

Absorptive Capacity and Innovation: Evidence from Pharmaceutical and Biotechnology Firms

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Abstract

Firms in many industries rely on knowledge generated outside of the firm as an input to their own research and development. When innovation depends heavily on external knowledge, as is the case for pharmaceutical and biotechnology firms that rely on research results generated by university scientists, firms that are better at identifying and incorporating this external knowledge have an advantage. Existing work has demonstrated that pharmaceutical and biotechnology firms with more internal research, an emphasis on basic science research, and more linkages with university scientists generate more patents than comparable firms in these sectors. This has been interpreted as evidence of the “absorptive capacity” benefits of these firm activities, although there is no direct empirical evidence that firms with these characteristics exploit external knowledge more than other firms. This paper adds to this literature in three dimensions. First, I empirically examine the relationship between firm research activities and exploitation of published scientific research. Second, I employ a novel performance metric to evaluate innovative performance: the pace of knowledge exploitation. Results suggest that more in-house basic science research and collaboration with university scientists by a firm are associated with more exploitation of published scientific research and shorter lag times between existing knowledge and new firm inventions exploiting this knowledge. Finally, I present evidence that more citations to published scientific research and a faster pace of knowledge exploitation are associated with a superior economics performance for the firm. These results have implications for firm managers as well as the policy debates surrounding the university-industry interface.

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1 Introduction

Why are some firms better able to exploit knowledge that exists outside the boundary of the firm? The president of Centocor, a biotechnology company, claims that by providing their scientists the freedom to stay current with and make contacts in the scientific community, “Centocor should know about major research at least a year before its published.” (Gibson, 1985). By developing scientific expertise, keeping up recent scientific discoveries, and maintaining a social network within the scientific community, the company enhances its ability to identify and make use of relevant scientific discoveries from outside of the firm. The first goal of this paper is to examine whether or not there is evidence that these firm research activities are associated with enhanced exploitation of external knowledge. The context for this empirical analysis is the use of public science (that is, scientific research published in the open literature) by pharmaceutical and biotechnology firms. A majority of this scientific research is generated by researchers in universities and other research institutions.

Universities are an important source of research results for firms in many industries, and this importance has been growing over time (Narin et al., 1997). Public science is particularly important as an input to innovation in the biotechnology and pharmaceutical industries. Firms rely on basic science developments in biology and biochemistry, and many new drugs and delivery systems have their origins in discoveries in universities or government labs.¹ 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). Timely and effective access to university based research knowledge clearly benefits the innovation process of firm researchers.

Traditionally associated with strong norms of open science, publication, collaboration, and sharing of research results, universities have increasingly focused on patenting the research results generated by university researchers and profiting from licensing these results. As university patenting increased dramatically following the 1980 Bayh-Dole Act, which standardized procedures for patenting the results of federally funded university research, concerns about secrecy and limitations of access to university research results surfaced. Many studies have found that university researchers that once freely shared data and results and quickly published research results now have stronger incentives to hide results and slow competing researchers in order to establish a patent claim (Economist, 1984; Louis et al., 2001; Blumenthal et al., 1986; Campbell et al., 2002). Since the early 1980s, pharmaceutical and biotechnology firms have increased their funding of and collaboration with university scientists in recognition of the important technology generated at these institutions (Smith and Clark, 1986). There is evidence that as university and industry links grew during the same period, norms from the corporate world seeped or were forced into the academic

¹Cockburn and Henderson (1998) summarize case studies of many important drug developments with their origins in public sector science.

world, and open publication was sometimes compromised in favor of greater secrecy (Thursby and Thursby, 2000b; Blumenthal et al., 1996). In addition, even when patented university research results are made public through publication or other means, they are only available for use by firms that obtain a license to the patent. A researcher in a biotechnology firm interviewed by Walsh et al. (2003) reported that university patenting of research tools causes them to work around the university intellectual property, often slowing down their research progress.

As university patenting increased, the disparity of exploitation of public science across firms increased. Prior work has demonstrated that the variance across firms of citation to public science in their patents has increased in technology areas in which university patenting increased (Fabrizio, 2004). Some firms appear better able to identify, access, and incorporate research results from universities in their own inventions than others as university patenting increased. Firms followed different strategies for maintaining innovative competitiveness. For example, Merck focused on building internal research expertise, with an internal organization that rewards scientific inquiry. Merck's early internal research regarding the formation of cholesterol and chemical links in the cholesterol chain 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 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 come to discuss recent cutting edge work. This paper investigates whether specific firm research activities provide an advantage in terms of exploiting knowledge generated outside of the firm.

Cohen and Levinthal (1989) discuss the role of the firm's R&D in developing the necessary absorptive capacity make use of external knowledge. Other literature has identified the importance of in-house basic science 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). Still 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 work collectively highlights the importance of these activities in enhancing the amount, quality, and timing of the university-based research results available to the firm researchers for use in their own research and development.

In several empirical studies, internal basic science 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), controlling for the scale of R&D performed by the firm. The number of patents generated by a firm is certainly a well-established measure of inventive performance. Although these studies suggest that internal basic

science research and collaborations with university scientists enhance inventive production, they provide no direct evidence of the underlying mechanism.

This paper seeks to fill a gap in the literature with an empirical evaluation of firms in the biotechnology and pharmaceutical sectors. I test the prediction that a firm's investment in basic science research and collaborations between firm and university researchers are associated with the firm's ability to identify and exploit public science. In addition, I test the performance implications of these firm activities using a novel measure of the pace of knowledge exploitation achieved by the firm. My empirical analysis is based on two outcome variables: citations to published scientific research in a firm's patent applications and the lag time between existing inventions and firm inventions that build upon them. The first of these is a proxy for the firm's exploitation of public science. The later reflects how quickly the firm is able to develop new inventions. In order to test these predictions, I develop a panel data set covering up to 21 years for each of 83 biotechnology and pharmaceutical firms including information on annual firm R&D expenditures, sales, and employees, as well as the scientific publications, publications co-authored with university scientists, and patents by each firm.

Results suggest that firms with higher levels of internal basic science research and more numerous collaborations with university researchers cite more public science in their inventions. These activities also enable firms to exploit knowledge more quickly, reflected in a shorter time lag between prior patented inventions and new firm inventions building on this existing knowledge. These results are consistent with the predicted absorptive capacity benefits of internal research and external researcher linkages, provide more direct evidence regarding the extent and consequences of firm exploitation of public science, and highlight a previously unexplored performance implication of these firm research activities. In addition, I present evidence that the benefits associated with collaborations with university scientists decreases for firms that are overly focused on external collaborations relative to internal research. A final analysis explores the implications for the economic performance of the firm to assess whether these differences across firms matter. Results of the analysis of the firms' Tobin's Q provide evidence of the economic performance benefits associated with more extensive citation of public science and a faster pace of knowledge exploitation for large pharmaceutical firms.

The paper proceeds as follows. Section 2 discusses theory related to knowledge transfer, absorptive capacity, and the search for innovation by a firm and proposes the hypotheses to be tested. Section 3 describes the key measures employed in the analysis. The methodology and data are discussed in Section 4, followed by a brief example based on a fundamental discovery generated by university scientists. Section 5 presents results of the empirical analysis, limitations of which are discussed in Section 6. Section 7 concludes 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 and sustained performance, especially when these capabilities are difficult to imitate and are not available through a market transaction.² 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 highlighted the effects of these differences on firms' innovative performance.³ This paper adds to this literature by examining differences in firms' research-related activities and the implications of these activities for a firm's inventive and economic performance.

One stream of research on knowledge transfer has examined the effect of geographic proximity on the diffusion of knowledge. For example, Jaffe et al. (1993) and Audretsch and Feldman (1996) provide empirical evidence that physical proximity to a knowledge source provides advantage in terms of the degree to which and speed with which a focal firm receives knowledge, even controlling for the clustering of similar technological activity.⁴ As described by von Hippel (1994), research-related knowledge often resides with the researcher, and is "sticky" and difficult to transfer. Even when some of the research results are codified, for example in a published article, in many cases there is complementary knowledge that remains uncoded. Especially for tacit, fine-grained knowledge, personal interaction facilitates knowledge transfer. Geographic proximity may be necessary to allow for the interactive, face-to-face contact needed to assimilate such knowledge into the firm in order to make use of the published research.

Geographic proximity, however, is just a mask for the underlying processes of local knowledge transfer. It is critical to control for the relative location of firms, but this effect is mediated by the capabilities developed by the firm. In the context of innovative performance, the relevant capabilities of a firm include internally focused capabilities, such as the expertise of firm researchers and organizational routines that promote creativity and knowledge sharing, and externally focused capabilities, such as the strategic network within which the firm operates. Both of these classes of capabilities affect the ability of the firm to identify and integrate knowledge from outside the firm. Here I will focus on the implications of these competencies for increasing the knowledge base available to the firm, thereby improving the search process for innovation.

²For example, see Cockburn et al. (2000).

³For example, see Gulati et al. (2000); McGahan and Porter (2002); Gambardella (1992); Henderson and Cockburn (1994); Cockburn et al. (2000).

⁴Other studies demonstrating the relationship between proximity and knowledge spillovers include Autant-Bernard (2001b,a); Agrawal (2002).

2.1 Absorptive Capacity

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. 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). In order to explore the role of various firm strategies in providing absorptive capacity benefits, I focus on the exploitation of scientific research results published in the open literature, often generated by university scientists, in biotechnology and pharmaceutical firm inventions.

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). Reliance on university-based research is especially strong in the pharmaceutical and biotechnology sectors (McMillan et al., 2000). 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 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).

Cohen and Levinthal (1989) describe the “two faces of R&D,” referring to the dual benefits of firm research for innovation by the firm. Internal research and development generates new innovations and improves the internal expertise of the firm. In addition, the scientific expertise developed through the R&D process allows firm researchers to identify useful external knowledge, such as public science, incorporate this knowledge into the research of the firm, and thereby exploit the external knowledge to the benefit of the firm. Without the necessary expertise, firm researchers may not be aware of relevant external knowledge, much less be able to understand it and apply it to the research within the firm.⁵

Some commonality between the firm’s internal research and the external research may be necessary for successful knowledge transfer (Lane and Lubatkin, 1998; Prager and Omenn, 1980). For example, Mowery et al. (1996) find that post-alliance cross-firm citations among alliance partners increase more for alliance partners with higher levels of pre-alliance technological similarity, suggesting some absorptive capacity benefits of similarity in research experience for firms that form alliances. In the case of acquiring knowledge from universities, firms with more basic science research expertise will have existing knowledge that overlaps more with university science than firms

⁵Factors 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), and the market for intellectual property (Arrow, 1971; Williamson, 1975, 1985; Teece, 1981, 1989, 1996; Lamoreaux and Sokoloff, 1999; Nelson, 1959, 1982).

without such basic science research. Basic science research performed internally by the firm creates a bridge of familiarity between firm and university researchers and provides a common vocabulary that facilitate 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. In the Merck example above, without the expertise developed within Merck by performing basic science on the production and chemical structure of cholesterol, the company would not have been in a position to quickly exploit the discovery of the University of Texas researchers and create a new drug. Controlling for the overall research intensity of the firm, a firm with more internal basic science research will therefore be better equipped to make use of public science.

Hypothesis 1: The more basic science research done by the firm, the more the firm is able to exploit public science in their inventions.

In addition to the internal research expertise of the firm, collaborations between firm and external researchers aid in identifying and incorporating external science. The collaborative activity between firm and university researchers provides a firm with two advantages. First, Social networks and informal interactions provide an important avenue for exchange of research related knowledge (Liebeskind et al., 1996; Siegel et al., 1999) and are important to the development of the absorptive capacity necessary to internalize available knowledge and improve the research performance of a firm (Cockburn and Henderson, 1998). Personal contacts of firm researchers are often the source of information about technologies available from university research (Thursby and Thursby, 2000a). In fact, firms may seek to involve themselves in university research in order to stay abreast of recent developments, as Novartis does.

