Author*				0.024 (0.007)**		
*#Pubs/R&D$*$_{f,t}$, *Lo%UnivCo–Author*				−0.022 (0.022)		
*%UnivCo–Author, Hi#Pubs/R&D$*$_{f,t}$				0.113 (0.117)		
*%UnivCo–Author, Lo#Pubs/R&D$*$_{f,t}$				0.121 (0.131)		
R&D/Employee$_{f,t-1}$	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
ln(*#Employees*)$_{f,t-1}$	−0.053 (0.022)*	−0.048 (0.022)*	−0.043 (0.022)	−0.053 (0.021)*	−0.135 (0.075)	−0.034 (0.020)
ForeignFirmID$_f$	−0.063 (0.070)	−0.060 (0.068)	−0.063 (0.067)	−0.073 (0.066)		−0.051 (0.062)
biotech$_f$	0.143 (0.101)	0.157 (0.093)	0.154 (0.096)	0.153 (0.094)		0.142 (0.086)
Firmage$_{f,t}$	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)		0.000 (0.000)
ln(*#Citations*)$_{f,k,t}$	0.085 (0.029)**	0.084 (0.030)**	0.084 (0.030)**	0.083 (0.029)**	0.059 (0.026)*	0.165 (0.036)**
ln(*#Claims*)$_{f,k,t}$	0.124 (0.015)**	0.126 (0.015)**	0.124 (0.015)**	0.123 (0.015)**	0.133 (0.013)**	0.122 (0.014)**
%Self–Cites$_{f,k,t}$	−0.183 (0.081)*	−0.166 (0.080)*	−0.169 (0.079)*	−0.165 (0.080)*	−0.157 (0.071)*	−0.240 (0.096)*
ZeroForwardCites$_{f,k,t}$	−1.007 (0.034)**	−1.009 (0.033)**	−1.004 (0.033)**	−1.008 (0.033)**	−0.980 (0.034)**	−1.013 (0.035)**
ZeroPubs$_{f,t}$		0.203 (0.109)	0.222 (0.108)*	0.194 (0.095)*	0.123 (0.084)	0.210 (0.098)*
ln(*MeanCiteLag*)$_{f,k,t}$						−0.149 (0.025)**
Constant	0.802 (0.113)**	0.736 (0.119)**	0.709 (0.120)**	0.769 (0.110)**	1.350 (0.245)**	0.878 (0.116)**
Observations	4723	4723	4723	4723	4723	4647
R-squared	0.55	0.55	0.55	0.55	0.52	0.56

Subscripts *t* (time), *f* (firm), *k* (patent class).
The dependent variable is the natural log of the average number of citations received by patents in the firm-class-year.
Robust standard errors (clustered by firm) in parentheses; *significant at 5%; **significant at 1%.
All equations include year and technology class dummy variables.
Equation 5 includes firm fixed effects.

stable over time (Helfat and Peteraf, 2003), much of the variation of interest is likely to be between firms. With these caveats in mind, results of the specification included firm fixed effects (column 5 in Tables 4 and 5) are qualitatively similar to the results discussed above. Although the magnitude of the coefficients on publication and collaboration are reduced, both remain significant and negative in the citation lag regression and the publication intensity measure remains significant and positive in the forward citations regression.

A second concern with the interpretation of the analysis is the possibility that backward citation lags and number of forward citations received may be measuring the same thing, rather than proxying for pace of search and importance of resulting inventions, as I suggest here. I evaluate this possibility in two ways. First, I re-estimate both models including a control for the other dependent variable. If they are essentially measuring the same thing, the firm's publication intensity and collaboration activity should have little explanatory power once controlling for the other variable. Results, reported in column (6) of each table, demonstrate that this is not the case. Although the two dependent variables are certainly related–shorter average backward citation lags are associated with greater average importance–the results for the variables are interest are not substantially changed. Second, I estimate a model including both equations using Seemingly Unrelated Equations (SUR) to account for possible correlation in the error terms across the two equations. Results, not reported here in the interest of space, are nearly identical to the independent estimation of the two equations as reported in column (3) of both tables.[23] Both of these checks suggest that the two variables are in fact measuring different attributes of the firms' patented inventions.

