SCIENCE AS AN ELEMENT OF INNOVATION STRATEGY: EVIDENCE FROM THE PHARMACEUTICAL INDUSTRY

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My parents brought me to this world, nurtured me through difficult times, and taught me my very first lessons, so to them goes the first acknowledgement on an accomplishment like this. Being a few years younger than my siblings, I was fortunate to benefit from their experiences which made my journey through life less difficult, so to them goes my appreciation. But the family member who deserves the greatest acknowledgement for being on my side all the way during my journey through the PhD program is none other than my beloved wife. Faria exhibited exceptional patience, sacrifice, grace, and love during these years and the successful completions of the PhD program and this dissertation would have been too difficult without her support.

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DEDICATION

To my loving wife Faria, to my parents and siblings, and to the memory of my dearly-missed brother Amin, 1984-2008.

ABSTRACT

An extensive literature has informed us that science matters for firm innovation. But the primary question of interest to strategy research in this regard has remained unanswered: what drives the differences among firms in how tightly they couple science with the other elements of their innovation strategy, and what implications do such differences hold for firms' innovativeness. This study takes a first step to answer this question by focusing on the relationship between science and R&D alliances representing key elements of any firm's innovation strategy. Specifically, I conceptualize absorptive capacity as a latent construct that mediates the link between science productivity and the extent of new R&D alliance formations. I then hypothesize that two sets of factors (scientist-based and firm-based) moderate the strength of the baseline relationship by impacting either the resulting absorptive capacity for a given level of science productivity or the substitutability of absorptive capacity as a driver of new R&D alliance formations. I then move on to explore the role of absorptive capacity at the time of forming new R&D alliances on the long-term benefits of those alliance for the firm's innovative output. The results of the analysis of a longitudinal database on 216 publicly-traded pharmaceutical companies in US between 1990 and 2009 provide general support for the proposed theoretical framework of the study.

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1. INTRODUCTION

The role of science in firm innovation has inspired substantial research in various literatures including strategy, organization theory, economics, and sociology (Gambardella, 1992; Cockburn and Henderson, 1998; Zucker, Darby, and Brewer, 1998; Durand, Bruyaka, and Mangematin, 2008). Science has been generally identified in this research as a driver of a significant subset of innovations in various industries (Mansfield, 1991; Mansfield, 1997). Mansfield (1991), for instance, found that about one-tenth of all product and process innovations introduced between 1975 and 1985 in a wide range of industries including pharmaceuticals, chemicals, metals, oil, instruments, and information processing could not have been developed in the absence of recent basic scientific research. A common theme among these various lines of research is that firms do not consider science as a mere external entity existing in the public domain (Stern 2004; Huang and Murray, 2009). To the contrary, firms, especially in technology-driven industries, have been shown to actively pursue science by making significant investments in its creation and development (Gambardella, 1992; Gittelman and Kogut, 2003).

The observation that for-profit firms make significant investments in basic scientific research (Rosenberg, 1990), has presented a puzzle to scholars given the public good nature of its outcomes that generate no tangible rents for the firm in the traditional sense. Relatedly, this literature has also noted that significant heterogeneity exists among firms in their ability to benefit from knowledge created outside their

boundaries (Cohen and Levinthal, 1990; Gambardella, 1992). In particular, while a great deal of external knowledge, including public science, appears to be equally and inexpensively accessible to all firms, the actual efforts and investments by firms in the way of benefiting from this type of knowledge has proven to be far from trivial. By putting these two observations together, scholars have been able to offer some answer to this puzzle by arguing that firms invest in in-house basic research in order to develop the ability (i.e. absorptive capacity) to understand and utilize external knowledge (Cohen and Levinthal, 1990; Rosenberg, 1990; Gambardella, 1992). Absorptive capacity allows firms to monitor the flow of knowledge outside their boundaries, internalize relevant knowledge, and exploit this knowledge in the firm's internal innovation processes (Rosenberg, 1990).

In other words, internal science functions as an enabler of the firm's access to external knowledge and innovation, which explains the puzzling observation of scholars but also reveals a challenge that faces managers in designing the firm's innovation strategy, i.e. balancing internal investment with external access. Specifically, since the very idea behind external access of innovation is to minimize the need for internal investments, the argument that successful external access depends on making enough internal investments is likely to challenge managers in finding the right balance between internal investment in science and external access of knowledge and innovation. A key piece of information when facing such a challenge seems to be the answer to the question of 'how much of one side of the

equation corresponds to how much of the other side?' In other words, managers would naturally want to know how much external access they can afford for a given level of internal science activity.

There are as many aspects to firms' internal science activities as there are mechanisms for external access of innovation. Therefore, in order to further focus the scope of this study, I choose to direct my attention to the relationship between science productivity as the most pronounced aspect of a firm's in-house scientific activities, and R&D alliances as the most common mechanisms of external access to innovations. This narrower relationship has already received some attention in past literature where science productivity and its resulting absorptive capacity have been shown to function as drivers of R&D alliance formations (Arora and Gambardella, 1994). So the question then becomes 'how many R&D alliances are enabled by a given level of science productivity?' There is obviously no definite answer to this question because of the differences in circumstances across firms and across industries. However, what can be done in the way of further clarifying this issue and its implications is to try to understand the nature of this relationship. Is there a fixed, definite relationship? As scholars or managers should we always expect a given level of science productivity to provide the driving force or the bandwidth for a certain number of R&D alliances? Or is this relationship far from definite and fixed? And if so, what and how causes it to vary? I try to address these questions in this study by exploring the nature of the effect of science as a driver of R&D alliances and building

and testing a theory consisting of scientist-based and firm-based attributes that may be responsible for inducing such variations. I believe this is an important question because it not only highlights an important dilemma for managers who are facing an increasing shift in the locus of innovation from inside the individual firm to interfirm settings in their industries, it also contributes to our theoretical understanding of the dynamics of the relationship between two very important elements of every firm's innovation strategy.

As a first step in analyzing the link from science productivity to R&D alliances, I conceptualize absorptive capacity as a latent construct that mediates this link. The idea is that any given level of science productivity, contingent on the characteristics of the scientific publications, gives rise to a certain level of absorptive capacity in the firm that provides the bandwidth for a certain number of new R&D alliances. This conceptualization allows me to explore some interesting clues to the sources of variation in the strength of the original link from science productivity to new R&D alliances. I do so by proposing two sets of moderators. I suggest that variations among firms in the effect of science productivity on new R&D alliance formations are caused by factors that fall under either of the two categories of scientist-based or firm-based. Particularly, I argue that scientist-based moderators – i.e. *isolation of firm scientists*, *arm's length nature of their external coauthorships*, and *organizational dispersion of scientific activity* – operate by negatively impacting the absorptive capacity that results from a given level of science productivity, while

the firm-based factors – i.e. the firm's *current innovative output, R&D alliance experience*, and *size* –do so by increasing the substitutability of absorptive capacity. My theoretical model also includes a hypothesis about the contingency of science productivity for the effect of new R&D alliances on the firm's long-term innovative output to examine the implications of the variations caused by the moderators. In other words, I explore whether the firm's science productivity at the time of forming new R&D alliances enhances the long-term benefits of those alliances for the firm's innovative output.

I empirically test my proposed theory in the context of the pharmaceutical industry in US using data on a sample of 216 publicly-traded pharmaceutical companies. The pharmaceutical industry is known to be one of the most science-based of all technology-driven industries (Cardinal, 2001; Orsenigo, Pammolli, and Riccaboni, 2001), making it an appropriate context for testing a theory regarding the role of science in firms' innovation strategies. A longitudinal database was constructed by gathering information about the scientific and innovative output as well as the alliance activities of the companies in the sample over the span of 20 years, from 1990 to 2009. Data on scientific output came from Thompson Reuter's Science Citation Index accessed via Web of Science. Innovative output was captured by patent applications based on data from the United Sates Patents and Trademarks Office. Data on alliance activity was extracted from SDC Platinum's Mergers, Acquisitions, and Alliances database. Finally, financial data came from Standard and

Poor's Compustat. An extensive analysis of this longitudinal database using the state of the art econometric techniques produced results that support the proposed theoretical framework of this study.

In addition to advancing our understanding of the role of science in firms' innovation strategies (Gittelman and Kogut, 2003), the theory and findings of this study also hold implications for other lines of research. For instance, the literature on the role of social and human capital as components of firm strategy (e.g. Nahapiet and Ghoshal, 1998; Kor and Leblebici, 2005) stand to benefit from the arguments advanced here. Specifically, one can argue that the in-house scientific activities of a firm and their outcomes also reflect the skill sets, expertise, and other intellectual qualities of firm scientists that make up the firm's human capital in support of its innovation strategies (Kor and Leblebici, 2005; Galunic and Anderson, 2000). Relatedly, R&D alliances represent a common form of deploying the firm's social capital to tap into resources and capabilities available through partner firms (Nahapiet and Ghoshal, 1998; Adler & Kwon, 2002). Therefore, an analysis of the link between science productivity and R&D alliances essentially invokes a broader discussion about the intertwined role of social and human capital as building blocks of firms' innovation strategies. This study contributes to this broader discussion by highlighting the necessity of a careful balancing of the social and human capital dimensions in the architecture of the firm's innovation strategy (Subramaniam and Youndt, 2005; Laursen, Masciarelli, and Prencipe, 2012). Particularly, the human capital of firm

scientists is argued here to be an essential platform for mobilizing social capital in the form of R&D alliances (Mosey and Wright, 2007). More importantly, the findings indicate that these two types of capital are not fully substitutable and an innovation strategy that involves deploying one in the absence of a sufficient level of the other is less viable. Specifically, the strategic choice to overly expand the social capital dimension of the firm's innovation strategy relative to the human capital dimension by increasing the firm's R&D alliances in the absence of a proportional increase in internal science productivity, though a seemingly benign strategy in the short run, tends to undermine the firm's innovative capabilities in the long run.

This study also informs the broader literature on interorganizational relationships (Ring and Van de Ven; Uzzi, 1997; Gulati and Sytch, 2007) of a need for a closer examination of the long-term implications of organizational solutions based on external resources. Based mainly on evidence for short-term performance improvements such as favorable stock market reactions and sales growth, collaborative relationships between firms have been typically portrayed as external mechanisms that boost the firm's competitiveness. This study further highlights the need to deepen our understanding of the long-term effects of external collaborations, especially when they are indiscriminately incorporated in firm strategies. Particularly, the findings hint at ramifications of overreliance on resources embedded in interfirm relationships in the absence of sufficient internal capabilities to enable the firm to

properly absorb and integrate those resources toward sustained value creation in the long run.

In what follows, I first discuss the theoretical framework of the study followed by a more detailed theory development where I formulate testable hypotheses. The methodology section starts with a detailed account of the scientific and innovative activities of firms in the pharmaceutical industry, followed by a description of the database and variable definitions. The results section reports the main and supplementary analyses performed to test the hypotheses as well as the size and significance of the estimated effects. Finally, the discussion and conclusion section elaborates on the theoretical and practical implications of the study, as well as its limitations and avenues for future research.

2. THEORY AND HYPOTHESES

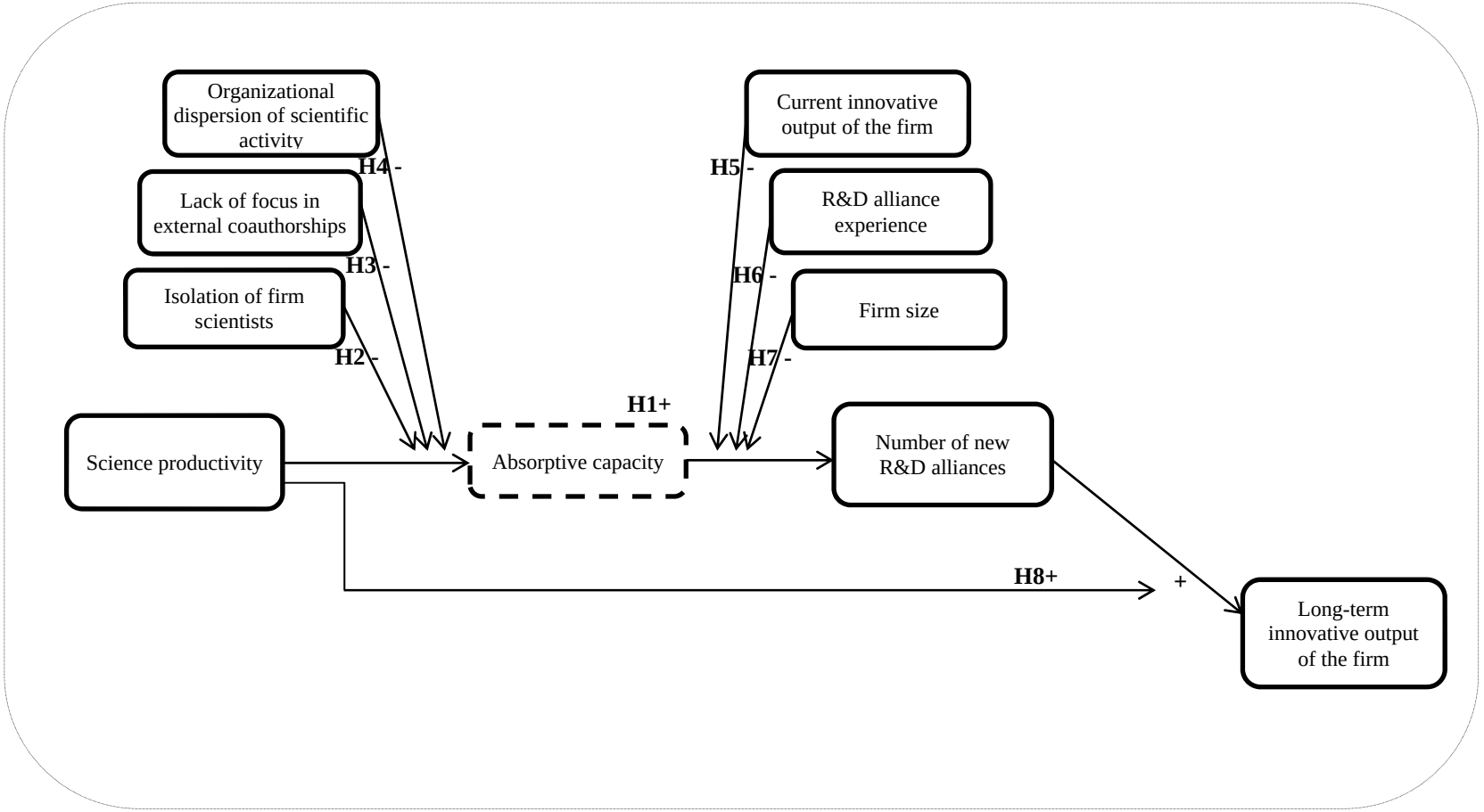
My general theoretical approach involves conceptualizing absorptive capacity as a latent construct that mediates the link from science productivity the formation of new R&D alliances. Therefore, the baseline relationship in my theoretical framework is the link from science productivity to R&D alliances as mediated by the latent variable of absorptive capacity. Further, to explain the variation in the predictive power of science productivity over the future extent of new R&D alliance formations, I augment this baseline relationship with two sets of contingencies. In particular, I suggest that variations among firms in the effect of science productivity on R&D alliances can be traced back to how these two sets of moderators influence the resulting absorptive capacity, on the one hand, and the substitutability of absorptive capacity, on the other hand.

2.1. Hypotheses development

The hypotheses development section is organized as follows: First, I establish a positive effect of science productivity on the number of new R&D alliances engaged in or initiated by the firm as mediated by the latent variable of absorptive capacity. Next, I examine two sets of moderators that affect the strength of this baseline relationship. Finally, I hypothesize about the role of science productivity at the time of the formation of new R&D alliances in enhancing the long-term benefits of those

Figure 1:

The theoretical framework of the study



alliances for the firm's innovative output. Figure 1 presents a summary of the hypotheses and the theoretical framework of this study. It is worth mentioning that while the conceptual effect of the two sets of moderators in Figure 1 may appear as influencing only one of the two links in the mediated relationship between science productivity and new R&D alliances, my actual theorizing does not hinge upon assuming a specific locus for the effects of either set of moderators. In other words, in what follows, I develop moderation hypotheses that predict how each moderator will weaken the effect of science productivity on new R&D alliance formations while avoiding any unnecessary assumptions that might restrict the influence of any moderator to either the link leading to the latent variable of absorptive capacity or the link emanating from it.