Networks provide access to information, resources, and technologies not available for purchase at arms length in a market (Gulati et al., 2000). In many cases, reading the published research results may not provide a researcher with enough knowledge to utilize the results. Through interactions with academic researchers, firm researchers may gain tacit knowledge components that are complementary to that which appears in published results. Knowledge transfer among a group with an ongoing social structure, such as the repeated interactions between cooperative alliance partners, is more fine-grained, tacit, cooperative than is possible through market transactions (Uzzi, 1996, 1997).⁶

Second, by interacting with several external knowledge centers, researchers of a firm are able to access different sets of knowledge. The scientists at each university have different backgrounds, expertise, and experiences, as well as different networks of their own, that the firm can tap into through collaborative interactions with scientists. Collaborating with university scientists provides

⁶As Uzzi (1997) stresses, embeddedness in a relationship of this sort also runs the risk of limiting the breadth of alternatives considered by the parties involved. I do not deal with this potential negative impact of strong network relationships here, but return to it in the discussion of future work below.

the firm with knowledge flows from several different bodies of external knowledge, allowing firm researcher access to more knowledge, diverse knowledge, and the potential for multiple views on similar problems. The ability to compare research knowledge across sources may be useful for assessing the validity of certain research knowledge, especially when the research area is very uncertain or undeveloped. Baum et al. (2000) provide evidence that biotechnology firms with more alliances, and a less redundant network of alliances, with universities at the time of founding experienced higher rates of patenting and higher revenue growth.

Collaborative interactions between firm and university researchers therefore provide the firm with superior access to and transfer of university research knowledge. Interactions with the 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 addition, the firm researchers may gain a timing advantage in terms of when they become aware of university research. For example, industry participants in the CITRIS research program at the University of California, Berkeley claim that their participation allows them an awareness of the future direction of university research so that they can prepare to take advantage of that research when it comes to fruition.

The pharmaceutical and biotechnology industries are characterized by a high degree of connectedness and knowledge transfer among the related firms and research entities (Walker et al., 1997; Powell et al., 1996). For pharmaceutical firms, links to science and external scientists have become more important as research in this field has become more dominated by rational, or science driven, drug design (Henderson and Cockburn, 1994). Cockburn and Henderson (1998) find that pharmaceutical firms with more publications co-authored with university scientists produce more patents, providing some evidence of performance benefits associated with linkages to university scientists. Similarly, in the biotechnology sector, Zucker et al. (2002) finds that firms with more collaborations with top university scientists generate more patents than other firms. Ties to the scientific community, and research universities specifically, are important predictors of firm formation (Zucker et al., 1998), new product introductions, and patenting (Zucker et al., 2002) in the biotechnology industry. Here I test for direct evidence of the absorptive capacity benefits of researcher collaborations.⁷

Hypothesis 2: The more collaborations between firm and university scientists, the more the firm is able to exploit public science in their inventions.

⁷One study that explores the existence of benefits of internal expertise for evaluating and incorporating external science is Arora and Gambardella (1994), in which the authors examine the number of collaborations as a function of internal expertise. The authors hypothesize that the firm's ability to utilize knowledge, measured by past patenting and R&D intensity, should be positively related to the number of collaborations a firm forms, while the firm's ability to evaluate which collaborations are 'good', related to in-house scientific capabilities measured by past scientific publications, should be negatively related to the number of collaborations. While the predictions are supported for collaborative linkages between firms, they do not explain the pattern of collaborations between firms and universities.

In addition, the value to the firm of collaborative interactions with university scientists is expected to display diminishing marginal benefits to the firm. At some point, the knowledge made available through additional interactions begins to overlap with knowledge available through existing collaborations, and the incremental collaborative interaction contributes less new knowledge to the firm. In addition, a firm that generates nearly all of its basic science research in collaboration with university scientists may lack some internal basic science expertise, relative to firms that are able to produce substantial scientific publications on their own.

Hypothesis 3: Collaborations between firm and university scientists demonstrate diminishing marginal benefits in terms of firm exploitation of public science.

2.2 Search and Innovation

Applied research performed within firms is critical to develop new innovations and remain competitive. The firm's search process for new innovations can be constructively conceptualized (in very simplified terms) as a series of random draws from an urn, or alternatively as a series of draws from a distribution with a given variance and mean (Evenson and Kislev, 1976). Sequential draws from the distribution make up the experiments of the search process. A search generates a new innovation when a draw provides an outcome above some threshold level.

As described in the search models of innovation presented by Evenson and Kislev (1976), Nelson (1982), and Kortum (1997), existing knowledge facilitates the search for new innovations by allowing researchers to focus their search in the most likely areas of opportunity (David et al., 1992). The experience, expertise, and knowledge base of the firm can improve this search process by shifting the mean, changing the variance, or opening new areas of the distribution to exploration (Evenson and Kislev, 1976). The knowledge base of a firm is composed of the expertise and knowledge of the in-house researchers and the set of external knowledge that the firm is able to make use of. The more relevant knowledge available to the firm, the more efficient and productive the search for new innovation. As described above, this paper builds on other work that has demonstrated a positive relationship between the number of scientific publication and co-authored publications by firm researcher on one hand and the number of patents produced by the firm on the other. This conceptualization of search for innovation provides hypotheses relating to a performance measure of firm innovation not examined in prior studies. I test whether a firm's absorptive capacity-related activities provide a benefit in terms of the pace of knowledge exploitation by the firm, as measured using the length of time between knowledge existing in previously patented inventions and a new patented invention by a firm building on that knowledge. If basic research improves the knowledge base available to the firm researchers, this is expected to result in more efficient search. In addition, firms with more internal basic research may be able to identify public science more quickly and therefore develop new inventions more quickly. I test the relationship between internal firm basic research and the pace of knowledge exploitation as follows:

Hypothesis 4: The more in-house basic research performed by firm researchers, the faster the pace of knowledge exploitation.

That is, controlling for the research intensity of the firm, a firm performing more basic science research will exploit existing knowledge more quickly in new inventions. This benefit results from the enhanced ability to identify and transfer relevant knowledge from external, particularly university, sources.

In addition, as reflected in Centocor’s claim described above, the relationships and collaborations between firm researchers and university scientists provide a firm with earlier, richer, and more comprehensive access to important university-based science. The improved access to university research knowledge, superior knowledge transfer capability, and timing advantages provided by collaborations are expected to provide advantage in terms of the pace of knowledge exploitation. As above, the benefit to the firm of additional collaborations with university scientists is expected to decrease as the percent of the firm’s publications that are co-authored with university scientists increases.

Hypothesis 5: The more collaborations between firm and university scientists, the faster the pace of knowledge exploitation by the firm.

Hypothesis 6: Collaborations between firm and university scientists have diminishing marginal returns for the pace of knowledge exploitation by the firm.

3 Measuring the Exploitation of Public Science and the Pace of Knowledge Exploitation

Figure 1 displays the first page of one of Merck’s patents filed in 1995. Under the “References Cited” heading (item 56), the patent lists U.S. and foreign patents cited as prior art and then lists “Other Publications” cited as prior art. These citations to other publications are typically referred to as non-patent prior art citations, which can include citations to journal articles, reports, text books, and other print references. This particular patent includes non-patent prior art citations to articles in journals such as “The Journal of Biological Chemistry” and “Science,” both of which are typically populated with articles by university scientists. I rely on a count of these non-patent prior art citations as a proxy for the amount of public science being exploited in a firm’s patented invention.⁸ This is not a direct measure of reliance on university science because non-university sources may be cited. However, industrial patents, and in particular pharmaceutical and biotechnology sector patents, have historically drawn upon university-based science for a large portion of the non-patent prior art that they cite, a characteristic that is true for the Merck patent

⁸I use the NBER patent database described by Hall et al. (2001) for patent data and the MicroPatent database at U.C. Berkeley for data on the citation of non-patent prior art in each patent.

as well. A count of non-patent prior art citations was used similarly by Deng et al. (1999) as a measure of the “science link” of a company’s patents.

Because I am using the count of these citation as a proxy for exploitation of published science from outside the firm, it is important to take a closer look at where these cited publications originate. In particular, it would be worrisome if firms were citing their own publications. Existing evidence suggests that these publications are largely academic in nature. In 1998, 73% of non-patent prior art citations were to papers authored at public institutions, especially academic institutions. The percentage is even higher for pharmaceutical and biotechnology sector patents (Narin et al., 1997).⁹

The dependent variable measuring the pace of knowledge exploitation is calculated based on each patent’s prior art citations to other patents; That is, the U.S. patents listed in the “References Cited” section of the patent. These patent prior art citations indicate the existing (patented) knowledge on which the new patent builds.¹⁰ The grant dates of the patents cited as prior art provide an indication of the age or vintage of the knowledge being built upon. The time lag between the cited patents 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.¹¹

Patents in technology classes experiencing more rapid advance will cite, on average, more recent

⁹In order to assess this further, I examined the non-patent prior art citations for 10 randomly selected patent for each of two companies in my sample: One company that produces a relative high number of publications (Cetus) and one that does not (Sterling Drug). The 10 patents by Cetus collectively included 79 non-patent prior art citations. Forty-six of the citations were to articles by university scholars. Another fifteen were from sources likely to be academic, such as textbooks, chemical abstracts, institute reports, and symposiums. Not including nine sources for which no source was identifiable (because it was not given by the SCI or the cited reference predates the addresses supplied by SCI), 87% of the citations were likely academic in nature. For this company with one of the highest publication to R&D ratio in the sample, only 1 of the 79 citations was to one of its own publications. Sterling’s patents contained 27 non-patent prior art citations in total, seven of which were identified with a university, seven of which were from likely academic sources, and thirteen of which were unidentifiable. (Interestingly, the sources cited by Sterling were on average much older, and therefore more often the affiliation of the author was unavailable from SCI.) Therefore, all of the identifiable sources were likely academic in nature. This evidence suggests that few of the non-patent prior art citations are to a firm’s own publications, but it is a concern with this data. Ideally, I would identify and exclude all non-patent prior art citations authored by firm researchers. However, mapping the cited references the the Science Citation Index to determine the affiliation of the authors is both very time consuming and incomplete.

¹⁰The 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 specifically.

¹¹This measure of the pace of knowledge exploitation is restricted to patented knowledge being exploited in follow-on patented inventions, and therefore can not capture knowledge exploitation in non-patented inventions or the age of knowledge relied upon that is not contained in earlier patents. I calculate the lag based on cited patents rather than cited non-patent prior art because it is much more difficult to obtain data on the publication date for each non-patent prior art citation, although this is the subject of future analysis. In addition, it is very difficult to exclude self-citation in non-patent prior art.

patents. Figure 2 displays the smoothed distribution of backward citation lags for citations made by patents applied for in 1985 in each of four patent classes: Medical Preparations, Stone Working, Hinges, and Semiconductors. Fields that we would expect to be 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.¹²

As a patent-level measure, the pace of knowledge exploitation is calculated as the mean backward citation lag for patent citations made by each patent. I exclude self-citations, that is citations where the assignee of the cited patent is the same as the assignee of the citing patent, following Mowery et al. (2002). In the Merck patent in Figure 1, for example, the first patent cited (granted in 1991) is a Princeton University patent. The second patent cited (granted in 1992) is a University of Texas patent. The other four cited patents are all Merck patents. Therefore, the mean backward citation lag for this patent (with an application year of 1995) is 3.5 years. In other empirical work, I found that industrial patents in technology classes in which university patenting was increasing (relative to other classes) were experiencing an increase in the mean backward citation lag (Fabrizio, 2004). If university patenting is associated with limitations on or a slow down of the dissemination of university research, this slowing pace of knowledge exploitation may be due to firm researchers inability to access and use university research results, slowing their own innovation process. The question to be answered here is whether firm research activities provide a firm with relative advantage in terms of exploiting existing research in new innovation.