[23] SUR estimation does not allow clustering to account for non-independence of standard errors within the firm, and the resulting standard errors are, as expected, much lower because of this.

5. Limitations

Aside from these econometric concerns, the use of patent citation data carries its own set of limitations. Obviously, this analysis is restricted to innovations that are patentable and that the firm chooses to patent. For biotechnology and pharmaceutical firms, patents are critical to competitive advantage and firms typically protect their innovations with patents. Firms in these industries rely on patents more heavily than do firms in other industries, so the use of patents as a proxy for innovations is more justified, but by no means perfect.[24]

Although considerable prior research has used the prior art citations in patents to identify the knowledge being built upon and trace knowledge flows, patent citation data has the problem that many citations are added by the patent examiner. Recent changes in patent office policy allow identification of prior art citations that are added by the patent examiner for recent patents. Sampat (2004) finds that as many as 60% of the citations to patented prior art are examiner-added. Analysis of the patents in the technology classes considered here for the year 2003 indicates that 38% of citations to patent prior art are examiner added.[25] In the analysis above, I use these citations to evaluate the age of the existing patented knowledge being exploited in a firm's new inventions. For this use, the source of the citation is less important because all citations reflect of the age of the technology being developed (whether the firm researcher knew of that technology or not).

Finally, this empirical investigation focused on two sectors that are notorious for their reliance on public science. Innovation in the biotechnology and pharmaceutical sectors is closely tied to fundamental science research performed in biology and chemistry departments at universities. Other industries may have less use for university-based research results, and so firms in these industries may not find research strategies aimed at acquiring such knowledge to be as useful. However, there are several very interesting industries for which university-based science is critical, and these industries are often characterized by substantial new inventions.[26] For example, the nano-technology industry was developed from university-based science and innovation in this area continues to be tied to basic research. Therefore, while the results should not be carelessly generalized across industries, they may be particularly applicable to the dynamic, highly innovative areas of technology that are closely related to basic science. In addition, the general result that internal research and collaboration with researchers at external knowledge sources assists knowledge transfer may apply to knowledge transfer from other sources, such as research consortia or other firms.

6. Discussion and conclusion

This paper set out to test the implications of absorptive capacity-generating firm research activities for the search process for innovation. Search theory predicts that access to a superior knowledge base, particularly of scientific knowledge, will result in more efficient search for new inventions that arrives at better search solutions. Results presented here demonstrate that investments in internal basic research and collaborations with university scientists do in fact provide search benefits in terms of both the pace of innovation and the importance of the results inventions. In addition, there is evidence that these two research activities are most effective for generating efficient search when used together; Firms with more internally developed research capabilities benefit more (in terms of faster search) from collaborations, and firms with more collaborations benefit more from their internal basic research (in terms of more important inventions).

While broadly supportive of the expected benefits of internally developed absorptive capacity and external research linkages, the results also uncover some intriguing differences by considering the timing of search outcomes in addition to the quality of outcomes. Internal basic research provides search benefits on both dimensions, while greater external collaboration provides benefits in terms of the pace of search (especially when the firm also possesses greater internal research capabilities) but does not independently affect the quality of search outcome. Although more work is necessary to examine this difference, it may reflect variation in how different types of knowledge are used in the innovation process. For example, the firm's own knowledge may be critical in project selection–choosing which problems to attempt to solve. As learning is cumulative and search is local in nature (Helfat, 1994), the firm's own research knowledge may largely determine the initial project selection. Project selection may be the primary driver of the importance of the inventive outcome. If firms elect to pursue incremental product improvements, for example, the resulting inventions may be of lesser importance. Connections to external knowledge sources, on the other hand, may be more important to provide access to knowledge useful in guiding the solution process, which would influence the efficiency of search. In addition, collaborations with external scientists may provide more timely access to research knowledge, resulting faster search. This would certainly be the case if firms with few collaborative connections only became aware of university research after it was published.