2.1.1. Science productivity, absorptive capacity, and R&D alliances

A long tradition of research (e.g. Rosenberg, 1990; Gambardella, 1992, Zucker, Darby, and Armstrong, 2002) has been concerned with understanding why for-profit firms engage in basic scientific research despite the public good nature of the outcome (Roach, 2009; Huang and Murray, 2009) and the low probability that good in-house science will necessarily translate to high-impact innovations for the firm (Gittelman and Kogut, 2003). We have come to learn from this research that engaging in in-house basic scientific research allows firms to stay abreast of external flows of scientific and technological knowledge and tap into such knowledge to boost innovation within the firm (Rosenberg, 1990). The need for in-house scientific

research is stronger in industries (e.g. Pharmaceuticals) where the boundaries between basic and applied research are blurred and scientific discoveries quickly find their way into the realm of commercial innovation. In such contexts, maintaining an active program of in-house scientific research becomes a strategic necessity that allows the firm to augment its internal knowledge base by assessing and acquiring knowledge generated outside the boundaries of the firm.

Gambardella (1992) is among the pioneering studies to examine the role of in-house basic research in the exploitation of external knowledge. The central question in Gambardella (1992) is whether the public nature of science necessarily makes it freely available to all firms. Evidence from a number of case studies on large US pharmaceutical companies coupled with the results of a statistical analysis of data on 14 pharmaceutical firms suggested that in-house basic research helps firms to more efficiently exploit both internal and external science toward boosting firm innovativeness. Specifically, Gambardella's (1992) found that company patents are positively correlated with scientific publications by firm employees, confirming that public science is not necessarily free to all and the ability of different firms in exploiting it in their innovations varies based on the extent of their in-house basic research programs.

Cockburn and Henderson (1998) go beyond the mere presence of in-house basic research and emphasize the need for its 'connectedness' to the external scientific community. Particularly, they argue that in addition to investments in basic

research firms need to stay actively connected to the scientific community if they are to benefit from the scientific advances in the public domain. According to Cockburn and Henderson (1998), connectedness to the broader scientific community essentially drives firms' ability to recognize, evaluate, and utilize basic scientific developments and thus, influences the organization and productivity of research inside the firm. By exploiting the publication patterns of the scientists employed by pharmaceutical companies, Cockburn and Henderson (1998) analyzed the nature and extent of interaction and connectedness of the corporate scientists with their colleagues in the public sector. Their empirical results suggested that coauthorship across institutions in correlated with firms' R&D output (measured as count of important patents), reflecting significant differences among firms in their ability to access and utilize public knowledge.

More recently, Roach (2009), examined the use of public science in firm R&D and found that the link between in-house basic and applied research activity and the use public science is stronger in firms with a higher proportion of employees with PhD or M.D. degrees. In other words, while in-house research helps firms in monitoring public science with potential value for their internal innovations, the actual exploitation of such external knowledge depends on the skills of employees with training in scientific research. Gilsing et al. (2012) examined the implications of simultaneously engaging in collaborative research both with universities and with other firms. Using data on 40 major pharmaceutical firms they found that, consistent

with prior research, only firms with sufficient in-house basic research realize the benefits of direct university alliances. They also found that attempting direct university ties in the absence of sufficient in-house research may undermine the benefits of the firm's alliances with other firms. Finally, Leten et al. (2012) in their study of the internationalization of R&D by multinational firms found that firms with a strong scientific orientation (measured as the number of scientific references in their patent portfolio) realize higher gains from the scientific research strengths of host countries and thus, benefit more from performing distributed R&D.

The capacity based on in-house scientific research to benefit from external knowledge is, in essence, an element of absorptive capacity (Cohen and Levinthal, 1990). Cohen and Levinthal's (1990) ground-breaking article introduced the notion of absorptive capacity to strategy and organizational research as a firm's ability to evaluate, assimilate, and apply external information and knowledge in its innovation processes. According to Cohen and Levinthal (1990), absorptive capacity is mainly a function of the firm's prior related knowledge which makes it highly path-dependent. As a result, the failure to make the necessary investments in an area of expertise early on substantially reduce a firm's odds of developing strong technological capabilities in that area. Prior knowledge underlying the firm's absorptive capacity in an area may include basic skills, shared language, and knowledge of the scientific and technological advances in that area.

Cohen and Levinthal (1990) argued that absorptive capacity provides a ready explanation for firms' investment in basic research, particularly given that its findings inevitably spill out into the public domain in the form of scientific publications. Specifically, they suggested that firms' true goal in conducting basic research is not the mere results of the research itself but also the creation and maintenance of the ability to benefit from externally-developed knowledge as it becomes relevant to the firm's own technologies. In other words, in-house basic research can be thought as "…broadening the firm's knowledge base to create critical overlap with new knowledge and providing it with a deeper understanding that is useful for exploiting new technical developments that build on rapidly advancing science and technology." (Cohen and Levinthal, 1990, p. 148). Cohen and Levinthal (1990) also discussed how absorptive capacity can help explain the patterns of R&D alliances among firms. Particularly, they noted that prior research had overlooked the costs of assimilating and exploiting knowledge generated within cooperative research ventures. Mere participation in a cooperative research venture does not guarantee that the firm will benefit from the outcomes. Firms need to complement their collaborative efforts with sufficient internal investment in the absorptive capacity that will allow them to effectively exploit the knowledge outputs of their research alliances.

A more nuanced understanding of the link between investments in basic research and the creation of absorptive capacity in support of firm innovation is possible based on Fleming and Sorenson's (2004) discussion about the role of science

as a map in technological search. They conceptualized technological innovation as a process of recombination, whereby inventions are developed and commercialized from combining technology components in novel ways. Scientific knowledge functions as a map in this process by providing a means of predicting untried applications and combinations of technological components. Such predictive power is rooted in the theoretical understanding of the underlying properties of technological components that results from scientific research. Moreover, science increases the effectiveness of the search process for new inventions by identifying fruitless directions before the inventors attempt them, as well as pointing to potentially fruitful directions to guide their search. Science also motivates inventors in the face of repeated failure and infuses them with scientific curiosity and optimism needed to continue the search. Fleming and Sorenson's (2004) analysis of patent citations to scientific publications revealed that the benefits of science as a map for inventors are not always the same and depends on the difficulty of the combinatorial inventive problem being addressed. Particularly, science proves most helpful as a guide when inventors try to recombine highly coupled components by allowing the inventors to avoid the inherent problems of performing uninformed local search on a rugged technological landscape.

R&D alliances represent one of the most common organizational mechanisms for deploying the firm's absorptive capacity toward accessing external sources of knowledge and innovation (Mowery, Oxley, and Silverman, 1996; Powell, Koput,

and Smith-doerr, 1996). My first hypothesis represents the baseline theoretical relationship on which the rest of my theory is built. In this hypothesis, I examine the role of science productivity and its resulting absorptive capacity in the formation of new R&D alliances by the firm. Specifically, I build on Arora and Gambardella's (1994) logic to argue that absorptive capacity impacts firms' ability and willingness to engage in future R&D alliances. Absorptive capacity provides the firm with enough bandwidth to take on more alliances. It also allows the firm to judge the true value of collaborative projects in their search for promising partnerships and increases the probability of selecting the right ones (Arora and Gambardella, 1994). Moreover, absorptive capacity offers assurance to firm managers that their scientists and knowledge workers possess the ability to effectively engage in collaborative efforts with their peers in partner firms within the framework of the R&D alliance. Such effective engagement implies that firm scientists will have a sufficient knowledge of the underlying components of the technology being jointly developed (Fleming and Sorenson, 2004), allowing them to internalize the tacit know-how required to deal with the new technology once the collaboration is dissolved.

The intimate knowledge of a focal firm's scientists about the nature and application of the technological components involved in the collaborative innovation project also enables the firm to more effectively assimilate and incorporate the jointly-developed innovation into its own technology base and new product development processes. Finally, absorptive capacity also alleviates the managers'

concerns regarding the appropriability concerns that typically plague cooperative R&D efforts (Gualti & Singh, 1998; Oxley and Sampson, 2004). That is, given the deep understanding and involvement of firm scientists in the process of developing the outcome of the joint R&D project, the firm will be better positioned to detect and deter any opportunistic behavior by alliance partners and ensure fair rent appropriation at the conclusion of the partnership (Gulati and Singh, 1998). By building on this line of reasoning, I propose in H1 that the firm's science productivity will impact the firm's extent of future R&D alliances by driving the latent construct of absorptive capacity as a crucial factor in the managerial decision processes in this regard.

It is worth mentioning that the arguments leading to H1 are based on the assumption that every firm faces an ample supply of potential future alliance partners. This assumption is reasonably justified in the empirical context of this study (i.e. pharmaceuticals) where R&D alliance activity is one of the highest of all industries and firms are constantly seeking R&D alliance partners to share the cost and risk of research and development efforts, as well as to keep up with the fast pace of scientific and technological developments. Therefore,

H1: Current science productivity will positively impact the firm's number of new R&D alliance formations.

2.1.2. Scientist-based moderators

As mentioned before, I examine two sets of moderators that impact the effect of the firm's science productivity on its number of new R&D alliances hypothesized in H1. The first set of moderators (i.e. isolation of firm scientists, arm's length external scientific alliances, and organizational dispersion of scientific activity) are scientist-based factors (i.e. factors rooted in the characteristics of the research output of firm scientists) that impact the resulting absorptive capacity based on a given level of science productivity.

2.1.2.1. Isolation of firm scientists

The public good nature of basic science implies that scientific advances result from the collective efforts of the broader scientific community. In the words, the locus of major developments in basic science is most likely to fall in the public domain consisting of all public and private institutions that engage in basic scientific research. Collaborations of firm scientists with external coauthors are the main mechanism through which the firm's internal research program stays plugged into the upstream advances in basic science. Research has shown that connectedness to the external scientific community not only enhances firms' ability to recognize, evaluate, and utilize scientific developments, it also increases research productivity inside the firm (Cockburn and Henderson, 1998).

The majority of external collaborations by firm scientists are with academic researchers who function as contact points for corporate researchers to stay current with major scientific developments in academia and other publicly-funded institutions that are dedicated to basic research. Such collaborations are especially important to firm scientists in that they provide a direct and hands-on mechanism for tapping into the rich body of knowledge at the forefront of scientific endeavor that is most often located within the academia. When knowledge is cumulative and builds on existing set of codes and symbols, barriers to it communication tend to be low. Such knowledge can be learned and transferred by reading a text or listening to a lecture. But tacit knowledge, including any major scientific discovery, tends to have unclear links to exiting codes and hence, requires a hands-on approach where the person holding the knowledge (i.e. the discovering scientist) works with others in a team to transfer the knowledge to them.

Prior research has highlighted the key role of university alliances by firm scientists in the transfer and commercialization of basic scientific discoveries. Zucker, Darby, and Armstrong (2002), for instance, argued that academic collaborations allow firm scientists to more effectively capture the tacit and complex knowledge underlying scientist discoveries that take place in university labs. The effectiveness of such collaborations are higher when they connect firm scientists to ‘star’ scientists most of whom work at top universities. In their panel analysis, Zucker et al. (2002) found that joint publications by firm scientists coauthored with a star scientist (i.e.

327 top bio-scientists based on their publications of genetic sequence discovery articles) increase the number and citation rates to firm patents. In earlier research, Zucker, Darby, and Brewer (1998) found that both start-up firms and existing firms entering a new technology area tend to collocate with the top start scientists of the field. The overall conclusion of this research is that in order to effectively access and benefit from science generated outside the boundaries of the firm, it is not enough for firms to hire top scientists and encourage them to remain research active; it is also important for the firm scientists to maintain an active level of collaboration with external scientists, particularly those in the public sector (Cockburn and Henderson, 1998).

Collaborations with non-academic coauthors (i.e. coauthors employed by other firms), though less frequent than academic collaborations, further indicate the extent of the connectedness of firm scientists to the external community involved in basic research. Moreover, such collaborations also indicate the willingness and experience of firm scientists with joint research projects involving colleagues in other firms, a propensity that can significantly facilitate the execution of R&D alliances once the firm enters them. The applied nature of research conducted in inter-firm R&D alliances may represent different challenges to firm scientists than the ones they face in basic research collaborations with scientists from other firms. Nevertheless, the existence of collaborative experience provides further assurance to firm managers that upon initiation of R&D alliances, the scientists in their employ will be more prepared

to handle the collaborative tasks involved in the inter-firm innovative effort than if they had no joint research experience with external coauthors from other firms.

Overall, connectedness to the broader scientific community through external co-authorships implies that firm scientists are involved in the generation of new knowledge at the forefront of the scientific discipline and have first-hand exposure to the knowledge behind scientific discoveries. Connectedness of scientists also reflects the existence of the experience with and the propensity to work side-by-side scientists from potential partner firms. Therefore, when firm scientists are isolated from the broader scientific community, the knowledge represented in a given level of their science productivity is likely to be distant from what's being developed at the forefront of the discipline, and hence, results in a lower level of absorptive capacity to drive new R&D alliance formations. Therefore,

H2: The positive effect of science productivity on the extent of new R&D alliance formations is weaker when the degree of scientist isolation is high.

2.1.2.2. Arm's length external coauthorships

The next moderation hypothesis complements the preceding arguments regarding the importance of external connectedness for firm scientists by examining the nature of the external collaborations of firm scientists. Specifically, Hypothesis 3 distinguishes between external collaborations that truly represent hands-on involvement of firm scientists in joint research projects with colleagues outside the firm, and those

resembling arm's length relationships where firm scientists only receive credit for their general attachment to the project without performing any serious collaborative work. The basic argument here is that publications where a large number of scientists representing a myriad of public and private organizations are listed as coauthors most often represent instances of the latter type of external collaborations (Cronin, 2001).

Numerous studies in various disciplines have reported a growing trend in the number of authors on a typical research publication – e.g. Cronin (2001) in biomedicine, Slafer (2005) in crop science, Gibelman and Gelman (2000) in social work, and Englebrecht, Hanke, and Kuang (2008) in accounting research. The shift from solo-authored to multiple-authored publications has been generally regarded as a justified reaction to historical changes in the nature of research and publishing such as the shifting patterns of research funding, increased specialization, demands for higher quality and precision of scientific inquiry, the growing professionalism in academia, the need to train apprentices, and the demand for cross-fertilizing across disciplines (Katz and Martin, 1997). However, systematic analyses of scientific publications and their patterns of coauthorship have also revealed a creeping trend toward overcrowded lists of coauthors and the organizations and institutions represented by them on a growing subset of coauthored publications. Gelman and Gibelman (1999), for instance, reported that among the papers published in 4000 journals indexed by the Institute for Scientific Information, the number of papers with 50 or more coauthors grew from 49 in 1981 to 407 in 1994. Such overcrowded lists of coauthors

and institutions have been generally associated with denigrating the scientific research process without offering any real added value per every additional listing beyond what constitutes a convincing size of the actual team of researchers and their supporting institutions behind the study (Woods, Youn, and Johanson, 2010).

Although the abnormally large number of coauthors generally functions as a hint to the arm's length nature of the research collaboration, I believe that the number of organizations and institutions listed on a publication is a more reliable indicator in this regard. Specifically, given the variety of specialties required in any drug development project as well as the high level of specialization in training and expertise of individual scientists (Serajuddin, 1998; Venkatesh and Lipper, 2000), many publications reporting significant discoveries necessarily involve a relatively large group of contributors. Therefore, basing the judgment about the arm's length nature of a collaborative effort simply on the number of coauthors might be misleading. At the same time, every public and private institution involved in pharmaceutical research is likely to have a wide range of specialties present among the scientists in its employ, precluding the need for the engagement of as many different institutions in a collaborative research project as there are individual scientists involved. As such, abnormally long lists of institutions listed on a publication are less likely to reflect a need for the contribution of different specialties by those institutions and more likely to indicate an instance of arm's length research

collaboration where most of the institutions and their representing scientists listed on the publication had no close involvement in an intensive cooperative research effort.

Thus, I argue that the presence of arm's length-type coauthored publications in the firm scientists' output will likely be a sign of the lack of engagement of firm scientists in rigorous joint efforts with the leading minds behind major discoveries in the discipline. Therefore, for a given level of science productivity, the resulting absorptive capacity will be lower, providing the bandwidth and drive for fewer R&D alliances. Therefore,

H3: The positive effect of science productivity on the extent of new R&D alliance formations is weaker when firm scientists engage in many external coauthorships of the arm's length type

2.1.2.3. Organizational dispersion of scientific activity

In the third moderation hypothesis, I examine the contingency of organizational dispersion of scientific activity. Specifically, Hypothesis 4 considers the implications of research activities that are dispersed across the corporate structure and are partially carried out by scientists employed at the subsidiaries. Distributed basic research activities result in scientific and technological know-how that is dispersed across the organization, and in order to mobilize and deploy this know-how toward its strategic goals, the organizations will have to incur non-trivial transfer costs (Teece, 1977). The basic argument here is that such a dispersion of basic research activity is likely to

introduce added integration costs to the process of mobilizing internal capabilities when forming and executing new R&D alliances.