4 Methodology

In order to test the hypotheses, I construct a panel data set of 83 firms in the biotechnology and pharmaceutical industries during the 1975-1995 period. Because firm capabilities are often path-dependent, developing slowing and remaining fairly stable over time, much of the variation of interest is likely to be between firms. This cross-firm analysis is in the spirit of deconstructing the firm fixed effect; It allows me to evaluate which firm activities contribute to the heterogeneity observed across firms. The goal of the analysis is to test whether a portion of the variation in performance across firms is due to variation in the focus and organization of firms' research activities. I explore the relationship between firm research activities and (a) the citation of published scientific

¹²Similarly, 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.

research in the firm's inventions, and (b) the speed with which the firm is able to exploit existing knowledge in new patented inventions with a reduced form model. The implicit null hypothesis is that the variation across firms for these variables are not systematically related to the firm's research activities.

4.1 Sample, Data, and Variables

One of the strengths of this analysis is that the sample contains many more firms than the samples used in prior empirical work described above. The sample of firms is developed in a way that (attempts to) avoid the survivor bias associated with selecting a sample of companies in existence at the end of the period. I select the 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 2003.¹³ For each company listed, I collected firm-specific data covering the 1975-1995 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. These classes account for 80% of all patents associated with the sample companies.¹⁴

I rely on *corptech*, *Hoovers Online*, *Mergent*, *Lexis-Nexis* article searches, and the *Capital Changes Reports* for corporate structure information detailing the founding date, geographic location, and mergers and acquisitions for each firm.¹⁵ I collect data on the number of employees, annual sales, and annual R&D expenditure from *compustat* (for U.S. companies and foreign companies listed on a U.S. exchange) and *datastream* (for other foreign companies). I was able to locate the required data for 83 companies.¹⁶ Many of the firms do not span the entire 21 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.

To test the hypotheses described above, I develop proxies for the the basic science research performed by the firm and the collaborative linkages between the firm and university scientists based on the measures used in existing research. The variables and data sources are summarized in Table 1. A count of the annual scientific publications by firm researchers has been used as a measure

¹³These industries were not surveyed in the 1980 edition.

¹⁴The international patent classes that I include are A01N, A61B, A61F, A61K, A61M, C07C, C07D, C07F, C07H, C07K, C08F, C08G, C12N, C12P, and G01N.

¹⁵When 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. I collected all publication and patent data for all firms that were acquired by firms in my sample, and these publications and patents are attributed to the sample company beginning in the year following the acquisition.

¹⁶I could not include companies with no identifiable patents during the sample period, so all results should be interpreted as conditional on having patented.

of the internal basic science expertise of the firm (Gambardella, 1992; Arora and Gambardella, 1994).¹⁷ I rely on the same measure here, with counts of annual firm publications generated from the Science Citation Index, as a proxy for internal basic science research. This measure of internal basic science research is not without problems, but does provide a consistent, observable measure of internal research activity that would otherwise be unmeasurable. The data do reflect underlying research focus and activity. For example, Figure 3 displays the annual count of publications for researchers at Merck and Genentech. Merck is well known for a strong focus on internal research rather than external collaborations, as well as an organization 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 science research established by founders from academe, also generates more publications per year than the average firm in the sample. This graph also demonstrates the importance of controlling for the size of the company, as Merck is a considerably larger company than Genentech, with research and development expenditures four time greater than Genentech even in 1995.

Although the two companies both pursue internal basic science research, Genentech is much more active in developing research collaborations outside of the firm. For example, Genentech's "Find Program" is specifically designed to interact 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 researchers (Economist, 1997). I proxy for collaboration with university scientists with the percent of the publications by a firm in a year that are co-authored with university scientists, also generated based on counts from the Science Citation Index.¹⁸ Figure 4 plots this co-authorship percentage for Merck, Genentech, and the sample mean. 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 for these firms.

Both of these publication-based measures likely encompass more than the firm's publication activity. For example, 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.

One determinant of knowledge dissemination demonstrated in existing literature is geographic proximity. In order to explore potential geographic proximity effects, I create a variable measuring

¹⁷Cockburn and Henderson (1998) use the count of firm publications per R&D dollar as a measure of investment in basic science research. As in that study, I use the address field for the researcher to identify the company or university affiliation.

¹⁸This same measure of 'connectedness' to university science was used in Cockburn and Henderson (1998).

the distance to the closest doctoral/research university, as identified by the Carnegie classification.¹⁹ I looked up the zip code for each of these universities (based on the city and state) on the U.S. postal service website and collected zip code data for each firm in the sample from Mergent and SEC filing records. The distance between each university and firm location is calculated based on the center of the zip code for each.²⁰ The minimum distance to a research university was selected to represent proximity to a university. This measure is unavailable for non-U.S. firms, and so when I include this measure in the analysis I also include a dummy variable indicating non-U.S. firms.

I control for several other firm-level characteristics. I control for the firm's research intensity using the ratio of annual R&D expenditures to sales at the firm level, as did Cohen and Levinthal (1989). This adjusts the R&D expenditures for firm size, although sales may include unrelated businesses for diversified firms, and therefore may be an inaccurate scaling metric. I control for firm size with the annual expenditure on R&D, consistent with Gambardella (1992), as well as the annual number of employees.²¹ In some specifications, I also include a dummy variable "Biotech" equal to one for companies that were first listed as biotechnology companies in the Standard & Poor's Industry Surveys.²²

In the equations examining the pace of knowledge exploitation, I control for two additional patent-level characteristics that in other work I have shown to be significantly related to the backward citation lag. First, I control for the number of citations to patent prior art, which serves two purposes. It controls for the fact that since the distribution of the citation lag has a long right tail 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. It also controls for the complexity of the patent, where more complex patents may cite more prior art and may also take longer to develop. Second, I control for the total number of patents in the same technology class and application year as the patent. 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 for the variables of interest are reported in Table 2. There is considerable variation within the sample for all of the variables of interest. These summary statistics do reinforce the strong science base in these fields. The mean number of publications for these firms each year is 167, with a range of zero to 846.²³ Likewise, the mean percentage of publications co-authored

¹⁹ *The Carnegie Classification of Institutions of Higher Education 2003*, Carnegie Foundation for the Advancement of Teaching, Electronic data file, fourth revision.

²⁰ I am thankful to Daniel Snow for the code to calculate the distance between any pair of zip codes.

²¹ Mowery et al. (1996) found that large firms did not demonstrate as much absorptive capacity with respect to alliance partners relative to smaller firms.

²² 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.

²³ Merck has 846 publications in 1994.

with university scientists is 30%, and the range is from zero to 100%. Table 3 reports the simple correlation coefficients for these variables. First, note that the R&D expenditure of the company is highly correlated with the number of articles published by firm employees, as would be expected since large, research-oriented firms are likely to produce more publications. R&D expenditures are less correlated with the number of employees at the firm and the percentage of publications co-authored with a university scientists, and not correlated with the R&D intensity of the firm. The number of publications is positively correlated with the percentage of publications that are co-authored with university scientists, suggesting complementarity between internal basic science and collaborations with university scientists.

4.2 Example: Innovation Building on the Cohen-Boyer Patent

Before discussing the empirical evidence, an example is useful to clarify the analysis. One well known case of industrial exploitation of a university-based innovation is the use by firms of the method for manipulating DNA developed by Stanley Cohen and Herb Boyer. Both university scientists at the time, Cohen (at Stanford) and Boyer (at the University of California in San Francisco) developed this “recombinant DNA” technology and launched the biotechnology industry in the late 1970s.²⁴ Along with multiple academic publications relating to their discovery, the two researchers patented their invention in a patent applied for in 1979, granted in 1980, and assigned to Stanford University.²⁵ A license to use the patented technology was offered by Stanford to any interested company for a fee of \$10,000 per year, and many companies signed up to gain access to the ground-breaking technology. The non-exclusive licensing structure and modest, standardized, up-front cost for a license were intended to promote dissemination of the discovery.²⁶

The introduction of this fundamental, industry-changing innovation allows an investigation of which firms were able to successfully develop new inventions based on the technology. Treating the discovery as an exogenous occurrence, an analysis similar to an event study allows a simple examination of the research characteristics possessed by firms that were able to exploit the Cohen-Boyer invention more successfully than other firms. I examine the relationship between production of patented inventions building on the Cohen-Boyer patent (identified as patents that cite the Cohen-Boyer patent) and firm research intensity, internal basic research, and collaborations with university scientists.

I use a firm-year level panel data set based on the data described above to estimate the likelihood of a firm applying for a patent that cites the Cohen-Boyer patent in a given year. Using a cox proportional hazard rate model with the “failure” event as the firm’s application for a (successful) patent that cite to the Cohen-Boyer patent in a given year, I estimate the relationship between

²⁴For an interesting review of the advent of the biotechnology industry and the challenges faced by existing pharmaceutical companies trying to adapt, see Galambos and Sturchio (1998).

²⁵U.S. Patent number 4,237,224.

²⁶Victor Cohn, Washington Post, August 3, 1981.

this event and firm research characteristics. This is analogous to exploring the lag time between existing patents and the patents that build on and cite them, as described above. The difference is that this analysis is limited to one existing patent, where as the pace of knowledge exploitation described above considers the lag time from all patents being cited.

Kaplan-Meier survival estimates by ranges of firm publication production and the percentage of publications with university co-authors are presented in Figures 5 and 6. In both cases, the categories are one for below the mean and two for above the mean. For the publications, firms that generate more scientific publications developed inventions building on the Cohen-Boyer patent more quickly than those with fewer publications. For the university co-authorships, the pattern is similar. These graphs do not control for other firm characteristics, however, so I investigate this further with a multivariate survival analysis.

Results of the multivariate analysis are reported in Table 4. The first equation limits the analysis to one citation event per firm, in effect ignoring all of the data for a firm following the first year in which the firm generates a patent that cites the Cohen-Boyer patent. This analysis includes 789 observations for 83 firms. In this equation, the coefficient on the co-authorships with university scientists is positive and significant at the 6% level. The coefficient on the publications variable is positive, but not significant. The second equation considers all years of data, allowing for repeat “failures” or citation events for each firm. This analysis includes the same 83 firms, but the estimates are based on 930 observations because the years following the first citation event for each firm are also included. In this equation, both the university co-authorships and the firm publications variables have positive and significant coefficients. As one might expect in this industry characterized by entry of small research-intensive firms, smaller firms were faster to develop inventions exploiting the Cohen-Boyer patent than were larger firms, as reflected by the negative coefficient on the R&D variable.²⁷

The results suggest that firms with more collaborations with university scientists were able to exploit the Cohen-Boyer patent in new inventions more quickly. Collaborations with university scientists thus seem to enhance the ability of the firm to quickly and successfully exploit relevant university research results. Firms with higher amounts of basic science research, as indicated by scientific publications, were also able to exploit the Cohen-Boyer patent more successfully, although this result is only significant when one considers repeat citation. This suggests that internal basic science may be more helpful in terms of successful exploitation, while the collaborations with university scientists provided firms with more of a timing advantage. This example is only intended to be suggestive and offer insight into the analysis that follows, but does suggest that collaborative

²⁷These results are robust to two sample limitations. First, one might worry that some firms were never truly “at risk” of generating patented inventions building on the Cohen-Boyer technology. To attempt to control for this, I estimated the regression with only firms that ever co-author a publication with a university scientist. Second, one could argue that including Genentech in the sample causes some interpretation issues, since one of the founders of that company was also an inventor of the original technology. Results are robust to both conditioning on university co-authorship and excluding Genentech.

linkages to university researchers and internal basic science research assist firm exploitation of public science innovations.