Extending research regarding knowledge flows in networks, such as Owen-Smith and Powell (2004), this work emphasizes the importance of variation across the focal firm nodes. While, on average, firms with more collaboration with external researchers experience greater search efficiency, the effect is more pronounced for firms that also have more internally developed research. Research considering the impact of network structure on innovative outcomes should consider that the effects of network structure are likely to vary systematically as a function of focal firm characteristics, such as absorptive capacity.

This work also adds to the small but growing literature on the role of knowledge in the search for innovation in two ways. First, existing work has considered the role of scientific knowledge in determining only the importance of the resulting invention. This work proposes that the theory relating to search is applicable also to the speed with which firms are able to realize these inventions. Consistent with theory, results here demonstrate that internal research and external collaboration assist the search for innovation in terms of the pace of innovation. Second, further analysis demonstrates the important relationship between various aspects of the firm's research strategy. It also suggests a particular advantage associated with externally developed knowledge, possibly as a way to overcome the negative implications associated with overly-constrained local search.

Beyond theoretical and empirical contributions to these two literatures, this work has practical importance for managers. The outcome measures employed here, the backward citation lag and number of citations received, have been shown to be related to both invention importance and firm economic performance measures. Analysis of the patents in this sample indicates that, controlling for other patent characteristics, shorter backward citation lags are associated with a significantly higher number of citations received, suggesting more important inventions. Deng et al. (1999) report

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[24] Firms in the drugs and medical equipment industries report much stronger reliance on patents as an appropriability mechanism than firms in other industries (Cohen et al., 2000).

[25] This is consistent with Sampat's finding that patents in the Drugs and Medical category contain the lowest percentage of examiner added citations. I thank Bhaven Sampat for data on examiner added citations for this analysis.

[26] In this discussion I use the term "industry" very loosely. Whether or not these technological areas constitute industries is arguable and unimportant here.

results indicating higher market to book ratios for drug companies whose patents have shorter median backward citation lags and receive more citations. Hall et al. (2005) demonstrate that firm market value is positively associated with the number of forward citations received by the firm's patents. Research activities associated with decreasing the backward citation lag and increasing the number of forward citations received by patents should be of strategic interest to firm managers.

There are multiple avenues for further research in this area. First, this paper does not address the effects of environmental conditions of the absorptive capacity-performance relationship. Environmental factors, such as the appropriability environment, will determine both the optimal investment in absorptive capacity-building activities and the effectiveness of these activities in providing the firm with a competitive advantage. The biopharmaceutical industry studied here is one in which intellectual property right are notoriously strong. A similar study across contexts with varying intellectual property environments would be enlightening. Similarly, the intellectually property rights environment with respect to university researchers has changed considerably over time, and might also be an avenue for interesting study.

Further research might also explore the importance of the network structure of the linkages between university scientists and firm researchers. Theory on strategic networks suggests that linkages to many network partners may increase the breadth and variety of information to which a firm has access, while strong linkages to one or a few network partners may unproductively limit a firm's vision of alternatives (Gulati et al., 2000). Some work in this area with respect to the networks of biotechnology firms documents innovative and economic benefits of firm network ties only up to a certain threshold of network experience (Powell et al., 1999).

Finally, there is an opportunity for further research to contribute meaningfully to the growing literature on incumbent firm response to radical technological change. Pharmaceutical firms faced with the disruptive and performance-enhancing research method of "rational" drug discovery adopted the technique at different times. The firm's rate of adoption has been related to the previous basic research experience (Cockburn et al., 2000) and the recognition of the technological change on the part of the firm's senior managers (Kaplan et al., 2003). Results here suggest that collaborative interactions between the firm and university scientists may help the firm build their scientific expertise and successfully adopt this new science-based approach to drug discovery. This is consistent with recent literature framing absorptive capacity as a dynamic capacity of the firm (Cohen and Levinthal, 1994; Zahra and George, 2002).

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