Prior research has examined the difficulties associated with integrating the outcomes of distributed research activities across different corporate units and divisions. Singh (2008), for instance, studied how the geographic dispersion of a firm's R&D activities impacts the quality of its innovative output. Analysis of over half a million patents from 1127 firms revealed that geographic distribution of R&D not only does not necessarily improve the quality of innovations but also appears to be negatively impacting the value of innovations, offering evidence for the difficulty of knowledge integration across dispersed organizational units.

A main driver of the costs associated with the transfer of knowledge based on distributed research activities is knowledge 'stickiness' (Kogut and Zander, 1993; Szulanski, 1996). Knowledge stickiness refers to the idea that transfer costs are not only associated with transfer agents and transfer media, but also with the characteristics of the knowledge itself. By analyzing 122 best practice transfers in eight companies, Szulanski (1996) found that contrary to the previously-accepted wisdom, the major impediments to the transfer of knowledge are not rooted in motivational factors, but are due to the knowledge characteristics (e.g. causal ambiguity) that contribute to its stickiness. To overcome this inherent stickiness, organizations need to invest in appropriate organizational forms to motivate their employees to transfer tacit knowledge within and between teams (Osterloh and Frey,

2000). Organizations also need to invest in codifying their tacit knowledge to speed its internal transfer and in doing so, risk imitation of their innovative ideas by competitors (Zander and Kogut, 1995).

Thus, for a given level of science productivity, the resulting absorptive capacity to drive new R&D alliances will be contingent on the amount of effort required to deploy it due to the dispersion of scientific activity across the organization (e.g. subsidiaries). Therefore,

H4: The positive effect of science productivity on the extent of new R&D alliance formations is weaker when the organizational dispersion of scientific activity is high.

2.1.3. Firm-bases moderators

The second set of moderators (i.e. current innovative output of the firm, R&D alliance experience, and firm size) are agued to weaken the baseline relationship proposed in H1 by increasing the substitutability of absorptive capacity. I argue that these moderators are likely to represent potential substitutes for absorptive capacity due to the fact that they are associated with downstream innovative activities as opposed to the more upstream contributions of absorptive capacity as part of the innovation value chain. Such downstream capabilities are more tangible and less distant from the final output of the innovation process therefore increasing the possibility that managers assign a stronger weight to them in their decisions regarding the formation of new R&D alliances compared to the weight they assign to absorptive capacity.

2.1.3.1. Current innovative output of the firm

Hypothesis 5 examines the moderating effect of the current innovative output of the firm on the strength of the association between science productivity and the number of new R&D alliances. The logic here is that firms with a strong innovative output (reflected in their patenting activity) will regard their downstream innovative capabilities responsible for their high rate of patenting activity as a substitute for the upstream contributions of absorptive capacity to their innovation value chain.

Prior literature has shown that certain resources and capabilities may function as substitutes for each other. Makadok (2001), for instance, developed a model that predicted that the two rent creation mechanisms of resource picking and capability building, while complementary in some circumstances, tend to substitute each other in others. Relatedly, Rothaermel and Hess (2007), examined whether the individual-, firm-, and network-level antecedents to firm innovation are substitutes or complements, and found that these antecedents can have compensating or reinforcing effects on a firm's innovative output. Various types of capabilities may positively affect an organizational outcome despite the inherent differences in the nature of the capabilities as well as their impact. As such, managers are prone to making presumptions regarding their equifinality and substitutability, leading them to substitute one type of capability for another in their decision process pertaining to an organizational goal.

The possibility of managers viewing the firm's current innovative output as a substitute for absorptive capacity is particularly high since the former reflects the firm's downstream innovative capabilities that tend to be more tangible and less distant from the firm's actual innovations. Conversely, absorptive capacity as an upstream element in the firm's innovation processes holds less tangible connections with the firm's actual innovative output and hence, is prone to being regarded as less influential compared to its downstream counterparts. Therefore,

H5: The positive effect of science productivity on the extent of new R&D alliance formations is weaker when the firm's current innovative output is high.

2.1.3.2. R&D alliance experience

The next moderation hypothesis considers the role of the firm's R&D alliance experience. Experience with R&D alliances implies that the firm has been exposed to the challenges involved in managing the creation and transfer of new knowledge in collaborative settings. Therefore, more experienced firms are likely to have a propensity to engage in R&D alliances with less regard for the role of science productivity based on the expectation that they can compensate for it by drawing on their extensive R&D alliance experience.

Research has shown that firms learn to manage alliances and gain from their experiences with alliance management (Anand and Khanna, 2000; Kale and Singh, 2007; Gulati, Lavie, and Singh, 2009). Anand and Khanna (2000), for instance, found

evidence for the existence of significant learning effects in how firms manage joint ventures. Their results also indicated that the learning effects are strongest for research joint ventures. Similarly, Kale and Singh (2007) found that alliance learning involving the articulation, codification, sharing, and internalization of alliance management know-how improves the firm's overall success with new alliances. Sampson (2005) also analyzed a sample of 464 R&D alliances in the telecom equipment industry and found that the benefits of R&D alliance experience are highest when alliance activities are uncertain, and that, due to knowledge depreciating over time, only recent experience has a positive effect on collaborative returns from R&D alliances. Hoang and Rothaermel (2005) and Rothaermel and Deeds (2006) also provided empirical evidence in support of the performance benefits of alliance experience.

Thus, the learning that accrues to an experienced firm from prior R&D alliances is likely to cause its managers to feel increasingly confident that the contributions of absorptive capacity to the innovation process can be compensated for by tapping into the firm's growing experience repertoire and knowledge base on how to manage future R&D alliances more effectively. Therefore,

H6: The positive effect of science productivity on the extent of new R&D alliance formations is weaker when the firm's R&D alliance experience is high.

2.1.3.3. Firm size

In my final moderation hypothesis, I examine the moderating effect of firm size on the strength of the association between science productivity and the number of new R&D alliances. The logic here follows that of the previous two hypotheses in that the lowered necessity of absorptive capacity from managers' perspective is caused by the anticipation of the substitutability of other types of capabilities. Particularly, I argue that large firms can form alliances while worrying less about the availability of the necessary bandwidth or the ability to judge the true value of potential alliances knowing they can afford to dissolve less promising alliances after their formation.

We know from past research that firms exhibit varying tendencies in the amount of time and effort they dedicate to the process of partner selection and alliance formation (Bierly and Gallagher, 2007). Large firms are likely to be less calculative in their alliance formation decisions knowing that they can leverage their higher bargaining power to dissolve less satisfactory alliances with minimum repercussions. Large firms can also afford to cannibalize part of their vast resource bases to cover the costs incurred in forming and dissolving a less successful alliance. Moreover, large, resource-rich firms typically attract a large number of alliance partners as well (Park, Chen, and Gallagher, 2002), which implies that they can manage to forge a few beneficial partnerships even after dropping those that were formed without due diligence. Therefore,

H7: The positive effect of science productivity on the extent of new R&D alliance formations is weaker for larger firms.

2.1.4. Consequences for the firm's innovative output

Next, I turn to the consequences for the innovative output of the firm of building R&D alliances on a strong foundation of absorptive capacity. My basic argument here is that such a foundation not only increases the benefits of R&D alliances for the focal firms, it also minimizes their potential hazards including the internalization of technology components that are incompatible with the firm's existing knowledge and technology base. Avoiding such incompatible components minimizes the challenges to the firm's internal innovation processes and prevents the subsequent weakening of the firm's innovative capabilities. The arguments in this section build on a modular representation of firms' internal innovation systems that particularly suits the firms in industries with a fast pace of technological change (Sanchez and Mahoney, 1996; Pil and Cohen, 2006). Modular innovation systems encompass various loosely-coupled components of knowledge and technology whereby the loose coupling between components reduces the costs and difficulty of adaptation and increases the firm's speed and flexibility in responding to rapid technological changes (Ethiraj and Levinthal, 2004). The flexibility of the modular architecture is due to the fact that innovative products can be developed by substituting different modular components into the product architecture without the need to redesign other components. In other words, the 'mixing and matching' capacity of the modular system allows firms to

develop a potentially large number of innovations by recombining new or existing components of knowledge and technology (Henderson and Clarck, 1990; Sanchez and Mahoney, 1996).

The ability to recombine technological knowledge in novel ways to explore potential innovations that alter and advance the firm's current technological trajectories largely determines the innovative performance of a firm (Kogut and Zander, 1992; Tzabbar, 2009). Dividing organizational competence into component and architectural, Henderson and Cockburn (1994) argued that architectural competence, composed of the organizational control systems and the dominant values, allows a firm to exploit its component competence by integrating them in new and flexible ways. Henderson and Cockburn (1994) also suggested that in the context of the pharmaceutical industry the ability to access external knowledge and the ability to flexibly recombine and integrate knowledge across the various disciplinary and therapeutic class boundaries represent two forms of architectural competence that determine the innovative performance of the firm.

Successful exploitation of externally-sourced components of knowledge and technology requires a certain level of complementarity and compatibility to exist between those components and the firm's existing social and technological structures (Teece, 1986). That is, in order for the process of mixing and matching of components in a modular innovation system to work efficiently, every new knowledge and technology component must have a certain level of compatibility with

the existing structure of the system. Compatibility implies that the new and existing components can be connected using a common interface without needing any extraordinary translation and interpretation efforts. Since firms typically search for technological solutions that fall within the boundaries of their existing knowledge base (March and Simon, 1958), knowledge components that substantially deviate from this existing base significantly challenge the firm and its members as they attempt to comprehend and recombine them in crafting future innovations.

R&D alliances typically expose firms to unfamiliar technology landscapes without a map to guide the firm's search for compatible components (March, 1991; Fleming and Sorenson, 2003). If, due to a low level of absorptive capacity, the firm also lacks a clear understanding of the nature of knowledge and technology components involved in in the joint R&D projects, the search for new knowledge within the framework of R&D alliances will be a blind search on a rugged technological landscape. Such a blind search is likely to lead the firm to try to internalize any components that might appear to be relevant to the firm's internal knowledge base and fail to verify their actual compatibility. Incompatible components that are introduced into the firm's internal innovation system through R&D alliances present significant challenges to the firm in its attempts to incorporate them into ongoing recombination efforts and match them with existing knowledge and technology components. Particularly, attempting and discarding a multitude of potential configurations and combinations is likely to introduce a creeping element of

inefficiency into the firm's innovation processes leaving a negative impact on the firm's innovative output. Such a drop in the innovative output is likely to result from the gradual alterations of the firm's search routines to accommodate the inclusion of incompatible external components in new configurations.

Moreover, every new component of knowledge tends to deform and expand the search space of the firm's innovation system by suggesting new competing hypotheses and presenting previously unknown discovery paths (Orsenigo et al., 2001; Fleming and Sorenson, 2004). However, when new components are incompatible, such deformation of the search space is likely to throw the firm's innovation processes off their current functioning paths requiring extra effort over time to restructure the search space and restore the efficiency of the innovation processes. As time and other resources are invested toward reformation and restoration of the firm's innovation system, the inefficiency induced by incompatible knowledge components is likely to build up leading to a drop in the system's output over time.

Conversely, building R&D alliances on a strong foundation of absorptive capacity enables the firm to more effectively screen for compatible components of knowledge and technology while navigating the novel technology landscape. Absorptive capacity guides the firm's search on the less familiar technology landscapes that dominate the inter-firm search space and allows the firm to pick the most compatible from among the various components that might initially appear as

attractive additions to the firm's existing technology base (Fleming and Sorenson, 2004). Therefore, only those components will be internalized that imply a minimal impact on the efficiency of the firm's recombination efforts to introduce new innovations. Also, such compatible components will likely only deform the firm's innovation search space in ways that minimally impact its ongoing innovation processes. Given the gradual nature of the subsequent inefficiencies introduced into the firm's innovation system in R&D alliances not supported with sufficient absorptive capacity, I expect that the benefits of absorptive capacity in offsetting those inefficiencies to also emerge in the long run. Therefore,

H8: Science productivity at the time of forming new R&D alliances will enhance the benefits of those alliances for the firm's long-term innovative output.

3. METHODOLOGY

3.1. The empirical context

I use the context of the pharmaceutical industry to empirically test my proposed theoretical framework. The pharmaceutical industry is well-known for the key role of science in firm innovation. Pharmaceutical companies invest heavily in basic research and often organize their internal research efforts like academic departments (Gambardella, 1992). As such, the pharmaceutical industry provides the most suitable context for testing a theory about the role of science in firm innovation. Maintaining a strong and ongoing dedication to research and development is at the heart of the competitive advantage of every successful pharmaceutical company. Unrelenting investments in R&D and innovation are needed by firms since the drug discovery and development process, representing the main innovation effort in the industry, is lengthy, costly, and involves high attrition rates (Cardinal, 2001; Dunne and Dougherty, 2006). The process (depicted in more details in Appendix II) often costs upwards of a billion dollar and lasts an average of 12 years until the drug is launched to the market, during which out of about 10,000 compounds initially screened 250 enter preclinical testing. Of those entering preclinical testing five make it to clinical trials, and eventually, only one on average is approved by FDA. Faced with such a complex innovation process, pharmaceutical companies recruit scientists at the cutting edge of their scientific disciplines and provide them with ample resources to

experiment with a wide range of research trajectories (Cockburn and Henderson, 1998).

The nature of R&D activities in pharmaceutical companies has been profoundly impacted by the revolutionary advances in biological sciences such as biology, biochemistry, physiology, and pharmacology in the past few decades (Orsenigo et al., 2001). The 'molecularization' of most biological sciences has made it necessary for the drug discovery process to probe more deeply into the human body to uncover the biochemical interactions at the cellular and molecular levels. As a result, the development of new drugs has become increasingly reliant on the ability to generate more fundamental theories about the inner workings of cells and molecules in the human organism. Moreover, advances in biotechnology and genomics have started to supply the pharmaceutical industry with a large number of novel targets that are potentially related to a vast spectrum of diseases. Despite the fast growth of knowledge at the cellular, molecular, and genetic levels, the drug discovery continues to be a lengthy process with small chances of success. Particularly, the increase in the number of plausible targets has led to severe bottlenecks in the process as scientists keep looking for quicker and cheaper ways of discovering the potential matches between new targets and their related compounds (Orsenigo et al., 2001; Dunne and Dougherty, 2006).

Drug discovery requires a purposeful search for clues to indicate possible directions for discovery efforts. Searching for clues is an inherently exploratory and

science-based process where scientists try to understand how a portion of a biological system works with the hope of applying their understanding to drug discovery. Different companies tend to have different clues that may not have much value on their own. Therefore, pharmaceutical companies are constantly driven to seek out interfirm collaborators to complement their individual efforts toward discovering a certain drug. Thus, the pharmaceutical industry has one of the highest rates of alliance activity including R&D alliances (Powell at al., 1996) – yet another reason for the suitability of this context for testing my theory.

The process of drug discovery and development draws heavily on several scientific disciplines including biology, chemistry, and informatics (Dunne and Dougherty, 2006). Biology facilitates the early stages of drug discovery by providing an understanding of the mechanism of diseases, isolating potential targets for therapeutic intervention and assessing potential drug candidates. Chemistry helps with the development of safe and effective new chemical entities, or drug candidates, to address the identified targets. Informatics improves decision-making by classifying and reproducing the characteristics of successful drugs and creating databases to share current knowledge and predict future clinical success. The high intensity of scientific learning in drug discovery is due to the fact that human body is not only profoundly complex but also mostly unknown. Scientific learning accumulates as scientists try to determine possible pathways for a disease, understand the roles of various proteins in those pathways, and identify the molecular compounds, or ‘targets’, that bind to those

proteins. Pharmaceutical companies realize the key role of science in their innovation processes as well and actively support science-based learning. For example, one director of bioinformatics interviewed by Dunne and Dougherty (2006) claimed that their goal was to properly organize, categorize, and present scientific information to firm scientists in a way that would allow them to make such decisions as what molecules to design and what compounds to advance.

Most diseases (e.g. heart disease, cancer, stroke, Alzheimer's, arthritis) are associated with a complex set of multiple genes. Therefore, finding a drug for such diseases is a massive undertaking that cannot be broken down in to separate steps since the various activities are highly interdependent. Therefore, drug discovery requires extensive integration since the process involves many specialties, each with its own clues (Dunne and Dougherty, 2006). Integration occurs through iterating and reiterating among specialties to combine clues into patterns. Iterating helps turn clues into bodies of data and evidence and is based on interdisciplinary collaboration, since the insights of one science or function are deliberately juxtaposed with others to see how all these different insights fit into a pattern. The search for clues is complemented by integration and sensemaking through which scientists put together a body of data to support their core hypothesis that their drug works.