5 Empirical Results

5.1 Firm exploitation of public science

The first set of hypotheses predicts that firms with more basic science research focus, and more collaborations with university scientists will exploit public science more. In order to test these predictions, I estimate a reduced form model at the patent level for sample firms' patents applied for during the 1975-1995 period. The dependent variable of interest is the count of citations to non-patent prior art contained in the patent. This is a non-negative integer count variable, so ordinary least squares estimation would produce inefficient coefficient estimates. Accordingly, I estimate a negative binomial model.²⁸ The model to be estimated is as follows, for patent j by firm i in year t in technology class k :

$$E[\#NonPatentCites_{j,i,t}] = \exp\{\beta_1\#Pubs_{i,t} + \beta_2\%UnivCoAuthor_{i,t} + X1'_{i,t}\beta_4 + \Sigma_t\alpha_tYear_t + \epsilon_{i,j,t}\} \quad (1)$$

where $X1$ is a vector of firm characteristics. The year of the patent is the application year, most 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 publications therefore represent research activity from the previous year. The R&D expense to sales ratio, the log of the R&D expense, and the log of the number of employees are included with a lag of one year.²⁹ Because there are many (non-independent) observations for each firm, I use clustered standard errors to account for correlation across observations for a given firm and provide robust (White) standard errors.

The results of these estimations are reported in Table 5. All equations include year dummy variables to control for average time trends. The first equation includes only the R&D intensity variable, R&D scale variable, firm size measured by number of employees, and year dummy variables. Equation (2) adds to this specification with the firm-specific variables reflecting the firm's age, biotech designation, and the distance to the closest research university (as well as a foreign-firm dummy because I can not calculate the distance measurement for foreign firms). As one would expect from the traditional absorptive capacity literature (i.e. Cohen and Levinthal), the coefficient on the amount of R&D performed by the firm is positive once other firm characteristics are controlled for. The negative coefficient on the distance to the nearest research university is negative and significant at the 6% level, consistent with the literature on knowledge spillovers and geographic proximity. The biotech dummy variable is significant and positive, indicating the

²⁸A Wald test for overdispersion rejects the variance constraint of the Poisson model.

²⁹The same timing for publications, patents, and R&D was used by Gambardella (1992).

patents of biotechnology firm in the sample contain more than twice as many citations to public science as patents by the pharmaceutical firms.

Equation 3 introduced the count of articles published by the firm and the percentage of firm publications that are co-authored with university scientists.³⁰ The coefficients on both the publications and co-authorships variables are significant (the coefficient on publications is significant at the 7% level) and both are positively related to citation of public science by the firm. This suggests that firms engaging in more of these research activities are citing more public science in their patented inventions. Interestingly, once these more detailed variables reflecting specific research activities are included, the coefficient on the R&D variable is no longer significant.

The fourth equation re-introduces the firm-specific variables from equation (2), and the results for the geographic proximity to a research university are even stronger. With these controls, the coefficient on the number of firm publications falls in magnitude but is now significant at the 5.2% level. The coefficient on the university co-authorships also is lower in magnitude, but remains highly significant. The result that biotechnology firms typically cite more public science in their patented inventions remains. Using the coefficient estimates from this equation, a one standard deviation increase in publications by the firm (equal to 161 publications) is associated with an increase of citations to public science by a factor of 1.10, or a 10% increase in non-patent prior art citations. For the mean value of the number of citations, this is 0.6 additional citation. A one standard deviation increase in the percent of firm publications that are co-authored with university scientists (equal to an increase of 14% in the in percent of publications co-authored with university scientists) is associated with an increase in citations to public science by a factor of 1.14, or a 13% increase in these citations. For the mean number of citations, this is 0.8 additional citation. These results support hypotheses 1 and 2, that firm basic science research and collaborations with university scientists are associated with enhanced absorptive capacity of the firm.

The final equation in Table 5 includes both the percent of firm publications with university co-authors and this value squared in order to test the hypothesis that such collaborations demonstrate diminishing marginal returns. The significant negative coefficient on the squared term and the positive coefficient on the linear term support this hypothesis. The coefficients on these two variables together that the relationship between co-authorship and citation of public science is always positive (over the relevant range), but the marginal effect of co-authoring more of a firm's publications with university scientists is positive up to about 60% and then negative above that point. A firm that is too focused on external collaborations at the expense of building internal expertise appears to derive less benefit, in terms of citation of public science, from incremental university collaborations, as expected.

³⁰In order to make the coefficients easier to read, the count of publications is divided by 100 in all estimations. In addition, when the university co-authorship variable is included, I also include a dummy variable equal to one when there are no publications by the firm in a year, since the percent of publications that are co-authored with universities can not be calculated and is set to zero in these instances.

Note that the dummy variable indicating biotechnology firms is consistently positive and significant. This may suggest that the patented inventions of biotechnology firms are simply closer (in technology space) to the basic science performed at universities and published in the open literature. If these firms also do more basic science themselves and collaborate more with university scientists, these results may reflect heterogeneity across the firms in the sample. Ideally, I would control for the research area of each invention and compare inventions in each specific area across firms to control for the research focus. Lacking such research area classifications, I take several approaches to investigate the results further.

I split the sample into biotechnology and pharmaceutical firms and re-estimate the equations. The results are reported in Table 6. The results are broadly similar to those with the combined sample, although the co-authorships variable is not significant unless the non-linear term is included for the pharmaceutical firm sample. There are some very interesting differences across the two sets of firms, however. For example, a publication by a biotechnology firm's researcher is associated with significantly more citations to public science in the firms patents than a publication by a pharmaceutical firm's researcher (on the order of twice as many non-patent citations). Put differently, doing internal basic science research appears to provide a biotechnology firm with a larger advantage *over other biotechnology firms* than the advantage provided to a pharmaceutical company *relative to other pharmaceutical firms*. Similarly, biotechnology firms with a higher percentage of their publications co-authored with university scientists relative to other biotechnology firms have incrementally more citations to public science than a pharmaceutical firm with more co-authored publications relative to similar pharmaceutical firms. The threshold for diminishing returns to collaborations also appears to be at a higher level for biotechnology firms (60% versus 53% for pharmaceutical firms). All of this suggests that, while both biotechnology and pharmaceutical firms with more basic science research focus and more collaborations with university scientists have superior absorptive capacity with respect to university science, these research activities are more beneficial (on the margin) for biotechnology firms. Interestingly, note that being close to a research university is more important for pharmaceutical firms than for biotechnology firms, perhaps because their collaborative network does not perform as well as a mechanism to transfer knowledge.

A second approach I take to control for differences across firm research focus is the inclusion of technology class dummies reflecting the 15 four-digit international patent classification technology classes included in the sample. These technology class fixed effects control for the average number of citations to non-patent prior art in sample patents in each class. This control is far from perfect; There is no doubt considerable variation among the patents in a given class in terms of the reliance on basic science and university involvement in the underlying technology. The publication and co-authorships variables in these specifications test whether firms with more of these two activities cite more public science in a given patent relative to other patents in the same class. By including these fixed effects, the estimations will not reflect changes in a firm's portfolio of technologies. For example, if a firm that performed more internal basic science was able to move into a technology

area that was more basic science oriented (while other firms with less basic science expertise did not), that change will not be reflected in these results.³¹

Results including these fixed effects are reported in Table 7. The first column utilizes the combined sample and the second and third columns again split the sample into biotechnology and pharmaceutical firms. For the combined sample, the results for the co-authorships hold, but the firm publications variable is only significant at the 13% level. For the biotechnology firms, inclusion of the coefficients on the publications and co-authorships variables are reduced in magnitude relative to Equation 3 in Table 6, but remain positive and significant. For the pharmaceutical firms, the coefficients on the percent of publications with university co-authors and this value squared are both significant at the 10% level, and the coefficient on the publications variable remains significant. The reduction in magnitude of these variables with the inclusions of the technology class fixed effects suggests that technology areas in which patents typically cite more public science are populated by firms that, on average, have more publications and collaborations with university scientists, as one would expect.

A final approach to account for firm heterogeneity in my sample is to separate the consistent level of these research activities at the firm from the changes over time in these variable. I do so by including a variable reflecting the first year's values for the publications and co-authorships variables as well as the time varying value.³² Results with the combined sample, reported in the first column of Table 8 demonstrate the firms with higher first-year percentages of publications co-authored with university scientists cite more public science. However, looking across the estimations in this table using only the pharmaceutical or only the biotechnology firms, it is apparent that this result reflect the difference between biotechnology and pharmaceutical firms. Biotechnology firms co-author more of their publications in their first year with university scientists and also cite more public science. When the estimation is carried out separately for the two sub-samples, this effect due to heterogeneity does not hold, suggesting that at least this form of heterogeneity does not plague the sub-samples. In all estimations, firms that increase their production of scientific publications also increase their citation to public science in their patented inventions. Similarly, firms that increase their collaborations with university scientists over time cite more public science (up to a point), although the coefficient on university co-authorships is only significant at the 10% level for the pharmaceutical firm sample.

This analysis suggests that firms that are more active in basic research, pursue more collaborations with university scientists, and are located closer to a research university exploit public science more in their patented inventions. These results seem to reflect more than just heterogeneity across

³¹Importantly for the identification of these specifications, most firms patent in at least 5 different technology classes of the 15 considered here, and many patent in more.

³²By first year values, I mean the first year in which the firm entered my sample. In these estimations, I include a variable equal to the first year value and drop the first year's observations from the sample, resulting in the smaller sample size.

firms, although there is substantial evidence that research strategies that enable pharmaceutical firms to access and exploit public science may be different than those at work in biotechnology firms. However, these empirical results should be interpreted with caution. Firm research activities are not exogenously determined and therefore the causality is complicated. Firms following a strategy of exploiting public science may engage in basic science research and collaborations with university scientists for this purpose, while other firms that do not attempt to exploit public science will not. The underlying strategy of the firm is not observable, so the variables measuring publication and co-authorship activity reflect this strategy of the firm. 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 following two sections examine the innovative and economic performance implications of these firm research strategies in an effort to further evaluate whether these activities are in fact beneficial to the firm.

5.2 Implications for Inventive Performance

Hypotheses 4 through 7 predict that in-house basic science and collaborative linkages to university researchers will be associated with a faster pace of knowledge exploitation, and that university collaborations will exhibit diminishing benefits to the firm above some point. 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 citation lags of patents, I evaluate whether the firms' pace of knowledge exploitation is related to their research activities. I estimate the following equation for patent j by firm i in year t in technology class k :

$$\ln(\text{MeanLag}_j) = \beta_1 \text{Pubs}_{i,t} + \beta_2 \% \text{UnivCoAuthor}_{i,t} + X1'_{i,t} \beta_3 + X2'_j \beta_4 + \sum_t \alpha_t \text{Year}_t + \epsilon_{i,j,t} \quad (2)$$

where MeanLag is the mean backward citation lag of patent j as described above and $X2$ is a vector of patent characteristics. Results are reported in Table 9. The first equation includes only the firm size controls and the research intensity, along with the patent control characteristics. None of the firm characteristics are significant. Equation 2 adds to this several firm specific variables. Larger, older firms have a slower pace of knowledge exploitation, while more research intensity firms have a faster pace of knowledge exploitation, as one would expect. The relationship with firm age is mediated by the size of the firm. Equation 3 includes the count of firm publications and the percentage of firm publications co-authored with university scientists. 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 science research, in support of Hypothesis 4. The coefficient on percentage of university co-authored papers is also significant and negative, in support of Hypothesis 5. Controlling for other firm characteristics does not change these results (see equation 4). The dummy variable indicating biotechnology firms is not significant here. These results suggest that a one standard deviation increase in the number of publications by firm researchers is associated

with a 5% decrease in the backward citation lag, or about 4 months for the mean patent.³³ A one standard deviation increase in the percent of publications that are co-authored with university scientists is associated with a decrease in the mean backward citation lag of 3.7%, or about 3 months for the mean patent.