3.2. Sample

The sample analyzed in this study includes 216 publicly-traded pharmaceutical companies in US (listed in Appendix I) followed over a 20-year period from 1990 to 2009. During this period, the scientists employed by the 216 firms in the sample published over 86,000 research papers in journals indexed by the ISI Web of Science, and applied for over 39,000 patents with the US Patents and Trademarks Office. The firms in the sample also formed about 2,800 alliances during this period, of which over 1,400 were R&D alliances based on data extracted from SDC Platinum's M&A/Alliance database. I use scientific publications to capture firms' science productivity, and patent applications to capture their innovative output. I restricted the sample to publicly traded firms to ensure the availability of financial data and appropriate controls which came from Standard & Poor's Compustat. I started by identifying all the companies in Compustat with SIC code 2834, pharmaceutical preparations. To ensure the relevance of scientific research to all firms in the final sample, I included only those firms with at least one publication by their employees (i.e. at least one coauthor affiliated with the firm at the time the paper was published) in any of the journals indexed in ISI Web of Science during the 20 year span of the study. The final longitudinal database consists of 2,648 firm-year observations of 216 firms.

3.3. Measures

3.3.1. Dependent variables

The dependent variable for testing H1 through H7 is the number of new R&D alliance formations per $M of R&D expenditure (at time $t+1$). I scale the number of new R&D alliances (as well as the number of papers by firm scientists and the number of patent applications) with the firm's R&D expenditure to isolate any effects due to the sheer size of some firms' R&D expenditure and to capture a more basic relationship between science productivity and the firm's extent of new R&D alliance formations. While scaling by a variable (R&D expenditure in this case) is one way of controlling for its effect in the model, another way is to include the variable as a covariate in the model. One advantage of the latter techniques is that the main covariates do not have to be expressed as proportions making it easier to interpret their relationships. However, the main disadvantage is the possibility of this variable being correlated with the rest of the covariates, hence causing further unwanted multicollinearity in the model. Given the presence of a considerable level of multicollinearity in my models due the testing of multiple interaction terms that are based on the same main effect, I adopted the former approach (i.e. scaling) to avoid introducing any further multicollinearity in the models which could potentially mask the significance of the estimated effects.

Alliance data came from SDC Platinum's M&A/Alliance database. The dependent variable for testing H8 is the long-term innovative output of the firm measured as the number of patent applications per $M of R&D expenditure over a period ranging from *t+2* to *t+10*. The USPTO's patent database served as the source for the patent application data.

3.3.2. Independent variables

The main independent variable for testing H1 through H7 – i.e. science productivity (at time *t*) – is measured as the annual number of papers published by the firm scientists per $M of R&D expenditure. The extent of isolation of firm scientists is measured as the proportion of papers without any external coauthors (i.e. not affiliated with the focal firm). The arm's length nature of external coauthorships is measured as the number of external organizations listed on the average paper published by firm scientists (i.e. total number of external organizations on papers published in a given year divided by the number of papers for that year). A potential concern about this measure is that not all authors or institutions listed on a paper may be involved with the project on an arm's length basis. In other words, some authors might be actually responsible for the execution of the research project behind the publication while others manage to associate themselves with it to get credit or as an acknowledgement of their support. One potential solution might be to regard the first few authors as the lead authors and regard their contributions to the project as rigorous and authentic while weighting down the contribution of the rest of the

authors based on the order in which they appear on the list. However, a close look at the norms of listing coauthors on scientific papers reveals that this solution will not work since while in some cases the order in based on actual contributions, in many others the order simply reflects seniority or the size of the financial or logistic contribution to the project or, at a higher level, to the lab in which the project was carried out.

Organizational dispersion of scientific activity is measured as the proportion of papers published by the scientists employed by the subsidiaries of a corporation. Current innovative output of the firm is measured as the number of patent applications per $M of R&D expenditure. R&D alliance experience is measured as the total number of R&D alliances formed by the firm over the past three years. Firm size is measured as the number of employees (Park, Chen, Gallagger, 2002). In models testing H8, the independent variables include science productivity (described above) and the number of new R&D alliance formations per $M of R&D expenditure.

3.3.3. Controls

In models testing H1-H7 I include controls representing the firm's financial and stock market performance, i.e. sales, earnings before interest and tax (EBIT), earning per share (EPS) and the highest share price for the fiscal year. Since the dependent variable in models testing H1-H7 is scaled by firm's R&D expenditure, I also scale the control variables by firm's R&D expenditure to increase the consistency across

these models. Year dummies were also included in all models to control for the unobserved effects of fluctuations in industry and macroeconomic conditions over the study period.

4. RESULTS

4.1. Estimation results for H1-H7

Tables 1 and 2 present the descriptive statistics and correlations, respectively. Tables 3A and 3B present the fixed effects and random effects estimation results along with their corresponding Hausman test results to determine whether the fixed or random effects models are the more appropriate specification for my analysis. The results of the Hausman tests presented in Tables 3B reject (p<0.001) the null that the difference in the coefficient estimates of any given fixed and random effect model is not systematic, offering evidence that the random effects model is inconsistent and that the fixed effects model is the more appropriate specification for the analyses reported here. Therefore, I only discuss the results from the fixed effects models in Tables 3A.

I start by interpreting results from the fully-saturated model (i.e. Model 9) including all hypothesized effects. The estimation results from this model are most reliable since it is fully specified. Model 9 can be stated as:

$$\begin{aligned}RDALLiances_{i,t+1}/RDExp_{i,t+1} = {} & b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 ScientistIsolation_{i,t} + b_3 ArmsLength_{i,t} \\ & + b_4 OrgDispersion_{i,t} + b_5 Patents_{i,t}/RDExp_{i,t} + b_6 RDALLiExp_{i,t} + \\ & b_7 Firmsize_{i,t} + b_8 Papers_{i,t}/RDExp_{i,t} * ScientistIsolation_{i,t} + \\ & b_9 Papers_{i,t}/RDExp_{i,t} * ArmsLength_{i,t} + \\ & b_{10} Papers_{i,t}/RDExp_{i,t} * OrgDispersion_{i,t} + \\ & b_{11} Papers_{i,t}/RDExp_{i,t} * Patents_{i,,t}/RDExp_{i,,t} + \\ & b_{12} Papers_{i,t}/RDExp_{i,t} * RDALLiExp_{i,,t} + \\ & b_{13} Papers_{i,t}/RDExp_{i,t} * Firmsize_{i,t} + \\ & c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + \\ & c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + c_{23} Year\_2009 + e_{i,t}\end{aligned}$$

Table 1:
Descriptive statistics (Non-missing firm-year observations)

Variable	Obs.	Mean	Std. Dev.	Min	Max
No. of new R&D alliance formations	2648	0.56	1.47	0.00	14.00
No. of new R&D alliance formations per M$ of R&D expenditure	2390	0.04	0.44	0.00	14.49
No. of papers	2648	32.57	119.23	0.00	1129.00
No. of papers per M$ of R&D expenditure	2390	0.29	1.12	0.00	43.48
Annual citations to papers	2648	137.81	521.21	0.00	5345.33
No. of patents	2648	15.07	49.79	0.00	518.00
No. of patents per M$ of R&D expenditure	2390	0.28	1.29	0.00	37.04
Prop. of papers w/o external co-authors	1556	0.29	0.30	0.00	1.00
Prop. of papers by subsidiaries	1556	0.05	0.19	0.00	1.00
No. of ext. orgs. on an avg. paper	1556	2.06	1.83	0.00	32.00
R&D alliance experience	2648	1.60	3.89	0.00	35.00
No. of employees (thousands)	2309	4.75	15.89	0.00	122.20
Sales over R&D expenditure	2390	10.68	52.50	0.00	1765.29
EBIT over R&D expenditure	2390	0.36	18.81	-202.00	773.71
EPS over R&D expenditure	2386	-0.15	1.79	-50.00	40.00
Share price over R&D expenditure	2162	13.09	339.66	0.002	15294.27

Due to the inevitable multicollinearity that results from having multiple interaction terms with the same main effect in the model, Model 9 results offer support ($p<0.01$) only for the main effect of the number of papers per $M of R&D expenditure, along with three of the six hypothesized moderation effects – i.e. the interaction terms for isolation of firm scientists, organizational dispersion of scientific activity, and current innovative output. In other words, based on the results from the fully-specified model, only H1, H2, H4, and H5 are supported. In order to further

examine the stability of these findings, I estimate individual models corresponding to every individual hypothesis.

Model 1 is the baseline model that only includes the controls. Model 2 corresponds to H1 and introduces the main effect of science productivity. Model 2 can be stated as:

$$RDALLiances_{i,t+1}/RDExp_{i,t+1} = b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + c_{23} Year\_2009 + e_{i,t}$$

The coefficient estimates on science productivity is positive and significant ($p<0.05$), further confirming the support for H1. According to this model, every additional paper per $M of R&D expenditure corresponds to the formation of 0.356 new R&D alliances per $M of R&D expenditure. Model 3 introduces the interaction effect of the proportion of papers without external coauthors corresponding to H2 – i.e. that the relationship in H1 is weaker when firm scientists are isolated from the broader scientific community. Model 3 can be stated as:

$$RDALLiances_{i,t+1}/RDExp_{i,t+1} = b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 ScientistIsolation_{i,t} + b_3 Papers_{i,t}/RDExp_{i,t} * ScientistIsolation_{i,t} + c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + c_{23} Year\_2009 + e_{i,t}$$

Table 2:
Correlations along with their significance level

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. No. of new R&D alliances over R&D	1												
2. No. of papers over R&D	0.02	1											
3. Annual citations to papers	-0.03	0.01	1										
4. Prop. of papers w/o ext. coauthors	0.08***	0.00	0.02	1									
5. Prop. of papers by subsidiaries	-0.04	-0.03	0.06**	-0.01	1								
6. No. of ext. orgs. on an avg. paper	-0.06**	-0.07**	0.01	-0.54***	0.03	1							
7. No. of patents over R&D	0.02	0.09***	-0.03	0.10***	-0.04	-0.11***	1						
8. R&D alliance experience	0.01	0.03	0.71***	0.17***	0.13***	-0.09***	-0.01	1					
9. No. of employees	-0.04*	-0.03	0.77***	0.09***	0.27***	-0.05*	-0.04*	0.74***	1				
10. Sales over R&D	0.03	-0.02	-0.02	0.01	0.09***	-0.04	0.03	-0.04*	-0.01	1			
11. EBIT over R&D	-0.01	-0.09***	0.02	0.08***	0.13***	-0.01	-0.00	0.02	0.03	0.71***	1		
12. EPS over R&D	-0.06***	-0.04**	0.02	0.04	0.01	0.04	-0.12***	0.03	0.02	0.20***	0.69***	1	
13. Share price over R&D	-0.00	-0.01	-0.01	0.02	-0.05*	-0.03	0.01	-0.02	-0.01	0.20***	0.07***	-0.10***	1

* $p < .1$, ** $p < .05$, *** $p < .01$

The coefficient estimate on the interaction term is negative and significant (p<0.001) further confirming the support for H2. According to this model, every unit increase in scientist isolation weakens the original positive association between science productivity and new R&D alliances (i.e. that every additional paper per $M of R&D expenditure corresponds to the formation of 0.356 new R&D alliances per $M of R&D expenditure) by 0.652 alliances, causing the main effect to turn negative. Model 4 introduces the interaction effect of the number of external organizations on an average paper corresponding to H3 – i.e. that the relationship in H1 is weaker when a high proportion of the external coauthorships of firm scientists are of arm's length type. Model 4 can be stated as:

$$\begin{aligned} RDALLiances_{i,t+1}/RDExp_{i,t+1} = {} & b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 ArmsLength_{i,t} + \\ & b_3 Papers_{i,t}/RDExp_{i,t} * ArmsLength_{i,t} + \\ & c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + \\ & c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + \\ & c_{23} Year\_2009 + e_{i,t} \end{aligned}$$

The coefficient estimate on the interaction term is positive and not significant, failing to offer support for H3. Model 5 introduces the interaction effect of the proportion of papers by subsidiaries corresponding to H4 – i.e. that the relationship in H1 is weaker when scientific activity is highly dispersed across the organization. Model 5 can be stated as:

Table 3A:
Fixed effects estimation results for testing H1-H7;
Dependent variable is the future number of new R&D alliance formations per M$ of R&D expenditure;
Robust standard errors in parentheses;
* $p < .1$, ** $p < .05$, *** $p < .01$

		H1	H2	H3	H4	H5	H6	H7	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
No. of papers per M$ of R&D		0.356**	0.321***	0.037	0.139**	0.492**	0.427**	0.349**	0.609***
		(0.180)	(0.094)	(0.102)	(0.061)	(0.223)	(0.199)	(0.176)	(0.217)
No. of papers per M$ of R&D x			-0.652***						-0.730***
Prop. of papers w/o ext. coauthors			(0.204)						(0.239)
No. of papers per M$ of R&D x				0.055					-0.057
No. of ext. orgs. on an avg. paper				(0.051)					(0.076)
No. of papers per M$ of R&D x					-0.292***				-0.408***
Prop. of papers by subsidiaries					(0.081)				(0.113)
No. of papers per M$ of R&D x						-0.083*			-0.057***
No. of patents per M$ of R&D						(0.047)			(0.020)
No. of papers per M$ of R&D x							-0.070**		-0.015
R&D alliance experience							(0.035)		(0.012)
No. of papers per M$ of R&D x								-0.009**	0.007*
No. of employees								(0.003)	(0.003)
Prop. of papers w/o ext. coauthors			0.145***						0.170***
			(0.053)						(0.048)
No. of ext. orgs. on an avg. paper				0.001					0.019**
				(0.006)					(0.009)
Prop. of papers by subsidiaries					0.116				0.126*
					(0.073)				(0.067)
No. of patents per M$ of R&D						0.006			0.033
						(0.006)			(0.053)
R&D alliance experience							0.022*		0.005
							(0.011)		(0.004)
No. of employees								0.002**	-0.000
								(0.001)	(0.001)
Sales/R&D Expense	0.001	0.001	0.009	0.017	0.015	0.001	0.001	0.001	0.005
	(0.001)	(0.001)	(0.008)	(0.010)	(0.011)	(0.000)	(0.000)	(0.001)	(0.006)
EBIT/R&D Expense	-0.001	-0.001	-0.056**	-0.074*	-0.070*	-0.001	-0.001	-0.001	-0.052**
	(0.002)	(0.001)	(0.028)	(0.037)	(0.037)	(0.001)	(0.001)	(0.001)	(0.024)
EPS/R&D Expense	-0.002	-0.005	-0.478*	-0.544*	-0.527	-0.001	-0.004	-0.004	-0.348
	(0.009)	(0.007)	(0.282)	(0.324)	(0.322)	(0.006)	(0.006)	(0.006)	(0.223)
Share price/R&D Expense	-0.000	-0.000	0.055***	0.056***	0.058**	-0.000	-0.000	-0.000	0.047*
	(0.000)	(0.000)	(0.020)	(0.020)	(0.023)	(0.000)	(0.000)	(0.000)	(0.024)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.226*	0.103	-0.069	-0.134	-0.120	0.077	0.103	0.103	-0.117
	(0.131)	(0.139)	(0.176)	(0.195)	(0.194)	(0.133)	(0.134)	(0.140)	(0.128)
N	1947	1947	1223	1223	1223	1947	1947	1929	1211
R^2–within	0.043	0.281	0.736	0.693	0.688	0.350	0.327	0.274	0.774
R^2–between	0.027	0.127	0.477	0.414	0.451	0.148	0.215	0.203	0.489
R^2–overall	0.039	0.231	0.650	0.589	0.597	0.282	0.294	0.231	0.683

Table 3B:
Random effects estimation results for testing H1-H7;
Dependent variable is the future number of new R&D alliance formations per M$ of R&D expenditure;
Robust standard errors in parentheses;
* $p < .1$, ** $p < .05$, *** $p < .01$