The final equation includes both the linear and squared term for the percent of publications that include a university co-author. As above, co-authorships with university scientists are always associated with shorter lags for the relevant range of values, but the marginal value of more collaborations is negative when more than 51% of publications are co-authored with university scientists. This suggests that collaboration is beneficial, but the firm researchers also needs to develop their basic science expertise enough to “stand on their own two feet.”³⁴

Although the biotechnology dummy variable was not significant in these specifications, it is possible that the relationship between research strategies and the pace of knowledge exploitation differs for biotechnology and pharmaceutical companies. For completeness, I estimated the equation separately for the two sub-samples of companies. Results in Table 10 are quite interesting. The relationship between co-authorship activity and the pace of knowledge exploitation is similar across the two groups, but the relationship between publications and the pace of knowledge exploitation is not. An additional publication by biotechnology firm researchers is associated with a significantly greater decrease in the backward citation lag than an additional publication by pharmaceutical firm researcher. This is consistent with the results above that the benefit in terms of exploitation of public science follows the same pattern. The similarity across samples of the relationship with university co-authorship may reflect advantages other than access to public science, such as the timing advantage associated with collaboration or the transfer of tacit knowledge not contained in published scientific articles.

As an additional robustness check, I estimated the backward citation lag equations including the 15 technology class fixed effects. The results are robust to this inclusion (see Table 11). The magnitude of the coefficients on the variables of interest are again reduced slightly, but remain significant.³⁵

To further explore the role of fixed firm differences and changes over time, I again estimate equations including the first-year values for the publications and co-authorships of each firm. Results are reported in Table 12. As above, the first-year values for the percent of publications co-authored with university scientists is significant (and negative as would be expected) only for the combined sample. The coefficient on this variable remains negative for each sub-sample, but is

³³This is calculated by multiplying the coefficient time the standard deviation of publications, equal to 161 (scaled by dividing by 100) to generate the percent change in the backward citation lag. This percent change is multiplied by the mean backward citation lag for the sample of 7.17 years to calculate the change in months for the mean patent.

³⁴I also ran these specifications using the minimum lag, that is 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.

³⁵The university co-authorship variables are both significant at the 6% level in Equation 2.

not significant.³⁶ For the combined sample and both sub-samples, firms that increase publications or university co-authorships over time experience increasingly shorter backward citation lags over time, interpreted here as a faster pace of knowledge exploitation.

These results indicate that firms with more internal basic science research and more collaborative research with university scientists build more quickly on existing knowledge in new innovations. Collaborations with university scientists appear to provide similar benefits to pharmaceutical and biotechnology firms, and both sub-samples of firms exhibit negative marginal benefits from collaborations in excess of 45-55% of the firm's publications. Publications by the firm, on the other hand, appear to provide larger incremental benefits to biotechnology firms than to pharmaceutical firms, consistent with the differential knowledge exploitation relationship noted above.

5.3 Implications for Economic Performance

The results thus far suggest that firms with more internal basic science research and collaborations with university scientists produce patents that cite non-patent prior art more heavily (interpreted here as exploitation of public science) and more quickly cite previous patents (interpreted here as a faster pace of knowledge exploitation). A reasonable next question is whether or not citation of non-patent prior art and shorter backward citation lags are associated with superior economic performance. If, as I suggest, they represent firm advantage with respect to exploitation of public science and pace of knowledge exploitation, then the firm should experience superior economic performance. The firm's increased knowledge base should make search for new innovation more efficient in terms of cost, time, and success. A faster pace of knowledge exploitation provides a firm with advantage in terms of time to market, as well as being associated with more efficient search.

I examine these predictions empirically with annual, firm-year level data from compustat for the firms in my sample.³⁷ I use the methodology described in Hall (1990) and Hall et al. (2000) to construct an annual Tobin's Q ratio for each firm equal to the ratio of the market value of the firm at the close of the year to the book value of the firm's physical assets.³⁸ This is a standard measure of the market's valuation of a firm that avoids comparability problems associated with measures of innovation or product production. Table 13 reports the summary statistics for Tobin's Q. Note the large variance in this measure and unusually large range of values.³⁹ As is common in analyses of firms' market value, I limit my sample to firms above a given size threshold. Here I will consider

³⁶The p-values are 14% and 19% respectively.

³⁷The six non-U.S. firms that are not publicly traded in the U.S. are not in this data. Therefore, I exclude these observations in this analysis by necessity.

³⁸The market value is defined as the sum of the value of common stock, the value of preferred stock, the value of long-term debt, and the value of short term debt net of assets. The book value is the sum of the net plant and equipment, inventories, and investment in unconsolidated subsidiaries and intangibles.

³⁹The seemingly nonsensical negative values are due to the short term asset correction. The negative values occur either in the first year of a small firm or as a one-year dip below zero for a low value firm.

both the sample of firms excluding very small firms (less than 1,000 employees) and the sample of the 16 largest firms that in at least one year exceed 20,000 employees. The descriptive statistics for these two samples (in Table 13) verify that these limitations successfully eliminate the excess noise from the sample.⁴⁰

To examine the relationship between this measure of economic performance and the non-patent citations and backward citation lags of a firm's patents, I estimate a firm-year level reduced form model controlling for year effects and other firm characteristics using OLS. The results of this analysis are reported in Table 14, where the first two estimations use the sample of firms with more than 1,000 employees and the later two use the sample of 16 large firms.⁴¹ All equations include year dummy variables to control for year trends, which are quite significant.

The first equation of each pair includes the average number of non-patent citations in a firm's patents in a given year. For both samples, the coefficient on this variable is significant and positive, indicating that firms whose patents contain more citations to non-patent prior art have a higher market value. The second equation of each pair includes the average of the backward citation lag in a firm's patents in a given year. In both equations, the coefficient on this backward citation lag variable is negative and significant. Firms whose patents have longer backward citation lags (on average) have lower market values. This suggests that there are economic performance benefits associated with a faster pace of knowledge exploitation and enhanced exploitation of published scientific research. This is consistent with empirical research indicating higher market to book ratios for drug companies whose patents have more citations to published research and shorter median backward citation lags (Deng et al., 1999).

For the more inclusive sample, one additional non-patent citation in a firm's patents is associated with an increase of 0.06 in Tobin's Q, or about 1.5% for the mean firm. A decrease in the average backward citation lag of 1 year is associated with an increase in Tobin's Q of 0.08, or about 2%. For the sample of large pharmaceutical firms, an increase of one in the average number of non-patent citations in a firm's patents is associated with an increase in Tobin's Q of 3.3% for the mean firm, and a decrease in the backward citation lag is associated with an increase of 3.5% in Tobin's Q for the mean firm. Interestingly, the magnitude of the relationship is more substantial for large pharmaceutical firms than for the more eclectic sample.

6 Limitations

In addition to the limitations on interpretation (discussed above) stemming from the endogeneity of the right hand side variables of interest, the use of patent citation data carries its own set of

⁴⁰In the sample of firms with more than 1,000 employees, I also dropped 2 observations with a negative value for Tobin's Q.

⁴¹Note that the number of observations is lower for the equations including the mean lag because the firm-year observations in which the firm's patents do not have any backward citations can not be included.

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.⁴²

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. A quick 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.⁴³ 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).

Examiner additions of non-patent prior art citations, which I rely on to indicate firm exploitation of public science, are more worrisome for my analysis. If the examiner added a citation to a journal article that the firm researcher was unaware of, this citation should not be counted as public science being exploited by the firm. Luckily, far fewer of these citations are examiner added. For patents in the technology classes of interest here in 2003, less than 10% of the non-patent prior art citations were examiner added. These citations therefore reflect the knowledge base of the firm researchers more closely.

A third limitation with the use of patent data is that I can not separately evaluate identification and assimilation of external knowledge from exploitation of that knowledge. This is a problem inherent in all studies of knowledge transfer that rely on patent citation data to trace knowledge flows. Ideally, one could explore, for example, whether collaborations with university scientists enable a firm to better identify relevant public science research, while the internal basic science expertise of the firm researchers provide the firm with a superior ability to exploit such information. I can not make such distinctions with the data used here.

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 in universities. Other

⁴²Firms 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).

⁴³This 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 citation for this analysis.

industries have much 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 useful at all. However, there are several very interesting industries for which university-based science is critical, and these industries are often characterized by substantial creation of new innovation.⁴⁴ For example, the nano-technology industry was developed from university-based science and innovation in this area continues to be tied to basic science research. Therefore, while the results should not be carelessly generalized across industries, they may be particularly applicable to the highly innovative areas of technology that are closely related to basic science.

7 Conclusion

Firms in many innovation-driven industries exist not as disconnected islands but as part of a web of formal and informal knowledge flows and collaborative alliances. Firms that are better able to take advantage of the external environment can create a competitive advantage. As the results here demonstrate, the internal research activities and external scientific collaborations of firms are two aspects of a firm strategy that are associated with enhanced exploitation of relevant knowledge from outside of the firm. This provides an interesting look inside the black box of the firm at some of the mechanisms underlying the significant differences across firms.

This work builds on and adds to a literature that has uncovered innovative performance benefits of internal basic science expertise and university collaborations for firms in the biotechnology and pharmaceutical industries. I present evidence that firms investing in internal basic science and building a network of collaborations with university scientists exploit published scientific literature more in their patented inventions. This provides a window into the black box of absorptive capacity, suggesting one mechanism behind the innovative performance benefits noted in prior research.

The results reported here also explore a new dimension of the firm performance benefits of basic science research and university collaboration: the pace of knowledge exploitation evident in firm patents. Results suggest that, controlling for research intensity, a more significant firm focus on in-house basic science research is associated with a faster pace of knowledge exploitation. In addition, controlling for the magnitude and focus of the firm's research, firms that co-author more of their publications with university scientists also have a faster pace of knowledge exploitation. However, firms that rely too much on university co-authors in their basic science research activities benefit less than those firms that balance university co-authorships with internal basic science research.

The ultimate goal of decomposing the firm fixed effect is to determine what makes some firms more successful than others. Evidence presented here links the exploitation of published scientific research and the pace of knowledge exploitation by the firm to superior economic performance. This suggests both innovative and economic benefits associated with absorptive capacity-building firm

⁴⁴In this discussion I use the term "industry" very loosely. Whether or not these technological areas constitute industries is arguable and unimportant here.

activities. For managers of innovation-driven firms in industries where university-based research contributes to innovation, building internal scientific expertise and collaborative interactions with university scientists may allow firm researchers to make more use of public science, improve innovative performance, and ultimately enhance the economic performance of the firm.

In addition, this analysis suggests that the current policy debate concerning the interface between university and industry scientists should carefully consider the pros and cons of collaborative activity. The purpose of the Bayh-Dole Act was to promote industry commercialization of university-based research, primarily by granting patents rights and licenses to federally-funded university research results. Results here suggest that even in an industry where patents rights are relatively good at protecting intellectual property, collaboration between university and firm scientists promotes the transfer of knowledge between university and industry. Policies that restrict such collaborations may hamper this important avenue of knowledge transfer and leave firms less able to exploit university research results.

Further research will explore the differences between pharmaceutical and biotechnology firms uncovered here. For example, why is the correlation between firm publications and both citation to public science and the pace of knowledge exploitation so much greater for biotechnology firms than pharmaceutical firms? One possibility is that the scientific research represented by pharmaceutical firm publications is less related to university science than is the research represented by biotechnology firm publications. Another possibility is that biotechnology firm publications represent higher quality scientific research than do pharmaceutical firm publications, and high quality research enhances absorptive capacity more than lower quality research. Examining the role of the firm's past research experience, and how this accumulated experience interacts with the advantage obtained through basic science research or collaborations with university scientists may also uncover some interesting differences across these sectors.

There is also more research to be done on the network structure of the linkages between university scientists and firm researchers. Results here suggest a diminishing benefit to marginal collaborations, but do not capture the structure of the collaborative network of a firm. 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). Especially in the context of transferring research knowledge, a diverse network linking a firm to many university researchers, rather than repeat collaborations with one university researcher, may provide superior benefits to the firm. Some work in this area with respect to the networks of biotechnology firms has been done by Powell et al. (1999), who document innovative and economic benefits of firm network ties only up to a certain threshold of network experience. In addition, the ability of a firm to access and assimilate knowledge may be specific to the particular source of the external knowledge, because the relevant network characteristics and social ties vary by potential knowledge source (Dyer and Singh, 1998). A more detailed consideration of the collaboration networks of firm

researchers may provide additional insight on the importance of particular dyad relationships and network structures.

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United States Patent [19] [11] **Patent Number:** **5,534,537**
Ciccarone et al. [45] **Date of Patent:** **Jul. 9, 1996**

[54] **PRODRUGS OF INHIBITORS OF FARNESYL-PROTEIN TRANSFERASE**
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 [73] Assignee: **Merck & Co., Inc.**, Rahway, N.J.
 [21] Appl. No.: **412,830**
 [22] Filed: **Mar. 29, 1995**
 [51] **Int. Cl.⁶** **A61K 31/41**; C07D 403/12; C07D 233/56
 [52] **U.S. Cl.** **514/397**; 514/400; 514/450; 514/459; 514/472; 514/620; 548/312.7; 548/335.1; 548/335.5; 548/338.1; 548/341.1; 548/341.5; 549/266; 549/271; 549/293; 549/320; 564/164
 [58] **Field of Search** 514/397, 400, 514/450, 459, 472, 620; 548/312.7, 335.5, 338.1, 341.1, 341.5; 549/266, 271, 293, 320; 564/164

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[57] **ABSTRACT**
 The present invention comprises peptidomimetic compounds which comprise a suitably substituted aminoalkyl-benzamide moiety. The instant compounds inhibit the farnesyl protein transferase enzyme and the farnesylation of certain proteins. Furthermore, the instant farnesyl protein transferase inhibitors differ from those previously described as inhibitors of farnesyl-protein transferase in that they do not have a thiol moiety. The lack of the thiol offers unique advantages in terms of improved pharmacokinetic behavior in animals, prevention of thiol-dependent chemical reactions, such as rapid autoxidation and disulfide formation with endogenous thiols, and reduced systemic toxicity. Further contained in this invention are chemotherapeutic compositions containing these farnesyl transferase inhibitors and methods for their production.

17 Claims, No Drawings

Figure 1: Example of Patent Citation Data

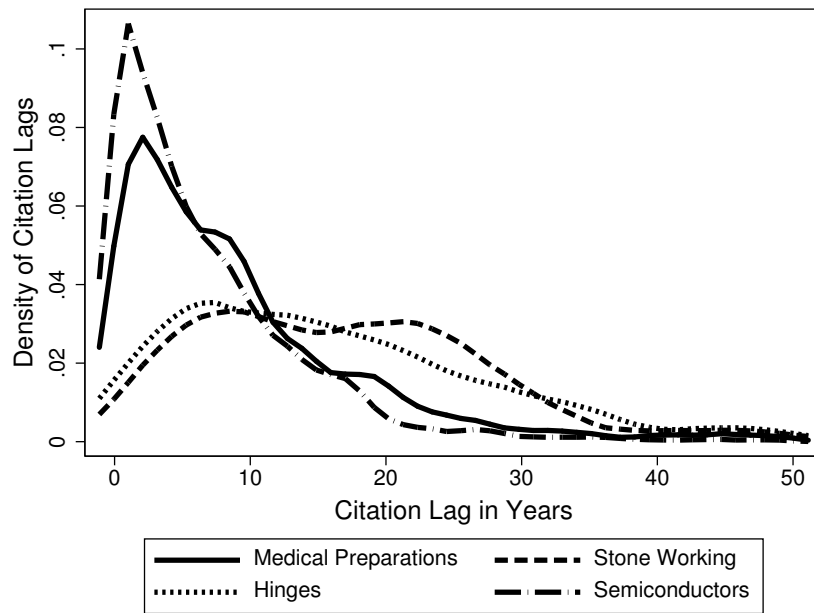


Figure 2: Distribution of Backward Citation Lags for Patents Applied for in 1985

Table 1: Description of Data and Sources

Measure	Data	Source
Exploitation of public science	Count of citations to non-patent prior art in the patent	MicroPatent database
Pace of knowledge exploitation	Mean backward citation lag excluding self-cites	NBER Patent Database
Collaboration with universities	% of firm publications co-authored with university scientists	Science Citation Index
Internal basic science research	# publications by firm researchers	Science Citation Index for publications
Firm research intensity	\$ R&D expenses per \$ sales revenue	compustat and datastream
Firm Expertise	Citation Weighted Count of Prior Firm Patents	NBER Patent Database
Firm age	Years since founding	Corpotech, Mergent, Lexis Nexis
Start Up	Equal to 1 in first 5 years after founding	Corpotech, Mergent, Lexis Nexis
Geographic proximity to universities	Minimum distance to a research university	Carnegie classification
Firm size	R&D expenses, # Employees	compustat and datastream
# Citations	Count cites to patent prior art, excluding self citations	NBER Patent Database
# Patents in Class	# patents applied for in year-class observation	NBER Patent Database

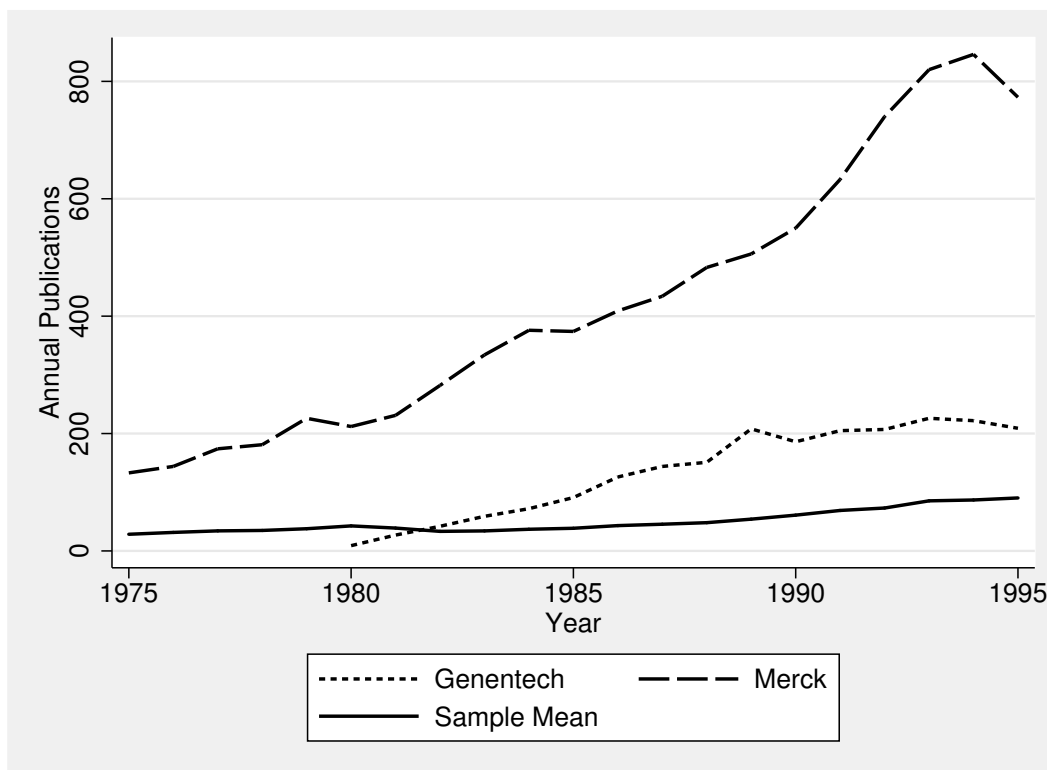


Figure 3: Publication count for Merck, Genentech, and Sample Average, 1975-95

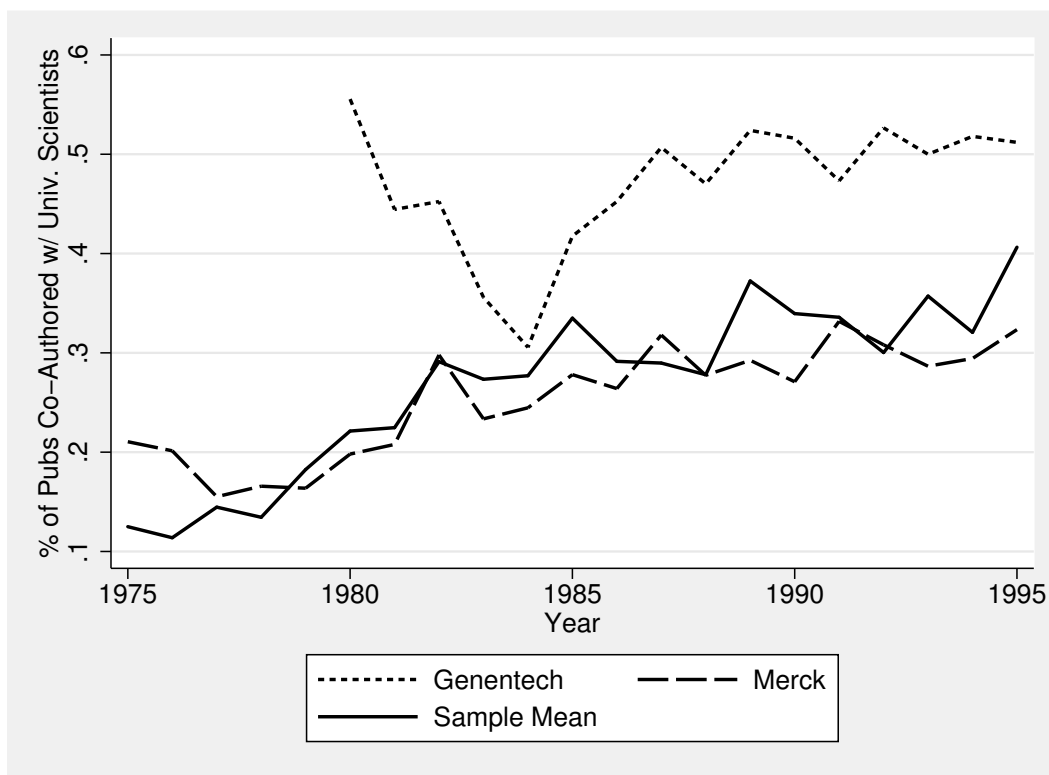


Figure 4: University Coauthoring for Merck, Genentech, and Sample Average, 1975-95

Table 2: Summary Statistics for regression sample, 1975-1995, N=24,263

Variable	Mean	St. Dev.	Min	Max
# Non-Patent Citations	5.89	16.42	0	438
Mean Backward Cite Lag	7.17	7.55	0	122
# Pubs	167	159	0	846
% Univ Co-authored Pubs	30.01%	13.78%	0	100%
<i>R&D/Sales</i>	0.23	2.34	0	201.29
R&D expense (MM\$)	455	389	0	1933
# Employees (M)	44.45	47.45	0.01	184.72
Firm Age	74.86	43.78	2	214
Min. Dist. to Univ.	8.17	7.77	0	47.71
Foreign ID	0.24	0.42	0	1
# Cites	4.52	6.89	0	169
# Pats	1884	1481	8	6679

Table 3: Correlation Coefficients

		1	2	3	4	5	6	7	8
1	<i>#Non – PatentCitations_i</i>	1							
2	<i>MeanBackwardCiteLag_i</i>	-0.02	1						
3	<i>#Pubs_{j,t}</i>	0.06	0.01	1					
4	<i>%Co – authoredPubs_{j,t}</i>	0.22	-0.01	0.21	1				
5	<i>R&D/Sales_{j,t-1}</i>	0.08	-0.02	-0.04	0.05	1			
6	<i>R&Dexpense_{j,t-1}</i>	0.04	0.08	0.78	0.28	-0.05	1		
7	<i>#Employees_{j,t-1}</i>	-0.11	0.11	0.21	-0.05	-0.05	0.45	1	
8	<i>FirmAge_{j,t}</i>	-0.14	0.00	0.06	-0.09	-0.08	0.14	-0.19	1

Subscripts t (time), j (firm), i (patent).