		H1	H2	H3	H4	H5	H6	H7	
	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
No. of papers per M$ of R&D		0.287*	0.298***	0.076	0.106***	0.396*	0.390**	0.307*	0.635***
		(0.154)	(0.0894)	(0.100)	(0.040)	(0.208)	(0.186)	(0.162)	(0.231)
No. of papers per M$ of R&D x Prop. of papers w/o ext. coauthors			-0.640***						-0.828***
			(0.226)						(0.265)
No. of papers per M$ of R&D x No. of ext. orgs. on an avg. paper				0.011					-0.100
				(0.049)					(0.073)
No. of papers per M$ of R&D x Prop. of papers by subsidiaries					-0.290***				-0.351***
					(0.076)				(0.106)
No. of papers per M$ of R&D x No. of patents per M$ of R&D						-0.070			-0.039**
						(0.050)			(0.018)
No. of papers per M$ of R&D x R&D alliance experience							-0.069**		-0.011
							(0.034)		(0.011)
No. of papers per M$ of R&D x No. of employees								-0.010**	0.004*
								(0.004)	(0.002)
Prop. of papers w/o ext. coauthors			0.164***						0.196***
			(0.060)						(0.059)
No. of ext. orgs. on an avg. paper				0.005					0.024**
				(0.007)					(0.011)
Prop. of papers by subsidiaries					0.169***				0.153***
					(0.054)				(0.045)
No. of patents per M$ of R&D						-0.003			0.008
						(0.006)			(0.039)
R&D alliance experience							0.014*		0.007*
							(0.008)		(0.004)
No. of employees								0.001*	0.000
								(0.001)	(0.001)
Sales/R&D Expense	0.001	0.001	0.004	0.007	0.007	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.006)	(0.007)	(0.007)	(0.001)	(0.000)	(0.001)	(0.005)
EBIT/R&D Expense	-0.001	-0.001	-0.028	-0.033	-0.034	-0.001	-0.001	-0.001	-0.031
	(0.001)	(0.001)	(0.026)	(0.031)	(0.031)	(0.001)	(0.001)	(0.001)	(0.022)
EPS/R&D Expense	-0.004	-0.006	-0.576**	-0.687**	-0.671**	-0.005	-0.005	-0.006	-0.406
	(0.010)	(0.009)	(0.289)	(0.339)	(0.332)	(0.008)	(0.007)	(0.008)	(0.248)
Share price/R&D Expense	-0.000	-0.000	0.052**	0.051**	0.052**	-0.000	-0.000	-0.000	0.053**
	(0.000)	(0.000)	(0.020)	(0.020)	(0.022)	(0.000)	(0.000)	(0.000)	(0.026)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.241*	0.144	0.050	0.082	0.099	0.123	0.119	0.148	-0.001
	(0.139)	(0.136)	(0.191)	(0.214)	(0.212)	(0.135)	(0.135)	(0.137)	(0.175)
N	1947	1947	1223	1223	1223	1947	1947	1929	1211
R^2–within	0.041	0.279	0.725	0.662	0.661	0.346	0.323	0.272	0.762
R^2–between	0.057	0.141	0.538	0.555	0.577	0.163	0.249	0.227	0.580
R^2–overall	0.041	0.233	0.669	0.621	0.625	0.284	0.303	0.237	0.712
Hausman test:	χ^2	97.12	225.56	271.08	256.19	131.88	56.05	79.79	218.30
Ho: Diff in coeffs. not systematic	*Prob.*>χ^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

$$RDALLiances_{i,t+1}/RDExp_{i,t+1} = b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 OrgDispersion_{i,t} + b_3 Papers_{i,t}/RDExp_{i,t} * OrgDispersion_{i,t} + c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + c_{23} Year\_2009 + e_{i,t}$$

The coefficient estimate on the interaction term is negative and significant ($p<0.01$), further confirming the support for H4. According to this model, every unit increase in organizational dispersion of scientific activity weakens the original positive association between science productivity and new R&D alliances (i.e. that every additional paper per $M of R&D expenditure corresponds to the formation of 0.356 new R&D alliances per $M of R&D expenditure) by 0.292 alliances. Model 6 introduces the interaction effect of the number of patents per M$ of R&D expenditure corresponding to H5 – i.e. that the relationship in H1 is weaker when the current innovative output of the firm is high. Model 6 can be stated as:

$$RDALLiances_{i,t+1}/RDExp_{i,t+1} = b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 Patents_{i,t}/RDExp_{i,t} + b_3 Papers_{i,t}/RDExp_{i,t} * Patents_{i,,t}/RDExp_{i,,t} + c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + c_{23} Year\_2009 + e_{i,t}$$

The coefficient estimate on the interaction term is negative and mildly significant ($p<0.1$) offering only partial support for H5 which is in line with the results of the fully-specified model. According to this model, every additional patent application per $M of R&D expenditure weakens the original positive association

between science productivity and new R&D alliances (i.e. that every additional paper per $M of R&D expenditure corresponds to the formation of 0.356 new R&D alliances per $M of R&D expenditure) by 0.083 alliances. Model 7 introduces the interaction effect of R&D alliance experience corresponding to H6 – i.e. that the relationship in H1 is weaker when the firm's R&D alliance experience is high. Model 7 can be stated as:

$$\begin{aligned} RDALLiances_{i,t+1}/RDExp_{i,t+1} = {} & b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 RDALLiExp_{i,t} + \\ & b_3 Papers_{i,t}/RDExp_{i,t} * RDALLiExp_{i,,t} + \\ & c_1 Sales_{i,t}/R\&DExp_{i,t} + c_2 EBIT_{i,t}/R\&DExp_{i,t} + c_3 EPS_{i,t}/R\&DExp_{i,t} + \\ & c_4 Shareprice_{i,t}/R\&DExp_{i,t} + c_5 Year\_1991 + \ldots + c_{23} Year\_2009 + e_{i,t} \end{aligned}$$

The coefficient estimate on the interaction term is negative and significant ($p<0.05$) which may be interpreted as partial support for H6 (even though no significance was found for this interaction term in the fully-specified model). According to this model, every unit increase in R&D alliance experience weakens the original positive association between science productivity and new R&D alliances (i.e. that every additional paper per $M of R&D expenditure corresponds to the formation of 0.356 new R&D alliances per $M of R&D expenditure) by 0.070 alliances. Model 8 introduces the interaction effect of the number of employees corresponding to H7 – i.e. that the relationship in H1 is weaker for larger firms. Model 8 can be stated as:

$$\begin{aligned} RDALLiances_{i,t+1}/RDExp_{i,t+1} = {} & b_0 + b_1 Papers_{i,t}/RDExp_{i,t} + b_2 Firmsize_{i,t} + \\ & b_3 Papers_{i,t}/RDExp_{i,t} * Firmsize_{i,t} + \end{aligned}$$

$$c_1Sales_{i,t}/R\&DExp_{i,t}+c_2EBIT_{i,t}/R\&DExp_{i,t}+c_3EPS_{i,t}/R\&DExp_{i,t}+ c_4Shareprice_{i,t}/R\&DExp_{i,t}+c_5Year\_1991+\ldots+c_{23}Year\_2009 + e_{i,t}$$

The coefficient estimate on the interaction term is negative and significant (p<0.05) which may be interpreted as partial support for H7 (even though no significance was found for this interaction term in the fully-specified model). According to this model, every additional employee weakens the original positive association between science productivity and new R&D alliances (i.e. that every additional paper per $M of R&D expenditure corresponds to the formation of 0.356 new R&D alliances per $M of R&D expenditure) by 0.009 alliances.

Given the fractional nature of multiple variables in this study, I also ran a set of models with standardized variables (i.e. subtracted the mean and divided by the standard deviation) to facilitate the interpretation of the findings in terms of the effect size. The results of this analysis are presented in Table 4. The coefficient estimate on the standardized number of papers per $M of R&D expenditure (Model 20) is 1.195 which implies that every standard deviation change in this number corresponds to a 1.195 standard deviation change in the future number of new R&D alliance formations per M$ of R&D expenditure in the same direction.

The coefficient estimate on the standardized interaction term for the proportion of papers without external coauthors is -0.658 (Model 21) which along with the coefficient estimate of 0.454 on the standardized number of papers per $M of R&D

expenditure imply that when the proportion of papers without external coauthors is at one standard deviations above the mean, the positive main effect of the number of papers per $M of R&D expenditure is significantly reduced and actually, becomes slightly negative (0.204 standard deviations drop in the future number of new R&D alliance formations per M$ of R&D expenditure corresponding to every standard deviations change in the number of papers per $M of R&D expenditure in the same direction).

The coefficient estimate on the standardized interaction term for the proportion of papers by subsidiaries is -0.187 (Model 23) which along with the coefficient estimate of 0.415 on the standardized number of papers per $M of R&D expenditure imply that when the proportion of papers by subsidiaries is at one standard deviations above the mean, the positive main effect of the number of papers per $M of R&D expenditure reduces to 0.228 standard deviations change in the future number of new R&D alliance formations per M$ of R&D expenditure corresponding to every standard deviations change in the number of papers per $M of R&D expenditure in the same direction.

The coefficient estimate on the standardized interaction term for the number of patents per $M of R&D expenditure is -0.359 (Model 24) which along with the coefficient estimate of 1.575 on the standardized number of papers per $M of R&D expenditure imply that when the number of patents per $M of R&D expenditure is at one standard deviations above the mean, the positive main effect of the number of

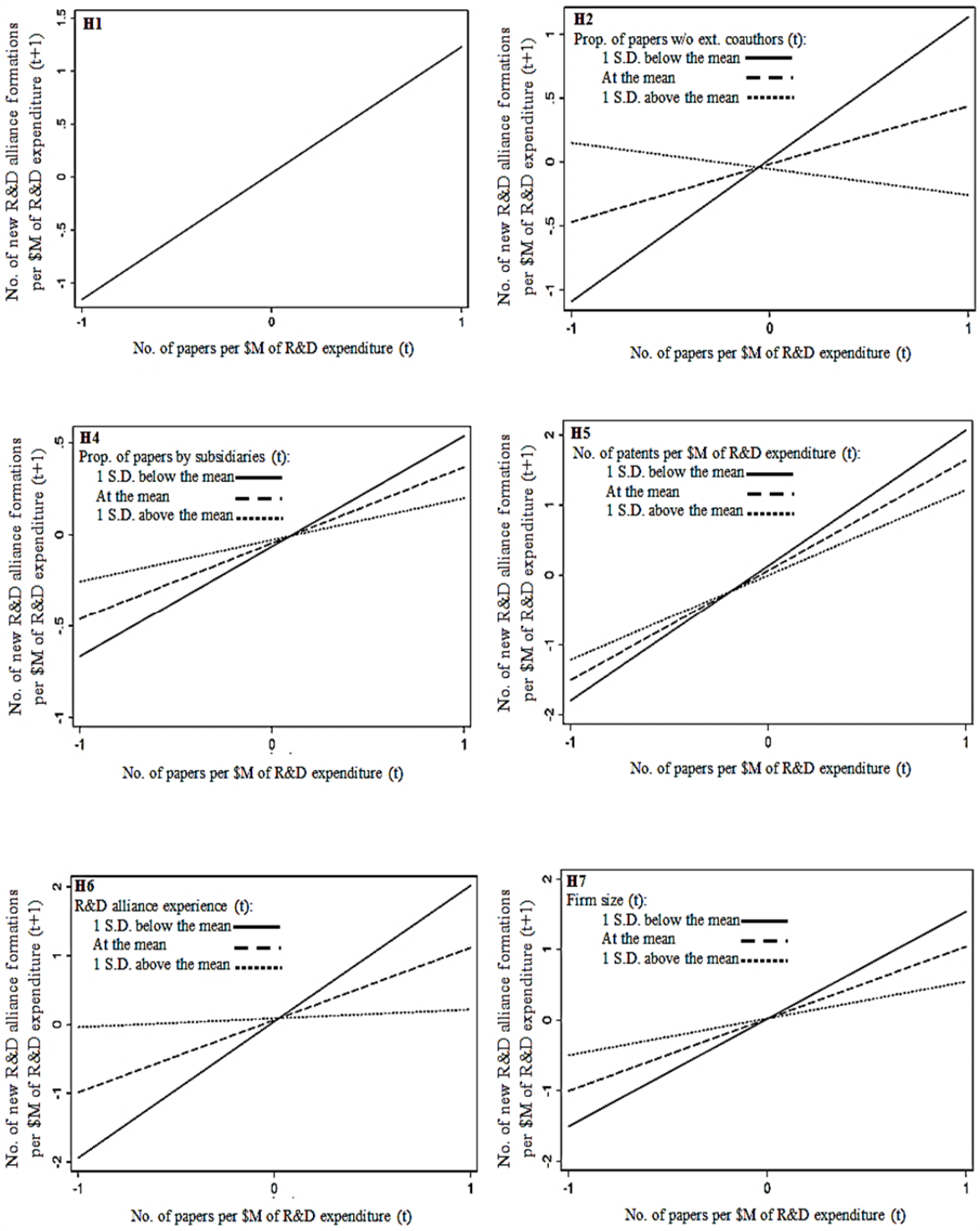
Table 4:
Fixed effects estimation results for models with standardized variables;
Dependent variable is the future number of new R&D alliance formations per M$ of R&D expenditure;
Robust standard errors in parentheses;
* $p < .1$, ** $p < .05$, *** $p < .01$

		H1	H2	H3	H4	H5	H6	H7	
	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27
No. of papers per M$ of R&D		1.195**	0.454***	0.509**	0.415**	1.575**	1.054**	1.024*	0.854***
		(0.603)	(0.157)	(0.201)	(0.195)	(0.705)	(0.500)	(0.547)	(0.235)
No. of papers per M$ of R&D x Prop. of papers w/o ext. coauthors			-0.658***						-0.737***
			(0.206)						(0.241)
No. of papers per M$ of R&D x No. of ext. orgs. on an avg. paper				0.341					-0.355
				(0.318)					(0.473)
No. of papers per M$ of R&D x Prop. of papers by subsidiaries					-0.187***				-0.262***
					(0.052)				(0.073)
No. of papers per M$ of R&D x No. of patents per M$ of R&D						-0.359*			-0.246***
						(0.206)			(0.089)
No. of papers per M$ of R&D x R&D alliance experience							-0.926**		-0.199
							(0.463)		(0.159)
No. of papers per M$ of R&D x No. of employees								-0.502**	0.387*
								(0.197)	(0.212)
Prop. of papers w/o ext. coauthors			-0.038						-0.035
			(0.023)						(0.037)
No. of ext. orgs. on an avg. paper				0.092*					0.014
				(0.052)					(0.078)
Prop. of papers by subsidiaries					0.018				0.005
					(0.037)				(0.029)
No. of patents per M$ of R&D						-0.068			0.064
						(0.054)			(0.188)
R&D alliance experience							0.024		0.015
							(0.036)		(0.023)
No. of employees								0.003	0.086*
								(0.061)	(0.051)
Sales/R&D Expense	0.148	0.090	1.459	2.633	2.467	0.097	0.081	0.089	0.851
	(0.151)	(0.083)	(1.319)	(1.707)	(1.729)	(0.075)	(0.073)	(0.082)	(0.988)
EBIT/R&D Expense	-0.112	-0.047	-3.152**	-4.165*	-3.957*	-0.066	-0.043	-0.049	-2.963**
	(0.129)	(0.067)	(1.585)	(2.120)	(2.124)	(0.070)	(0.062)	(0.068)	(1.370)
EPS/R&D Expense	-0.012	-0.027	-2.559*	-2.910*	-2.821	-0.006	-0.024	-0.024	-1.860
	(0.050)	(0.038)	(1.509)	(1.735)	(1.723)	(0.033)	(0.034)	(0.036)	(1.193)
Share price/R&D Expense	-0.019	-0.006	56.590***	57.240***	59.380**	-0.001	-0.004	-0.006	48.480*
	(0.021)	(0.010)	(20.850)	(20.680)	(23.950)	(0.007)	(0.009)	(0.010)	(25.320)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.590	0.519	2.552***	2.531***	2.607***	0.546*	0.588*	0.516	2.231**
	(0.386)	(0.342)	(0.745)	(0.691)	(0.834)	(0.327)	(0.332)	(0.349)	(0.912)
N	1947	1947	1223	1223	1223	1947	1947	1929	1211
R^2-within	0.043	0.281	0.736	0.693	0.688	0.350	0.327	0.274	0.774
R^2-between	0.027	0.127	0.477	0.414	0.451	0.148	0.215	0.203	0.489
R^2-overall	0.039	0.231	0.650	0.589	0.597	0.282	0.294	0.231	0.683

papers per $M of R&D expenditure reduces to 1.216 standard deviations change in the future number of new R&D alliance formations per M$ of R&D expenditure corresponding to every standard deviations change in the number of papers per $M of R&D expenditure in the same direction. The coefficient estimate on the standardized interaction term for the R&D alliance experience is -0.926 (Model 25) which along with the coefficient estimate of 1.054 on the standardized number of papers per $M of R&D expenditure imply that when the R&D alliance experience is at one standard deviations above the mean, the positive main effect of the number of papers per $M of R&D expenditure is reduced to 0.128 standard deviations change in the future number of new R&D alliance formations per M$ of R&D expenditure corresponding to every standard deviations change in the number of papers per $M of R&D expenditure in the same direction.

The coefficient estimate on the standardized interaction term for the number of employees is -0.502 (Model 26) which along with the coefficient estimate of 1.024 on the standardized number of papers per $M of R&D expenditure implies that when the number of employees is at one standard deviations above the mean, the positive main effect of the number of papers per $M of R&D expenditure reduces to 0.522 standard deviations change in the future number of new R&D alliance formations per M$ of R&D expenditure corresponding to every standard deviations change in the number of papers per $M of R&D expenditure in the same direction. Figure 2 presents a graphic depiction of the estimated effects based on the results presented in Table 4.