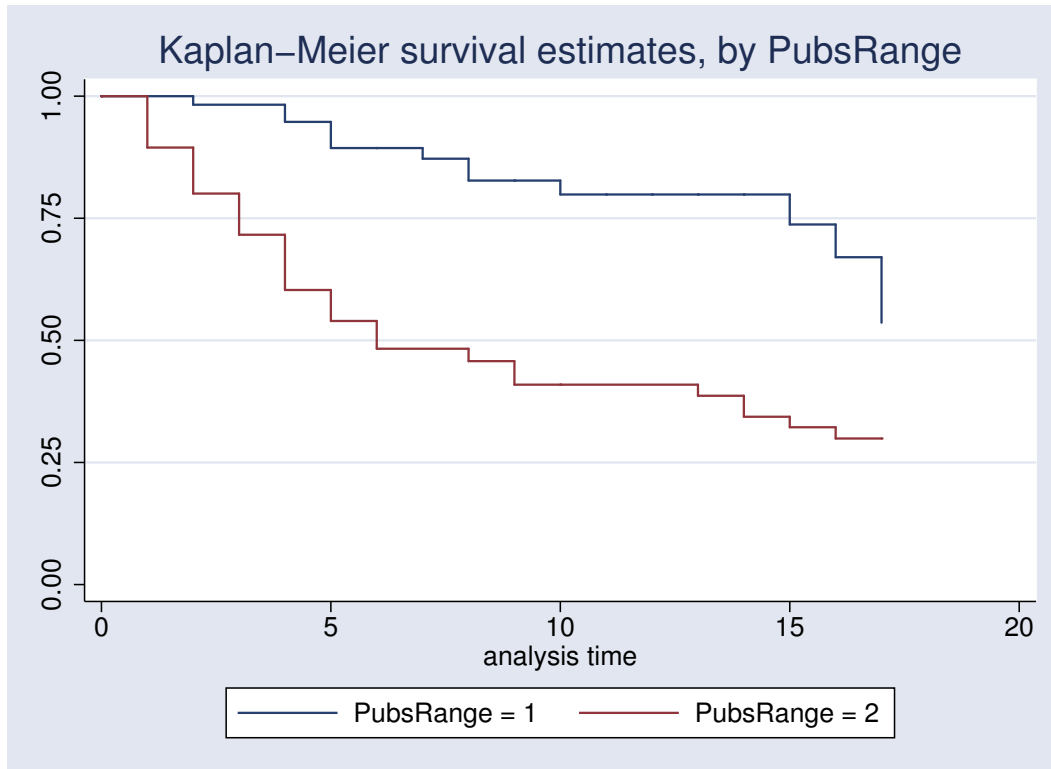


Figure 5: Hazard Rate by Low and High Publication Firms

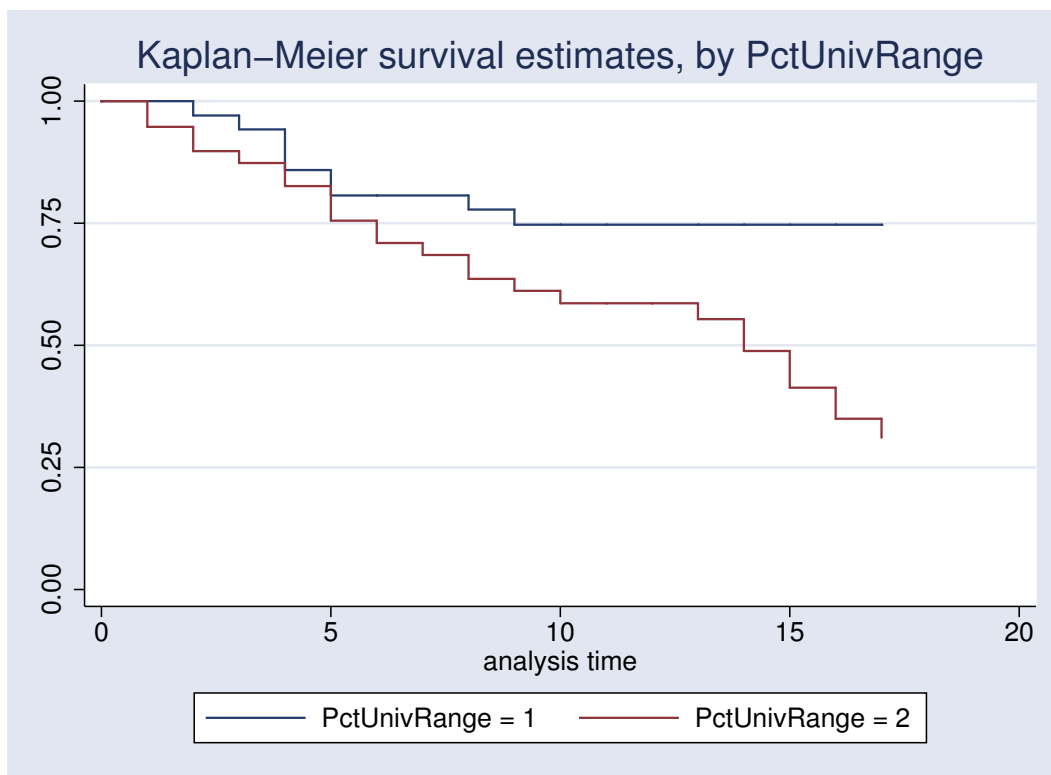


Figure 6: Hazard Rate by Low and High Percent of University Co-Authorship Firms

Table 4: Firm Citation of Cohen-Boyer Patent: Hazard Rate Analysis, Dependent Variable= Citation of Cohen-Boyer Patent

	Single Failure (1)	Multiple Failures (2)
<i>%UnivCo – Author_t</i>	1.789 (0.960)	1.477 (0.620)*
<i>#Publications/100_t</i>	0.767 (0.556)	1.268 (0.359)**
<i>R&D_t</i>	-0.005 (0.004)	-0.008 (0.003)**
<i>Employ_t</i>	0.015 (0.009)	0.010 (0.007)
<i>R&D/Sales_t</i>	0.006 (0.010)	0.003 (0.011)
<i>Firmage</i>	0.014 (0.006)*	0.007 (0.004)
Observations	789	930

* significant at 5%; ** significant at 1%.

Table 5: Citation of Public Science

	# NP Cites (1)	# NP Cites (2)	# NP Cites (3)	# NP Cites (4)	# NP Cites (5)
$\%UnivCo - Author_t$			2.020 (0.721)**	0.932 (0.377)*	2.482 (0.795)**
$\%UnivCo - Author_t^2$					-2.056 (0.755)**
$\#Publications/100_t$			0.089 (0.049)	0.062 (0.032)	0.061 (0.031)
$R\&D/Sales_{t-1}$	0.010 (0.011)	0.003 (0.002)	0.012 (0.016)	0.004 (0.003)	0.004 (0.003)
$\ln(Employees)_{t-1}$	-0.238 (0.245)	-0.225 (0.119)	-0.164 (0.210)	-0.149 (0.117)	-0.144 (0.116)
$\ln(R\&D)_{t-1}$	0.093 (0.306)	0.267 (0.103)**	-0.011 (0.297)	0.175 (0.124)	0.154 (0.121)
$\ln(MinDistUniv)$		-0.108 (0.059)		-0.109 (0.054)*	-0.108 (0.053)*
$ForeignID$		-0.287 (0.164)		-0.328 (0.150)*	-0.328 (0.147)*
$Firmage$		-0.024 (0.014)		-0.015 (0.014)	-0.014 (0.013)
$\ln(Employees)_{t-1} * Age$		0.002 (0.001)		0.001 (0.001)	0.001 (0.001)
$Biotech$		1.197 (0.398)**		1.202 (0.404)**	1.228 (0.395)**
$ZeroPub$			0.653 (0.304)*	0.396 (0.247)	0.590 (0.270)*
Constant	1.526 (3.246)	-1.466 (1.343)	2.223 (3.317)	-0.891 (1.708)	-0.792 (1.662)
Observations	27260	27260	27260	27260	27260

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.
All equations include year fixed effects.

Table 6: Citation of Public Science for Biotechnology and Pharmaceutical Sub-Samples

	# NP Cites (1)	# NP Cites (2)	# NP Cites (3)	# NP Cites (4)	# NP Cites (5)	# NP Cites (6)
	Biotech	Biotech	Biotech	Pharma	Pharma	Pharma
$\%UnivCo - Author_t$		0.664 (0.236)**	2.192 (0.701)**		0.465 (0.381)	1.529 (0.706)*
$\%UnivCo - Author_t^2$			-1.827 (0.743)*			-1.451 (0.784)
$\#Publications/100_t$		0.907 (0.196)**	0.834 (0.201)**		0.083 (0.034)*	0.083 (0.033)*
$R\&D/Sales_{t-1}$	0.004 (0.004)	0.004 (0.002)	0.003 (0.002)	3.608 (2.766)	3.024 (2.873)	3.037 (2.848)
$\ln(Employees)_{t-1}$	0.029 (0.167)	0.189 (0.111)	0.171 (0.109)	-0.041 (0.227)	0.067 (0.232)	0.073 (0.230)
$\ln(R\&D)_{t-1}$	0.307 (0.120)*	0.055 (0.138)	0.073 (0.124)	0.086 (0.153)	-0.073 (0.162)	-0.090 (0.163)
$\ln(MinDistUniv)$	-0.124 (0.107)	-0.165 (0.097)	-0.156 (0.097)	-0.111 (0.063)	-0.128 (0.055)*	-0.128 (0.054)*
$ForeignID$				-0.354 (0.172)*	-0.425 (0.167)*	-0.424 (0.164)**
$Firmage$	-0.187 (0.111)	0.085 (0.083)	0.083 (0.075)	-0.008 (0.024)	0.004 (0.025)	0.004 (0.025)
$\ln(Employees)_{t-1} * Age$	0.012 (0.012)	-0.029 (0.011)*	-0.028 (0.011)**	0.001 (0.002)	-0.000 (0.002)	-0.000 (0.002)
$ZeroPub$		0.536 (0.179)**	0.735 (0.202)**		0.053 (0.157)	0.193 (0.170)
Constant	-4.329 (1.656)**	-1.676 (2.129)	-2.065 (1.922)	-0.062 (1.421)	1.709 (1.731)	1.805 (1.730)
Observations	2414	2414	2414	24846	24846	24846

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.
All equations include year fixed effects.

Table 7: Citation of Public Science with Technology Class Fixed Effects

	# NP Cites (1)	# NP Cites (2)	# NP Cites (3)
		Biotech	Pharma
$\%UnivCo - Author_t$	1.440 (0.547)**	1.664 (0.605)**	1.074 (0.622)
$\%UnivCo - Author_t^2$	-1.236 (0.583)*	-1.408 (0.629)*	-1.210 (0.731)
$\#Publications/100_t$	0.041 (0.028)	0.744 (0.213)**	0.062 (0.031)*
$R\&D/Sales_{t-1}$	0.003 (0.002)	0.004 (0.003)	2.755 (2.722)
$\ln(Employees)_{t-1}$	-0.118 (0.104)	0.178 (0.099)	0.077 (0.233)
$\ln(R\&D)_{t-1}$	0.133 (0.107)	0.088 (0.114)	-0.084 (0.158)
$\ln(MinDistUniv)$	-0.122 (0.052)*	-0.128 (0.094)	-0.143 (0.052)**
$ForeignID$	-0.363 (0.129)**		-0.456 (0.151)**
$Firmage$	-0.015 (0.012)	0.089 (0.064)	0.002 (0.025)
$\ln(Employees)_{t-1} * Age$	0.001 (0.001)	-0.028 (0.010)**	-0.000 (0.003)
$Biotech$	0.982 (0.285)**		
$ZeroPub$	0.320 (0.161)*	0.600 (0.190)**	0.118 (0.154)
Constant	-2.289 (1.306)	-2.855 (1.908)	0.857 (1.728)
Observations	27260	2414	24846

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.

All equations include technology class and year fixed effects.