Figure 2:
Graphic depiction of the estimated effects (H1-H7)
(All variables are standardized and expressed in standard deviations around the mean)



4.2. Robustness check and alternative analysis for H1-H7

A legitimate concern to be addressed is that the inclination to form R&D alliances is highly path-dependent among firms (i.e. those who do more now will also do more in the future and vice versa) implying that a more robust empirical model must include lags of the dependent variable as a covariate. Therefore, as a robustness check, I ran a set of models using the Arellano-Bover/Blundell-Bond linear dynamic panel estimator. Linear dynamic panel models include lags of the dependent variable as covariates. By construction, the unobserved panel-level effects are correlated with the lagged dependent variables, making standard estimators inconsistent. Arellano and Bond (1991) derived a consistent generalized method of moments (GMM) estimator for this model, but the Arellano and Bond estimator can perform poorly if the autoregressive parameters are too large or the ratio of the variance of the panel-level effect to the variance of idiosyncratic error is too large. Later work by Arellano and Bover (1995) and Blundell and Bond (1998) led to the development of a system estimator that uses additional moment conditions.

The Arellano-Bover/Blundell-Bond method is in effect an instrumental variable method that uses the lags of both the endogenous variable as well as the dependent variable as instruments. I ran the Arellano-Bover/Blundell-Bond models with one lag of the dependent variable, while designating the main and interaction effects hypothesized in H1 to H7 as being endogenous. The results of the dynamic panel analysis are presented in Table 5.The results of the dynamic panel analyses

generally offer stronger statistical support than that provided by the previous fixed and random effects models. The stronger support is attributable to the inclusion of the lagged dependent variable which removes the path-dependent portion of the variance in the dependent variable and allows for a stronger traction on the hypothesized effects. The dynamic panel model is also more robust to the simultaneous inclusion of all the interaction terms as evident from the statistical significance ($p<0.001$) of four interaction terms (corresponding to H2, H3, H4, and H6) compared to only three in the fixed effects fully-specified model reported in Tables 3A.

As an additional alternative analysis, I also ran a set of models where I replaced the quantitative measure of science productivity – i.e. the number of papers per $M of R&D expenditure- with a quality-based measure – i.e. the annual citations to papers. The results of this analysis are reported in Table 6. Overall, the results are weak and only offer support for H1 ($p<0.05$), H3 ($p<0.1$), and H7 ($p<0.05$), indicating that the quantitative dimension of science productivity is more prevalent than the quality-based dimension in determining the availability of absorptive capacity by firms' managers.

Table 5:
Arellano-Bover/Blundell-Bond dynamic panel estimation results;
Dependent variable is the future number of new R&D alliance formations per M$ of R&D expenditure;
* $p < .1$, ** $p < .05$, *** $p < .01$

		H1	H2	H3	H4	H5	H6	H7	
	Model 28	Model 29	Model 30	Model 31	Model 32	Model 33	Model 34	Model 35	Model 36
No. of papers per M$ of R&D		0.122***	0.232***	0.051***	0.105***	0.201***	0.159***	0.123***	0.357***
		(0.008)	(0.008)	(0.007)	(0.006)	(0.010)	(0.008)	(0.008)	(0.015)
No. of papers per M$ of R&D x Prop. of papers w/o ext. coauthors			-0.374***						-0.471***
			(0.0178)						(0.021)
No. of papers per M$ of R&D x No. of ext. orgs. on an avg. paper				0.015***					-0.058***
				(0.003)					(0.004)
No. of papers per M$ of R&D x Prop. of papers by subsidiaries					-0.198***				-0.170***
					(0.028)				(0.028)
No. of papers per M$ of R&D x No. of patents per M$ of R&D						-0.034***			-0.007
						(0.003)			(0.005)
No. of papers per M$ of R&D x R&D alliance experience							-0.018***		-0.003**
							(0.002)		(0.001)
No. of papers per M$ of R&D x No. of employees								-0.005***	-0.001
								(0.001)	(0.001)
Prop. of papers w/o ext. coauthors			0.082***						0.122***
			(0.011)						(0.011)
No. of ext. orgs. on an avg. paper				-0.002					0.013***
				(0.001)					(0.002)
Prop. of papers by subsidiaries					0.079***				0.069***
					(0.015)				(0.015)
No. of patents per M$ of R&D						0.006*			-0.012
						(0.003)			(0.008)
R&D alliance experience							-0.000		0.000
							(0.001)		(0.001)
No. of employees								0.001*	0.000*
								(0.000)	(0.000)
Lagged dependent variable	0.207***	0.151***	-0.341***	-0.418***	-0.378***	0.191***	0.152***	0.153***	-0.248***
	(0.012)	(0.011)	(0.027)	(0.023)	(0.024)	(0.012)	(0.011)	(0.011)	(0.024)
Sales/R&D Expense	0.000	-0.000	-0.004***	-0.004***	-0.004***	0.000	-0.000	-0.000	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
EBIT/R&D Expense	-0.000	0.000	-0.000	-0.001	-0.000	-0.000	0.000	0.000	0.002*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EPS/R&D Expense	0.001	-0.001	-0.035**	-0.052***	-0.033**	0.001	-0.003	-0.002	-0.027**
	(0.004)	(0.003)	(0.015)	(0.013)	(0.013)	(0.003)	(0.003)	(0.004)	(0.011)
Share price/R&D Expense	0.000	0.000	0.027***	0.029***	0.027***	0.000	0.000	0.000	0.023***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.138***	0.091***	0.022	0.109***	0.015	0.071***	0.061***	0.117***	-0.010
	(0.020)	(0.020)	(0.016)	(0.012)	(0.014)	(0.020)	(0.019)	(0.016)	(0.016)
N	1889	1889	1198	1198	1198	1889	1889	1871	1186

Table 6:
Fixed effects estimation results with annual citations as a measure of science productivity;
Dependent variable is the future number of new R&D alliance formations per M$ of R&D expenditure;
Robust standard errors in parentheses;
* $p < .1$, ** $p < .05$, *** $p < .01$

	Model 37	Model 38	Model 39	Model 40	Model 41	Model 42	Model 43	Model 44	Model 45
Annual citations to papers		0.000**	-0.000	0.000*	-0.000	0.000**	0.000**	0.000**	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Annual citations to papers x Prop. of papers w/o ext. coauthors			0.000** (0.000)						0.000 (0.000)
Annual citations to papers x No. of ext. orgs. On an avg. paper				-0.000* (0.000)					-0.000 (0.000)
Annual citations to papers x Prop. of papers by subsidiaries					-0.000 (0.000)				-0.000 (0.000)
Annual citations to papers x No. of patents per M$ of R&D						0.000 (0.000)			0.000 (0.000)
Annual citations to papers x R&D alliance experience							-0.000 (0.000)		-0.000 (0.000)
Annual citations to papers x No. of employees								-0.000** (0.000)	-0.000 (0.000)
Prop. of papers w/o ext. coauthors			-0.077** (0.033)						-0.053 (0.037)
No. of ext. orgs. on an avg. paper				0.011* (0.005)					0.007 (0.005)
Prop. of papers by subsidiaries					0.042 (0.069)				0.029 (0.072)
No. of patents per M$ of R&D						0.006 (0.007)			-0.054 (0.040)
R&D alliance experience							0.001 (0.003)		0.002 (0.004)
No. of employees								0.003** (0.001)	0.001 (0.002)
Sales/R&D Expense	0.001 (0.001)	0.001 (0.001)	0.018 (0.011)	0.018 (0.011)	0.018 (0.011)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.018 (0.011)
EBIT/R&D Expense	-0.001 (0.002)	-0.002 (0.002)	-0.088** (0.039)	-0.089** (0.039)	-0.089** (0.039)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.091** (0.040)
EPS/R&D Expense	-0.002 (0.009)	-0.002 (0.009)	-0.567* (0.338)	-0.567* (0.339)	-0.567* (0.340)	-0.000 (0.010)	-0.002 (0.009)	-0.001 (0.008)	-0.563 (0.342)
Share price/R&D Expense	-0.000 (0.000)	-0.000 (0.000)	0.064** (0.026)	0.064** (0.026)	0.064** (0.026)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.064** (0.026)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.226* (0.131)	0.230* (0.131)	-0.036 (0.191)	-0.088 (0.193)	-0.075 (0.197)	0.226* (0.131)	0.229* (0.131)	0.206 (0.132)	-0.034 (0.177)
N	1947	1947	1223	1223	1223	1947	1947	1929	1211
R^2	0.043	0.044	0.667	0.667	0.665	0.045	0.044	0.043	0.670

4.3. Estimation results for H8

In order to test the last hypothesis, I estimate nine models where the dependent variable is the innovative output of the firms measured as the number of patent applications per $M of R&D expenditure. These nine models are meant to capture the joint effect of science productivity (at time *t*) and new R&D alliances (at time *t+1*) on the firm's innovative output starting from the following year (i.e. *t+2*) and stretching out by nine years (to *t+10*). Table 7 presents the fixed effects estimation results for these nine models. I present and focus on the fixed effects estimation results here since the Hausman tests comparing the fixed and random effects models (not reported) point to the relative appropriateness of the fixed effects estimator in this case.

The results from Table 7 fail to offer support for H8. The estimated coefficient on the interaction term between the number of new R&D alliances per M$ of R&D expenditure at *t+1* and the number of papers per M$ of R&D expenditure at *t* is only marginally significant ($p<0.1$) in Model 53 (*t+9*). Despite the general lack of statistical significance, an interesting pattern is noticeable in the sign of the estimated coefficient on the interaction term. While for the first five years following the formation of new R&D alliances the sign of this coefficient is negative, the sign flips at *t+7* and stays positive for the remaining three years. A potentially surprising interpretation of this faint finding might be that science productivity and R&D alliances substitute each other's effect on the firm's innovative output in the short and

medium run while complementing each other's effect in the long run. Another observation worth mentioning is that in models with a positive coefficient estimate on the interaction term (i.e. Models 51 to 54) the main effect of R&D alliances is consistently negative. This might imply that contrary to my expectation, the role of absorptive capacity may be to lower the negative long-term impact of R&D alliances rather than enhance their benefits. However, the consistent lack of statistical significance for these coefficient estimates across the models makes any further speculation in this regard tenuous at best.

Table 7:
Fixed effects estimation results for testing H8;
Dependent variable is the number of patent applications per M$ of R&D at *t+2* to *t+10*;
Robust standard errors in parentheses;
* $p < .1$, ** $p < .05$, *** $p < .01$

	Model 46	Model 47	Model 48	Model 49	Model 50	Model 51	Model 52	Model 53	Model 54
DV: No. of patent applications per M$ of R&D at:	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
No. of new R&D alliances per M$ of R&D (t+1) x	-0.005	-0.005	-0.020	-0.010	-0.004	0.002	0.002	0.009*	0.018
No. of papers per M$ of R&D (t)	(0.005)	(0.010)	(0.013)	(0.010)	(0.006)	(0.005)	(0.003)	(0.005)	(0.015)
No. of new R&D alliances per M$ of R&D (t+1)	0.007	-0.010	0.160	0.124	0.004	-0.054	-0.002	-0.037	-0.063
	(0.048)	(0.078)	(0.126)	(0.103)	(0.051)	(0.036)	(0.033)	(0.038)	(0.058)
No. of papers per M$ of R&D (t)	-0.004	0.047	0.013	0.007	0.030	0.029	-0.034	-0.029	-0.009
	(0.026)	(0.061)	(0.023)	(0.020)	(0.039)	(0.041)	(0.025)	(0.026)	(0.015)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.232***	0.668	0.250***	0.514***	0.186**	0.306***	0.270***	0.297***	0.221**
	(0.081)	(0.412)	(0.061)	(0.086)	(0.072)	(0.081)	(0.091)	(0.100)	(0.103)
N	1952	1746	1544	1351	1178	1022	874	751	640
R^2-within	0.021	0.030	0.051	0.048	0.031	0.029	0.027	0.024	0.020
R^2-between	0.037	0.059	0.094	0.069	0.055	0.035	0.012	0.011	0.052
R^2-overall	0.021	0.034	0.053	0.049	0.037	0.035	0.020	0.022	0.024

To complement the fixed effects estimation results reported in Table 7, I also ran a set of models using the Arellano-Bover/Blundell-Bond dynamic panel estimator with results reported in Table 8. These results resemble those reported in Table 7 in

Table 8:
Dynamic panel estimation results for testing H8;
Dependent variable is the number of patent applications per M$ of R&D at *t+2* to *t+10*;
Robust standard errors in parentheses;
* $p < .1$, ** $p < .05$, *** $p < .01$

DV: No. of patent applications per M$ of R&D at:	Model 55 t+2	Model 56 t+3	Model 57 t+4	Model 58 t+5	Model 59 t+6	Model 60 t+7	Model 61 t+8	Model 62 t+9	Model 63 t+10
No. of new R&D alliances per M$ of R&D (t+1) x No. of papers per M$ of R&D (t)	-0.004 (0.015)	-0.010 (0.008)	-0.035*** (0.010)	0.008 (0.010)	0.018* (0.011)	0.010 (0.011)	-0.002 (0.012)	0.006 (0.031)	0.019 (0.035)
No. of new R&D alliances per M$ of R&D (t+1)	-0.135 (0.124)	0.050 (0.069)	0.271*** (0.080)	-0.007 (0.086)	-0.284*** (0.090)	-0.110 (0.094)	-0.013 (0.098)	-0.057 (0.109)	-0.090 (0.118)
No. of papers per M$ of R&D (t)	0.091** (0.044)	0.047* (0.026)	0.054* (0.029)	-0.010 (0.032)	0.051 (0.034)	0.005 (0.034)	-0.001 (0.038)	0.012 (0.049)	0.018 (0.056)
Lagged no. of patents per M$ of R&D (t+2)	0.008 (0.016)								
Lagged no. of patents per M$ of R&D (t+3)		0.036* (0.011)							
Lagged no. of patents per M$ of R&D (t+4)			0.291*** (0.033)						
Lagged no. of patents per M$ of R&D (t+5)				0.397*** (0.040)					
Lagged no. of patents per M$ of R&D (t+6)					0.393*** (0.045)				
Lagged no. of patents per M$ of R&D (t+7)						0.492*** (0.055)			
Lagged no. of patents per M$ of R&D (t+8)							0.616*** (0.071)		
Lagged no. of patents per M$ of R&D (t+9)								0.546*** (0.086)	
Lagged no. of patents per M$ of R&D (t+10)									0.455*** (0.112)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.337*** (0.092)	0.243*** (0.058)	0.360*** (0.064)	0.242*** (0.055)	0.133** (0.061)	0.007 (0.078)	0.032 (0.083)	-0.022 (0.083)	-0.039 (0.097)
N	1822	1612	1410	1222	1048	892	756	643	541

that the sign of the interaction term starts out as negative and flips to positive after a few years (*t+5*). With the exception of *t+8*, the sign of the coefficient stays positive after *t+5*, further supporting the speculation that science productivity and R&D alliances may function as substitutes in the short and medium run and as complements in the long run. In terms of statistical significance, only the coefficient estimate on the interaction term in Model 59 (*t+6*) is marginally significant ($p<0.1$). Overall, the estimation results from Tables 7 and 8 fail to offer support for the prediction in H8 regarding the positive moderation effect of science productivity on the long-term benefits of R&D alliances for the firm's innovative output.

Table 9 presents a summary of the empirical findings of this study. Overall, the results of the empirical analysis provided stronger support for the first part of the theoretical framework on the link between science productivity and R&D alliances than for the second part regarding the long-term impact on the firm's innovative output.

Table 9:
Summary of empirical findings

Hypothesis	Prediction	Coeff. estimate (absolute)	Finding
H1	*Current science productivity is positively related to the firm's future number of R&D alliances*	0.356	Supported (p<0.05)
H2	*The relationship in H1 is weakened as the isolation of firm scientists increases*	-0.652	Supported (p<0.01)
H3	*The relationship in H1 is weakened as firm scientists engage in higher levels of external coauthorships of the arm's length type*	0.055	Not supported
H4	*The relationship in H1 is weakened as the organizational dispersion of scientific activity increases*	-0.292	Supported (p<0.01)
H5	*The relationship in H1 is weakened as the current innovative output of the firm increases*	-0.083	Supported (p<0.01)
H6	*The relationship in H1 is weakened as the firm's R&D alliance experience increases*	-0.070	Partially supported
H7	*The relationship in H1 is weakened as firm size increases*	-0.009	Partially supported
H8	*Science productivity at the time of forming new R&D alliances will enhance the benefits of those alliances for the firm's long-term innovative output*	0.009	Not supported

5. DISCUSSION AND CONCLUSION

5.1. Discussion and implications

This study joins a lively stream of research that aims to explain how science relates to firms' innovation strategies (Gambardella, 1992; Zucker, Darby, and Brewer, 1998; Gittelman and Kogut, 2003; Tzabbar, 2009). Firms invest in basic research to develop absorptive capacity that allows them to recognize, access, and exploit knowledge and technology developed outside their boundaries (Cohen and Levinthal, 1990; Gambardella, 1992; Roach, 2009). As a common indicator of absorptive capacity, the publication productivity of firm scientists is believed to influence managerial decision processes regarding the firm's engagement in R&D alliances as a main interorganizational mechanism for accessing external knowledge (Arora and Gambardella, 1994). Acknowledging the general importance of basic science for firms as established by prior research, this study set out to investigate why firms exhibit differences in the weights they assign in their innovation strategies to science productivity, and what implication such differences hold for firm innovation. In particular, this study explored why firms differ in the strength of link between their science productivity and the extent of their engagement in R&D alliances (Arora and Gambardella, 1994).

I argued that the differences among firms in the predictive power of science productivity over the formation of new R&D alliances can be explained using two sets of moderators at the scientist and the firm level. I then built on this general

theoretical framework to develop testable hypotheses. The baseline hypothesis was rooted in prior research (Arora and Gambardella, 1994) and proposed a positive effect of science productivity on the extent of the firm's engagement in new R&D alliances. The first set of moderators– i.e. isolation of firm scientists, arm's length nature of scientists' alliances, and organizational dispersion of absorptive capacity – corresponded to factors that impact the resulting absorptive capacity based on a given level of science productivity. The second set – i.e. current innovative output of the firm, R&D alliance experience, and firm size – corresponded to factors that increased the substitutability of absorptive capacity. I also hypothesized that science productivity at the time of forming new R&D alliances will enhance the long-term benefits of those alliances for the firm's innovative output. Analysis of a longitudinal database on the scientific and innovative performance as well as the alliance activities of a large sample of publicly-traded pharmaceutical companies offered general support for the proposed theoretical framework.

The primary contribution of this study and its finding is to our understanding of the role of science in firms' innovation strategies. Specifically, the theory and findings offer a first explanation for the differences among firms in terms of the link between in-house basic research and the other elements of their innovation strategy such as R&D alliances (Gittelman and Kogut, 2003). The findings showed that isolation from the external scientific community and the organizational dispersion of scientific activity both lower the firm's availability of absorptive capacity. An

implication of these findings for the process of managing and organizing basic research in firms concerns the case of firms with well-developed hierarchical structures where the firm's in-house basic research program is likely to be managed relatively independently from the rest of the firm's innovation system. The executives in charge of the basic research program in such situations may be better off, based on the findings of this study, by encouraging external scientific collaborations by the scientists in their employ and to try to consolidate basic research activities in the organization (Cockburn and Henderson, 1998). This way, the outcomes of the basic research program may be given a stronger weight by the managers and decision makers in charge of the other elements of the firm's innovation strategy. In other words, by encouraging external alliances and consolidating basic research in the organization, the executives in charge of the firm's basic research program may be able to boost the impact of science as an input to the firm's innovation processes and potentially ensure that basic research maintains its status as an engine behind the firm's innovativeness. The findings also showed that the firm's current innovative output, experience with R&D alliances, and size are all likely to increase the substitutability of absorptive capacity. These findings imply that executives in charge of the basic research programs in large, innovative, and experienced firms may have to face higher barriers to recognition regarding the outcome of the basic research projects they advocate within the firm, particularly as relates to the firm's R&D alliance strategy.

The theory and findings also contribute to the literature on the nature and origin of firm capabilities by painting a multi-layered picture of the innovative capabilities of firms (Teece, Pisano, and Shuen, 1997; Eisenhardt and Martin, 2000). To understand the nature of innovative capabilities, prior research has typically focused either on the internal or the external dimension of what constitutes a firm's innovative capability. Subramaniam and Youndt (2005), for instance, examined the influence of intellectual capital in a firm on its innovative capabilities. Hagedoorn and Duysters (2002), on the other hand, explored the differences in firms' preferences toward external sources of innovative capabilities such as strategic alliances or mergers and acquisitions. This study highlights the need to reconceptualize innovative capabilities as multilayered constructs with internal components (e.g. science productivity) and external elements (e.g. R&D alliances) that are closely-knit and nearly impossible to dissect and analyze independently. In fact, innovative capabilities may be better understood as residing not only in individual internal and external components, but also in the quality of the architecture connecting these components within the organizational structure (Henderson and Cockburn, 1994).

This study also holds implications for how firms deploy social and human capital within the framework of their innovation strategies (Subramaniam and Youndt, 2005). Specifically, the human capital of firm scientists is shown to provide the necessary foundation for deploying the firm's social capital to access external innovations (Mosey and Wright, 2007). Particularly, the findings imply that social

capital and human capital are not fully substitutable within firms' innovation strategies and their roles have to be balanced to avoid the negative long-term consequences for firm innovativeness.

Relatedly, this study also holds implications for an ongoing discussion on the "dark side of social capital" (Gargiulo and Benassi, 1999; Edelman et al., 2002; Villena et al., 2011). Gargiulo and Benassi (1999), for instance, argued that strong ties to cohesive contacts limit the manager's ability to keep control on the composition of his network and jeopardize his adaptability to adapt to changing task environments. Similarly, Edelman et al. (2002) questioned the notion that the accumulation of social capital has a positive and proportionate effect on the performance of projects in organizations and found a host of less beneficial aspects to utilizing social capital. This study contributes to this stream of research by arguing that the dark side of social capital as an element of firms' innovation strategy might manifest itself as the ignorance toward the necessity of balancing the deployment of social capital with a sufficient level of human capital. In other words, a lopsided attention to solutions based on social capital in the formulation of innovation strategies is likely to increasingly obscure the urge to invest in maintaining the firm's human capital as a foundation on which those solutions are implemented, thus leading to a gradual weakening of the firm's innovative capacities.

The theory and findings also contribute to the research on the enablers and impediment of the thriving of human capital in firms (Kor and Leblebici, 2005;

Galunic and Anderson, 2000). Particularly, this study begins to answer the baffling question of why would firms not invest in the enhancement of their human capital despite being aware of its pivotal role in the firm's competitiveness and prosperity. The answer revealed here is one that implicates strategic choices motivated by short-termism and the pursuit of readily-available and non-resource-intensive remedies to the firm's internal deficiencies. Past research typically frames social and human capital as complementary building blocks of firm's competitive capabilities (Nahapiet and Ghoshal, 1998; Adler & Kwon, 2002). However, perceptions of difference in the cost and speed of developing and deploying these two types of capital may imply that in situations of strategic vulnerability, firms might discount their complementary nature and conceive of them as substitutes. Moreover, organizational actors generally espouse expectations of equifinality regarding the ultimate strategic impact of social and human capital further suggesting that, under certain circumstances, firms may be driven to view these two types of capital as substitutes and hence, fail to make the necessary investments in restoring and improving the quality of the firm's human capital. This study highlighted the need to further examine the implications of such strategic decisions for the firm's long-term competiveness and the prosperity of its human capital.

The findings also hold implications for the broader literature on interorganizational relationships (Zaheer & Venkatraman, 1995; Uzzi, 1997; Dyer & Singh, 1998; Adler and Kwon, 2002). Scholars studying alliances and networks have

portrayed collaborative relationships as means of gaining access to and leveraging resources essential to the firm's competitiveness (Eisenhardt & Shoonhoven, 1996; Chung, Singh, & Lee, 1999; Park et al., 2002). However, the body of evidence that has accumulated in this literature in support of the beneficial impact of interorganizational solutions is based predominantly on short-term organizational outcomes (e.g. stock market reactions, sales growth). As such, the nature of the long-term effects of interorganizational solutions is yet to be examined in this literature. This study takes a step in this regard by highlighting the trade-offs that firms face in making long-term vs. short-term strategic decisions and emphasizing the need to further explore the long-term implications of such trade-offs.

The arguments in this study hinted at the fact that indiscriminate reliance on resources embedded in interfirm relationships in firms while ignoring a relevant internal dimension such as science productivity may lead to negative long-term ramifications. While external access and internal development do not have to be considered as mutually exclusive, one might argue that resorting to external solutions in the face of internal decline tends to weaken the drive behind the restoration of internal qualities. The example of a 'lazy eye' disorder (officially known as amblyopia) may help in further explaining the delicate balance between internal development and external access. This disorder affects some children where the brain partially or wholly ignores input from one eye, leading to its diminishing ability over time. The most common treatment for this visual disorder is to force the use of the

lazy eye by patching the good eye. In other words, as long as the good eye remains accessible, the brain increasingly relies on its function and further ignores the condition of the lazy eye. Failing to balance the firm's attention to internal development and external access may be thought of as being tantamount to letting the brain increase its reliance on the good eye while ignoring the lazy eye, leading to long-term deterioration of the overall vision. As such, this study hints at some nuanced mechanisms through which excessive reliance on external sources may prove detrimental to the firm's long-term performance.

5.2. Limitations of the study

A number of limitations warrant discussion. First and foremost, this study views the decision process for formation of new R&D alliances simply from the perspective of the focal firm. This issue represents an obvious limitation since an ideal conceptualization of the alliance formation process needs to take into account the mutual role of both partners rather than that of a single partner. An immediate implication of adopting the point of view of the focal firm is the lack of attention to the motives of potential partners in allying with the focal firm. For instance, a potential alternative explanation for the positive effect of science productivity on number of new R&D alliance formations may be that future partners are attracted to the focal firm due to its strong in-house research capabilities and intend to benefit from those capabilities within the framework of the alliance. In other words, instead of the focal firm's increased bandwidth that allows it to take on more partnerships, it

may be the attractiveness of its internal capabilities that lures a greater number of future partners to seek partnerships with the firm. Due to the differences in the underlying mechanisms that are theorized to cause the effect of interest, the implications that ensue from such alternative explanations may also be different from those proposed based on the single-firm perspective of the study.

Second, this study does not distinguish among the firm's alliance partners (e.g. for-profit vs. nonprofit, small start-up vs. large incumbent firm) and treats all future R&D alliances as equal. However, research has underlined the differences in the types of knowledge and information that is available from different types of partners (Arora and Gambardella, 1994). Such differences may imply the necessity of gearing the firm's absorptive capacity toward certain partners to maximize the benefits from the firm's R&D alliance portfolio. Unfortunately, my data in its current format does not allow me to make such distinctions among future alliance partners. However, the theory and the empirics of this study were designed to preserve their applicability across different types of alliance partners and different types of knowledge and technology available from those partners, thus minimizing the threats to the external validity of the study.

Third, relying on the number of publications to capture science productivity may raise some concerns since not all results from a research project get published and not all publications are true reflections of scientists' productivity. Yet, the accepted norms of the institution of public science and the individual drive for

professional recognition is likely to create strong inclinations in every corporate scientist to try to publish as much of their research findings as possible, therefore minimizing the concerns about the accuracy of the number of publications as a measure of science productivity. Fourth, using the proportion of scientific activity performed in subsidiaries as a measure of the overall dispersion of scientific activities within the firm presents a limitation since even scientific activity that is concentrated in the headquarters may still be dispersed across the organizational structure of the HQ. Unfortunately, the current setup of the database does not allow me to capture such intra-unit dispersion and as such, the measure based on the proportion of activities in subsidiaries is the closest I can come to capturing the true organizational dispersion of the firm's scientific activities.

Fifth, using patent applications as a measure of the firm innovative output may raise some traditional concerns regarding the distinction between inventions (mostly associated with patenting activities) and innovations (associated with the development of new products through commercialization of inventions). Ideally, a comprehensive measure of the innovative output of the firm must also include an element of new product development. However, the arguments developed in this study regarding the role of absorptive capacity as a foundation for future R&D alliances and its impact on long-term innovative output of the firm tend to resonate more with the invention dimension of the innovation process than with the new product development dimension. Therefore, I believe that there is a reasonable level of consistency between

the theoretical arguments behind this construct and the empirical operationalization of it, lending enough legitimacy to the findings and their implications for research and practice.

Finally, measuring scientist isolation as the proportion of papers without external coauthors and, at the same time, measuring science productivity as the number of all papers with at least one coauthor employed by the firm may present a challenge in that these two measures may be confounded at some level. A potential remedy might be to redefine science productivity as merely the count of papers that include only internal scientists as coauthors to partially separate these two measures. Unfortunately, doing so with the current database reduces the estimation sample size too dramatically, making the results unstable and less reliable. However, a future step might be to construct a sample with enough observations where firms' science productivity is based only on internally-coauthored papers, so that an estimation of the moderation effect of scientist isolation would be possible with less complication.

5.3. Future research directions

There are a number of avenues for future research to build on and extend the findings of this study. For instance, research could extend the theory and findings of this study by replacing the single-firm perspective adopted here on the process of selecting and forming future partnerships with a joint perspective that takes into account the motives of both partners in the formation of the alliance. After building a theory that

incorporates the alternative theoretical mechanisms that result from a joint perspective, future research could then proceed by devising appropriate empirical tests to support or rule out such alternative mechanisms, and to determine which arguments and findings from this study would remain robust and which ones would require further qualification or modification.

Future research could also examine the nature of R&D alliances in more details to determine if the alliances that are not based on sufficient absorptive capacity involve a systematically different set of partners that might have been attracted to the focal firm for such reasons as favorable terms of partnership. Another avenue of future research involves distinguishing between alliance partners both in terms of their type (e.g. nonprofit vs. for-profit, academic vs. non-academic, small biotech vs. large pharma) and their quality (e.g. innovative performance, market share, technological leadership). This would allow for a more nuanced understanding of the role of absorptive capacity in driving future R&D alliances by examining if different types of partners tend to enter the firm's alliance portfolio at different levels of absorptive capacity. Arora and Gambardella (1994), for instance, found that academic R&D alliance partners tend to be more important as providers of scientific knowledge and capabilities rather than new innovations. Given such potential differences in the benefits available from different types of partners, future research could determine if different levels (or potentially, different dimensions) of absorptive capacity are more conducive to absorbing knowledge and innovation from different types of partners.

Also, future research could examine if collaborating on scientific projects with external colleagues from the same firms with which the focal firm has partnered in R&D alliances results in any special type of absorptive capacity that impacts the benefits of R&D alliances in a special way or guides the future patterns of inter-firm alliance activity in unexpected directions. Finally, on a more technical note, a closer analysis of the scientific publication records by future studies can help create a more accurate measure of the dispersion of scientific activities in firms. That is, by going beyond the mere association with a given firm and comparing the actual physical addresses of the coauthors listed on publications, research can construct a more elaborate measure of the physical dispersion of scientific activity across the same organization. Such an improved measure can then provide a stronger and more reliable empirical support for the moderation hypothesis involving the dispersion of scientific activity across the organizational structure of the firm.

5.4. Concluding remarks

In addition to being the basic ingredient and the building block of any technology and innovation, science is also an important dimension of firms' innovation strategies, particularly in technology-driven industries (Fleming and Sorenson, 2004). As such, any description of the process of firm innovation that does not consider the role of basic science is essentially incomplete. Guided by the question of why firms differ in the strength of the link between science and other elements of their innovation strategy, this study took a first step in unraveling the nuances of the inner workings of

the innovation process in firms at various epistemological levels (i.e. basic science, applied knowledge, and commercialized technology). By building on such a nuanced and multilayered conception of the innovation process in firms, researchers and practitioners alike can begin to enhance the accuracy of the theoretical and analytical models they use to study and manage the development of science, invention, and innovation in firms.