Table 8: Citation of Public Science, Controlling For First Year Values

	# NP Cites (1)	# NP Cites (2)	# NP Cites (3)
		Biotch	Pharma
<i>1stYear%Univ</i>	0.616 (0.302)*	-0.258 (0.242)	0.521 (0.579)
<i>%UnivCo – Author_t</i>	1.918 (0.784)*	2.296 (0.625)**	1.339 (0.825)
<i>%UnivCo – Author_t²</i>	-1.681 (0.757)*	-1.991 (0.631)**	-1.235 (0.898)
<i>1stYearPubs</i>	-0.001 (0.001)	-0.021 (0.020)	-0.001 (0.001)
<i>#Publications/100_t</i>	0.072 (0.033)*	0.870 (0.184)**	0.088 (0.037)*
<i>R&D/Sales_{t-1}</i>	0.007 (0.004)	0.003 (0.002)	2.573 (3.051)
<i>ln(Employees)_{t-1}</i>	-0.123 (0.122)	0.149 (0.151)	0.115 (0.237)
<i>ln(R&D)_{t-1}</i>	0.159 (0.112)	0.117 (0.116)	-0.055 (0.170)
<i>ln(MinDistUniv)</i>	-0.123 (0.064)	-0.160 (0.095)	-0.137 (0.071)
<i>ForeignID</i>	-0.344 (0.191)		-0.465 (0.202)*
<i>Firmage</i>	-0.012 (0.014)	0.079 (0.081)	0.010 (0.024)
<i>ln(Employees)_{t-1} * Age</i>	0.001 (0.001)	-0.027 (0.011)*	-0.001 (0.002)
<i>Biotech</i>	1.082 (0.429)*		
<i>ZeroPub</i>	0.637 (0.303)*	0.566 (0.226)*	0.244 (0.191)
Constant	-1.631 (1.335)	-2.073 (2.004)	1.045 (1.670)
Observations	27246	2400	24846

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.

All equations include year fixed effects.

Table 9: Pace of Knowledge Exploitation

	ln(meanlag) (1)	ln(meanlag) (2)	ln(meanlag) (3)	ln(meanlag) (4)	ln(meanlag) (5)
$\%UnivCo - Author_t$			-0.348 (0.122)**	-0.266 (0.111)*	-1.073 (0.288)**
$\%UnivCo - Author_t^2$					1.042 (0.285)**
$\#Publications/100_t$			-0.043 (0.008)**	-0.031 (0.010)**	-0.030 (0.010)**
$R\&D/Sales_{t-1}$	-0.003 (0.003)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.002)	-0.001 (0.002)
$\ln(Employees)_{t-1}$	0.044 (0.033)	0.159 (0.030)**	0.040 (0.025)	0.134 (0.031)**	0.134 (0.031)**
$\ln(R\&D)_{t-1}$	0.012 (0.044)	-0.074 (0.024)**	0.046 (0.042)	-0.025 (0.033)	-0.017 (0.033)
$\ln(MinDistUniv)$		0.002 (0.027)		0.005 (0.026)	0.004 (0.024)
$ForeignID$		0.003 (0.078)		0.009 (0.069)	0.007 (0.064)
$Firmage$		0.015 (0.003)**		0.012 (0.003)**	0.012 (0.003)**
$\ln(Employees)_{t-1} * Age$		-0.002 (0.000)**		-0.001 (0.000)**	-0.001 (0.000)**
$\ln(numcites)_i$	0.634 (0.030)**	0.641 (0.030)**	0.632 (0.029)**	0.639 (0.030)**	0.639 (0.030)**
$\ln(numrats)_i$	0.035 (0.015)*	0.028 (0.014)*	0.031 (0.015)*	0.028 (0.014)*	0.027 (0.014)
$ZeroPub$			-0.007 (0.143)	0.011 (0.116)	-0.093 (0.118)
$Biotech$				0.009 (0.131)	-0.006 (0.128)
Constant	-0.049 (0.568)	0.455 (0.359)	-0.519 (0.614)	-0.088 (0.427)	-0.118 (0.438)
Observations	24263	24263	24263	24263	24263
R-squared	0.28	0.29	0.29	0.29	0.29

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.

All equations include year fixed effects.

Table 10: Pace of Knowledge Exploitation for Biotechnology and Pharmaceutical Sub-Samples

	ln(meanlag) (1)	ln(meanlag) (2)	ln(meanlag) (3)	ln(meanlag) (4)
	Bitoech	Biotech	Pharma	Pharma
$\%UnivCo - Author_t$	-0.195 (0.103)	-0.832 (0.341)*	-0.178 (0.154)	-0.866 (0.361)*
$\%UnivCo - Author_t^2$		0.735 (0.305)*		0.937 (0.371)*
$\#Publications/100_t$	-0.271 (0.054)**	-0.251 (0.050)**	-0.030 (0.011)*	-0.029 (0.011)*
$R\&D/Sales_{t-1}$	-0.001 (0.002)	-0.001 (0.002)	-0.110 (0.130)	-0.118 (0.127)
$ln(Employees)_{t-1}$	-0.075 (0.062)	-0.069 (0.058)	0.144 (0.050)**	0.142 (0.050)**
$ln(R\&D)_{t-1}$	0.121 (0.052)*	0.114 (0.047)*	-0.019 (0.041)	-0.011 (0.042)
$ln(MinDistUniv)$	0.084 (0.033)*	0.077 (0.032)*	0.005 (0.030)	0.005 (0.028)
$ForeignID$	0.000 (0.000)	0.000 (0.000)	-0.004 (0.077)	-0.004 (0.073)
$Firmage$	0.011 (0.055)	0.005 (0.049)	0.013 (0.005)*	0.013 (0.005)*
$ln(Employees)_{t-1} * Age$	0.005 (0.008)	0.006 (0.007)	-0.001 (0.001)*	-0.001 (0.001)*
$ln(numcites)_i$	0.542 (0.025)**	0.540 (0.026)**	0.644 (0.033)**	0.645 (0.033)**
$ln(numrats)_i$	0.028 (0.028)	0.027 (0.028)	0.022 (0.014)	0.022 (0.014)
$ZeroPub$	-0.043 (0.111)	-0.132 (0.129)	0.117 (0.116)	0.028 (0.119)
Constant	-1.084 (1.017)	-0.898 (0.897)	-0.162 (0.650)	-0.196 (0.681)
Observations	2259	2259	22004	22004
R-squared	0.44	0.44	0.28	0.29

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.
All equations include year fixed effects.

Table 11: Pace of Knowledge Exploitation with Technology Class Fixed Effects

	ln(meanlag) (1)	ln(meanlag) (2)	ln(meanlag) (3)
		Biotech	Pharma
$\%UnivCo - Author_t$	-0.883 (0.231)**	-0.707 (0.354)	-0.740 (0.260)**
$\%UnivCo - Author_t^2$	0.961 (0.227)**	0.629 (0.320)	0.974 (0.260)**
$\#Publications/100_t$	-0.029 (0.009)**	-0.220 (0.046)**	-0.030 (0.009)**
$R\&D/Sales_{t-1}$	-0.001 (0.002)	-0.001 (0.002)	-0.088 (0.121)
$\ln(Employees)_{t-1}$	0.115 (0.028)**	-0.063 (0.057)	0.104 (0.046)*
$\ln(R\&D)_{t-1}$	-0.001 (0.030)	0.099 (0.044)*	0.013 (0.037)
$\ln(MinDistUniv)$	-0.003 (0.020)	0.076 (0.030)*	-0.004 (0.022)
$ForeignID$	-0.047 (0.060)	0.000 (0.000)	-0.049 (0.070)
$Firmage$	0.011 (0.003)**	0.012 (0.048)	0.010 (0.005)*
$\ln(Employees)_{t-1} * Age$	-0.001 (0.000)**	0.005 (0.007)	-0.001 (0.000)*
$\ln(numcites)_i$	0.659 (0.025)**	0.543 (0.028)**	0.673 (0.027)**
$\ln(numrats)_i$	-0.116 (0.039)**	0.208 (0.051)**	-0.127 (0.039)**
$Biotech$	0.076 (0.119)		
$ZeroPub$	-0.031 (0.105)	-0.105 (0.122)	0.081 (0.103)
Constant	0.577 (0.403)	-2.150 (0.861)*	0.883 (0.492)
Observations	24263	2259	22004
R-squared	0.31	0.45	0.30

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.

All equations include technology class and year fixed effects.

Table 12: Pace of Knowledge Exploitation, Controlling for First Year Values

	ln(meanlag) (1)	ln(meanlag) (2)	ln(meanlag) (3)
		Biotech	Pharma
FirstYr_PctUniv	-0.213 (0.097)*	-0.111 (0.076)	-0.189 (0.142)
%UnivCo – Author _t	-0.854 (0.297)**	-0.769 (0.352)*	-0.768 (0.372)*
%UnivCo – Author _t ²	0.928 (0.289)**	0.688 (0.318)*	0.913 (0.373)*
FirstYr_Pub	0.001 (0.000)*	0.003 (0.008)	0.001 (0.000)*
#Publications/100 _t	-0.039 (0.010)**	-0.258 (0.052)**	-0.038 (0.011)**
R&D/Sales _{t-1}	-0.002 (0.002)	-0.002 (0.002)	-0.215 (0.112)
ln(Employees) _{t-1}	0.114 (0.031)**	-0.130 (0.099)	0.079 (0.050)
ln(R&D) _{t-1}	-0.020 (0.030)	0.139 (0.050)**	-0.019 (0.038)
ln(MinDistUniv)	0.005 (0.023)	0.067 (0.031)*	0.001 (0.025)
ForeignID	-0.036 (0.049)	0.000 (0.000)	-0.039 (0.059)
Firmage	0.010 (0.003)**	-0.020 (0.056)	0.007 (0.006)
ln(Employees) _{t-1} * Age	-0.001 (0.000)**	0.009 (0.008)	-0.001 (0.001)
ln(numcites) _i	0.638 (0.030)**	0.540 (0.026)**	0.645 (0.033)**
ln(numrats) _i	0.026 (0.013)	0.025 (0.026)	0.021 (0.014)
ZeroPub	-0.095 (0.135)	-0.159 (0.138)	0.021 (0.136)
Biotech	0.010 (0.127)		
Constant	0.247 (0.453)	-0.857 (0.888)	0.581 (0.688)
Observations	24249	2245	22004
R-squared	0.30	0.44	0.29

Robust standard errors in parentheses; * significant at 5%; ** significant at 1%.

All equations include year fixed effects.

Table 13: Tobin's Q Summary Statistics by Firm Size

	# Obsv	Mean	St. Dev.	Min	Max
Whole Sample	654	7.43	12.38	-46.76	169.31
Excl. Small Firms	376	4.11	3.06	0.19	31.87
16 Large Firms	278	3.83	1.91	1.06	11.59

Table 14: Economic Performance Analysis

	Tobins Q Excl. Small (1)	Tobins Q Excl. Small (2)	Tobins Q 16 Large (3)	Tobins Q 16 Large (4)
<i>FirmAvgCite</i>	0.060 (0.025)*		0.127 (0.050)*	
<i>FirmAvgLag</i>		-0.079 (0.039)*		-0.134 (0.044)**
$\ln(R\&D)_{t-1}$	1.434 (0.320)**	1.595 (0.310)**	1.227 (0.504)*	1.651 (0.492)**
$\ln(Employees)_{t-1}$	-1.611 (0.340)**	-1.865 (0.319)**	-1.082 (0.533)*	-1.628 (0.522)**
$R\&D/Sales_{t-1}$	-4.478 (1.858)*	-3.563 (1.794)*	-16.496 (8.835)	-22.967 (8.858)*
Constant	-8.891 (3.379)**	-6.454 (2.924)*	-6.994 (3.879)	-7.861 (3.822)*
Observations	378	375	278	278
R-squared	0.34	0.33	0.43	0.43

Standard errors in parentheses; * significant at 5%; ** significant at 1%.
All equations include year fixed effects.