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APPENDIX I:
List of pharmaceutical companies in the sample

	Company name	Ticker symbol	First year in sample	Last year in sample	Total years in sample
1	3-DIMENSIONAL PHARMA	DDDP	1995	2001	7
2	ABBOTT LABS	ABT	1990	2009	20
3	ABLE LABS INC	ABLSQ	1990	2004	15
4	ACCESS PHARMACEUTICALS INC	3ACCP	1990	2009	20
5	ACUSPHERE INC	ACUSD	1998	2007	10
6	ADOLOR CORP	ADLR	1997	2009	13
7	AEOLUS PHARMACEUTICALS INC	3AOLS	1995	2009	15
8	AGOURON PHARMACEUTICALS	AGPH	1990	1998	9
9	AKORN INC	AKRX	1990	2009	20
10	ALEXZA PHARMACTCLS INC	ALXA	2002	2009	8
11	ALIMERA SCIENCES INC	ALIM	2005	2009	5
12	ALLERGAN INC	AGN	1990	2009	20
13	ALLERGY RESEARCH GROUP INC	3ALRG	1999	2007	9
14	ALNYLAM PHARMACEUTICALS	ALNY	2002	2009	8
15	ALPHARMA INC	ALO.2	1990	2007	18
16	ALSERES PHARMACEUTICALS	ALSE	1990	2009	20
17	ALZA CORP	AZA.1	1990	2000	11
18	AMYLIN PHARMACEUTICALS INC	AMLN	1990	2009	20
19	ANADYS PHARMACEUTICALS	ANDS	2001	2009	9
20	ANESIVA INC	ANSVQ	2001	2008	8
21	ANESTA CORP	NSTA	1990	1999	10
22	APP PHARMACEUTICALS INC	APPX	1999	2007	9
23	ARONEX PHARMACEUTICALS	ARNX	1991	2000	10
24	ARYX THERAPEUTICS INC	ARYX	2002	2009	8
25	ATHEROGENICS INC	AGIXQ	1998	2008	11
26	ATRIX LABS INC	ATRX	1990	2003	14
27	AVANIR PHARMACEUTICALS INC	AVNR	1990	2009	20
28	AXYS PHARMACEUTICALS INC	AXPH	1991	2000	10
29	BALCHEM CORP	BCPC	1990	2009	20
30	BARR PHARMACEUTICALS INC	BRL	1990	2007	18
31	BARRIER THERAPEUTICS INC	BTRX.	2001	2007	7
32	BAUSCH & LOMB INC	BOL	1990	2006	17
33	BENTLEY PHARMACEUTICALS	BNT.3	1990	2007	18
34	BIOCRAFT LABS INC	BCL.1	1989	1994	6
35	BIODELIVERY SCIENCES INT	BDSI	2000	2009	10
36	BIOFORM MEDICAL INC	BFRM	2003	2009	7

	Company name	Ticker symbol	First year in sample	Last year in sample	Total years in sample
37	BIONOVO INC	BNVI	2004	2009	6
38	BIOSANTE PHARMACEUTICALS	BPAX	2000	2009	10
39	BONE CARE INT INC	BCII	1995	2004	10
40	BRISTOL-MYERS SQUIBB CO	BMY	1990	2009	20
41	CAMBRIDGE NEUROSCIENCE INC	3CNSI	1990	1999	10
42	CATALYTICA INC	CTAL.1	1992	1999	8
43	CELGENE CORP	CELG	1990	2009	20
44	CELL PATHWAYS INC	CLPA	1993	2002	10
45	CELLEGY PHARMACEUTICALS	4437B	1994	2007	14
46	CELTRIX PHARMACEUTICALS	CTRX.1	1989	1998	10
47	CEPHALON INC	CEPH	1990	2009	20
48	CHATTEM INC	CHTT	1990	2009	20
49	CHIRON CORP	CHIR	1990	2005	16
50	CIMA LABS INC	CIMA	1993	2003	11
51	CLEVELAND BIOLABS INC	CBLI	2003	2009	7
52	COCENSYS INC	3COCN	1990	1998	9
53	COLLAGENEX PHARMACEUTCLS	CGPI.	1995	2007	13
54	COLUMBIA LABS INC	CBRX	1990	2009	20
55	COPLEY PHARMACEUTICAL INC	CPLY	1989	1998	10
56	COR THERAPEUTICS INC	CORR.	1990	2000	11
57	CORCEPT THERAPEUTICS INC	CORT	1999	2009	11
58	CORTEX PHARMACEUTICALS INC	CORX	1990	2009	20
59	CUBIST PHARMACEUTICALS INC	CBST	1995	2009	15
60	CUMBERLAND PHARMA	CPIX	2004	2009	6
61	CYCLACEL PHARMACEUTICALS	CYCC	2003	2009	7
62	CYTOKINETICS INC	CYTK	2001	2009	9
63	DEPOMED INC	DEPO	1996	2009	14
64	DEPOTECH CORP	DEPO.	1990	1997	8
65	DEPRENYL ANIMAL HEALTH INC	3DAHI	1990	1995	6
66	DEXTER CORP	DEX.1	1990	1999	10
67	DOV PHARMACEUTICAL INC	DOVP	1998	2007	10
68	DURA PHARMACEUTICALS INC	DURA	1990	1999	10
69	DURAMED PHARMACEUTICALS	DRMD	1990	2000	11
70	DURECT CORP	DRRX	1998	2009	12
71	DUSA PHARMACEUTICALS INC	DUSA	1992	2009	18
72	EMISPHERE TECHNOLOGIES INC	3EMIS	1990	2009	20
73	ENTREMED INC	ENMD	1995	2009	15
74	EON LABS INC	ELAB	1997	2004	8
75	EPICEPT CORP	EPCT	2002	2009	8

	Company name	Ticker symbol	First year in sample	Last year in sample	Total years in sample
76	EPIMMUNE INC	EPMN	1990	2004	15
77	ESPERION THERAPEUTICS INC	ESPR	1998	2003	6
78	ESSENTIAL THERAPEUTICS INC	ETRXQ	1993	2002	10
79	EYETECH PHARMACEUTICALS	EYET	2000	2004	5
80	FOREST LABS	FRX	1989	2008	20
81	GELTEX PHARMACEUTICALS INC	GELX	1992	1999	8
82	GENELABS TECHNOLOGIES INC	GNLB	1990	2007	18
83	GENENTECH INC	DNA	1990	2008	19
84	GENVEC INC	GNVC	1998	2009	12
85	GLIATECH INC	GLIAQ	1992	2001	10
86	GLYCOMED INC	GLYC	1990	1994	5
87	GTX INC	GTXI	2001	2009	9
88	GUILFORD PHARMACEUTICAL	GLFD	1993	2004	12
89	HOSPIRA INC	HSP	2002	2009	8
90	HOUSTON BIOTECHNOLOGY INC	HBI.1	1990	1995	6
91	ICAGEN INC	ICGN	2001	2009	9
92	ICOS CORP	ICOS	1990	2005	16
93	IDM PHARMA INC	IDMI	2001	2008	8
94	IGI LABS INC	IG	1990	2009	20
95	IMAGENETIX INC	3IAGX	2002	2008	7
96	IMMULOGIC PHARMACEUTICAL	IMULZ	1990	2001	12
97	IMMUNOGEN INC	IMGN	1990	2009	20
98	IMPAX LABS INC	IPXL	1994	2009	16
99	INDEVUS PHARMACEUTICALS	IDEV	1990	2008	19
100	INFINITY PHARMACEUTICALS	INFI	2002	2009	8
101	INKINE PHARMACEUTICAL CO	INKP	1994	2004	11
102	INSPIRE PHARMACEUTICALS INC	ISPH	1998	2009	12
103	INTEGRATED BIOPHARMA INC	3INBP	1996	2009	14
104	INTROGEN THERAPEUTICS INC	INGNQ	1999	2007	9
105	ISIS PHARMACEUTICALS INC	ISIS	1990	2009	20
106	ISTA PHARMACEUTICALS INC	ISTA	1998	2009	12
107	IVAX CORP	IVX.	1990	2004	15
108	JAVELIN PHARMACEUTICALS	JAV	2001	2009	9
109	JOHNSON & JOHNSON	JNJ	1990	2009	20
110	KERYX BIOPHARMACEUTICALS	KERX	1998	2009	12
111	KING PHARMACEUTICALS INC	KG	1996	2009	14
112	KOS PHARMACEUTICALS INC	KOSP	1995	2005	11
113	KOSAN BIOSCIENCES INC	KOSN	1998	2007	10
114	LARGE SCALE BIOLOGY CORP	LSBC	1995	2004	10

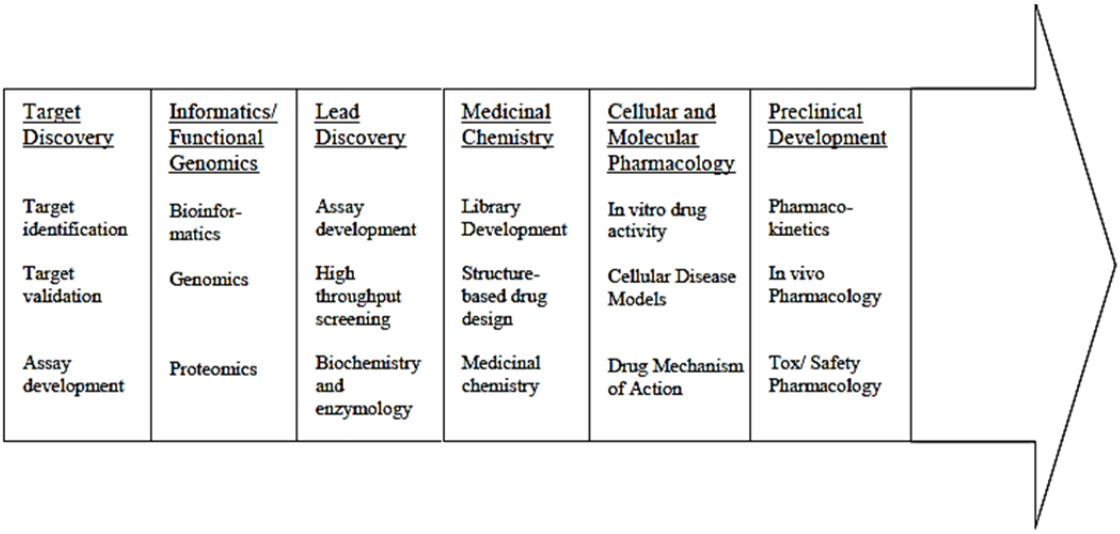
	Company name	Ticker symbol	First year in sample	Last year in sample	Total years in sample
115	LIGAND PHARMACEUTICAL INC	LGND	1991	2009	19
116	LILLY (ELI) & CO	LLY	1990	2009	20
117	MACROCHEM CORP	3MACM	1989	2007	19
118	MANNATECH INC	MTEX	1997	2009	13
119	MANNKIND CORP	MNKD	2002	2009	8
120	MAP PHARMACEUTICALS INC	MAPP	2004	2009	6
121	MARION MERRELL DOW INC	MKC.1	1990	1994	5
122	MATRIX PHARMACEUTICAL INC	MATX	1990	2000	11
123	MEDCO RESEARCH INC	MRE	1990	1998	9
124	MEDICAL NUTRITION USA INC	MDNU	1990	2008	19
125	MEDICIS PHARMACEUT CP	MRX	1990	2009	20
126	MEI PHARMA INC	MSHL	2002	2009	8
127	MERCK & CO	MRK	1990	2009	20
128	METABASIS THERAPEUTICS INC	MBRX	1999	2008	10
129	MGI PHARMA INC	MOGN	1990	2006	17
130	MIDDLEBROOK PHARMA	MBRKQ	2000	2009	10
131	MIRAVANT MEDICAL TECH	MRVT	1994	2004	11
132	MYOGEN INC	MYOG	2001	2005	5
133	NEKTAR THERAPEUTICS	NKTR	1993	2009	17
134	NEUROGEN CORP	NRGN	1990	2008	19
135	NEXSTAR PHARMACEUTICALS	NXTR	1990	1998	9
136	NEXTERA ENTERPRISES INC	NXRA	1997	2007	11
137	NITROMED INC	NTMD	1998	2008	11
138	NORTHWEST BIOTHERAPEUTICS	3NWBO	1999	2009	11
139	NOVABAY PHARMACEUTICALS	NBY	2002	2009	8
140	NOVADEL PHARMA INC	NVDL	1999	2009	11
141	NUPATHE INC	PATH	2005	2009	5
142	NUTRITION 21 INC	NXXIQ	1990	2009	20
143	OBAGI MEDICAL PRODUCTS INC	OMPI	2002	2009	8
144	ONYX PHARMACEUTICALS INC	ONXX	1995	2009	15
145	OPTIMER PHARMACEUTICALS	OPTR	2002	2009	8
146	ORAPHARMA INC	OPHM	1996	2001	6
147	ORPHAN MEDICAL INC	ORPH	1994	2004	11
148	PAIN THERAPEUTICS INC	PTIE	1998	2009	12
149	PAR PHARMACEUTICAL COS INC	PRX	1990	2009	20
150	PENEDERM INC	DERM	1990	1997	8
151	PENWEST PHARMACEUTICALS CO	PPCO	1998	2009	12
152	PERRIGO CO	PRGO	1991	2009	19
153	PFIZER INC	PFE	1990	2009	20

	Company name	Ticker symbol	First year in sample	Last year in sample	Total years in sample
154	PHARMION CORP	PHRM.	2000	2007	8
155	PHARMOS CORP	PARS	1990	2009	20
156	POINT THERAPEUTICS INC	POTP	1993	2006	14
157	POZEN INC	POZN	1998	2009	12
158	PRAECIS PHARMACEUTICALS	PRCS	1996	2005	10
159	PROCYTE CORP	3PRCY	1990	2003	14
160	PROTALEX INC	3PRTX	2000	2008	9
161	PROVECTUS PHARMACEUTICAL	3PVCT	1990	2009	20
162	QUESTCOR PHARMACEUTICALS	QCOR	1992	2009	18
163	REGENERON PHARMA	REGN	1990	2009	20
164	REGENERX BIOPHARMA	3RGRX	1989	2009	21
165	RENOVIS INC	RNVS	2000	2007	8
166	REPLIDYNE INC	RDYN	2001	2008	8
167	REPROS THERAPEUTICS INC	RPRX	1992	2009	18
168	REXALL SUNDOWN INC	RXSD	1992	1999	8
169	RIBAPHARM INC	RNA	1997	2002	6
170	RIGEL PHARMACEUTICALS INC	RIGL	1998	2009	12
171	ROBERTS PHARMACEUTICAL	RPC.2	1990	1998	9
172	ROCKWELL MED TECHNOLOGIES	RMTI	1997	2009	13
173	SALIX PHARMACEUTICALS LTD	SLXP	1998	2009	12
174	SANO CORP	SANO	1991	1996	6
175	SANTARUS INC	SNTS	2002	2009	8
176	SCHEIN PHARMACEUTICAL INC	SHP.	1993	1999	7
177	SCHERER (R P)	SHR.1.	1989	1997	9
178	SCHERING-PLOUGH	SGP	1990	2008	19
179	SCICLONE PHARMACEUTICALS	SCLN	1991	2009	19
180	SCOLR PHARMA INC	SCLR	2001	2009	9
181	SEPRACOR INC	SEPR	1990	2008	19
182	SEQUUS PHARMACEUTICALS INC	SEQU.1	1990	1997	8
183	SHAMAN PHARMACEUTICALS	SHPH	1991	2000	10
184	SHEFFIELD PHARMACEUTICALS	3SFPH	1992	2002	11
185	SICOR INC	SCRI	1990	2002	13
186	SOMAXON PHARMACEUTICALS	SOMX	2003	2009	7
187	SUNESIS PHARMACEUTICALS	SNSS	2002	2009	8
188	SYNTA PHARMACEUTICALS	SNTA	2002	2009	8
189	TANOX INC	TNOX	1997	2006	10
190	TARGACEPT INC	TRGT	2002	2009	8
191	TELIOS PHARMACEUTICALS INC	TLIOQ	1990	1994	5
192	TERCICA INC	TRCA	2001	2007	7

	Company name	Ticker symbol	First year in sample	Last year in sample	Total years in sample
193	THERAGENICS CORP	TGX	1990	2009	20
194	THERATECH INC UTAH	THRT	1990	1997	8
195	THERAVANCE INC	THRX	2002	2009	8
196	THRESHOLD PHARMACEUTICALS	THLD	2002	2009	8
197	TITAN PHARMACEUTICALS INC	3TTNP	1994	2009	16
198	TREGA BIOSCIENCES INC	TRGA	1991	1999	9
199	TRIANGLE PHARMACEUTICALS	VIRS	1995	2001	7
200	TRIUS THERAPEUTICS INC	TSRX	2005	2009	5
201	TULARIK INC	TLRK	1994	2003	10
202	UNIMED PHARMACEUTICALS INC	UMED.	1990	1998	9
203	UNITED THERAPEUTICS CORP	UTHR	1998	2009	12
204	USANA HEALTH SCIENCES INC	USNA	1995	2009	15
205	VALEANT PHARMACEUTICALS	VRX.1	1990	2009	20
206	VALERA PHARMACEUTICALS INC	VLRX	2000	2006	7
207	VEREX LABS INC	VRXL	1990	2001	12
208	VERTEX PHARMACEUTICALS INC	VRTX	1990	2009	20
209	VICURON PHARMACEUTICALS	MICU	1995	2004	10
210	VIROPHARMA INC	VPHM	1995	2009	15
211	VIVUS INC	VVUS	1993	2009	17
212	WARNER-LAMBERT CO	WLA	1990	1999	10
213	WATSON PHARMACEUTICALS	WPI	1992	2009	18
214	WYETH	WYE	1990	2008	19
215	XCYTE THERAPIES INC	XCYTD	1999	2005	7
216	ZILA INC	ZILA	1990	2008	19

APPENDIX II:
The process of drug discovery and clinical development
Adapted from Dunne and Dougherty (2006)

Key activities during drug discovery, from ideas to molecules:



Different phases of clinical development: