ESSAYS ON COOPERATION AND/OR COMPETITION WITHIN R&D COMMUNITIES

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ESSAYS ON COOPERATION AND/OR COMPETITION WITHIN R&D COMMUNITIES

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To my families and friends

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SUMMARY

This dissertation attempts to contribute to our understanding of how firms can manage and/or benefit from a community of R&D organizations and individuals working towards similar targets. Each of the three essays in this dissertation highlights the competitive or cooperative dynamics within this community and the implications.

In the first essay, I examine how established firms can leverage a broad R&D community to invent successfully during the early stage of a technological change. Incumbent firms are often thought to focus on incremental innovations and only respond to a major technological change once its impact on established markets and/or dominant designs becomes clear. I argue, however, that incumbent firms have many reasons to proactively invent early in cycles of technological change. My interest is in the strategies that allow incumbents to be successful in this endeavor during the infancy of an emerging field–the period before it is clear how the field will affect dominant designs. Our evidence counters the stereotypical view that incumbent firms play a passive role in major technological changes by adhering to incremental inventions in the existing dominant designs. Rather, I find significant inventions by incumbents outside the existing dominant designs and relate their success to their willingness to search novel areas, explore scientific knowledge in the public domain, and form alliances with a balanced portfolio of partners. I find support for the hypotheses using data from the global semiconductor industry between 1989 and 2002.

In the second essay, I examine a classical choice within an R&D community: cooperation or competition with other firms along a technology supply chain. Prior research has suggested various factors affecting the choice, including the transaction costs of licensing, strength of intellectual property protection rights, and asset

cospecialization in the buyers' industries. The novelty of this paper is that in addition to these factors, I consider the role of firm capabilities, including the supplier's knowledge transfer capability and a typical buyer's productivity in developing licensed inventions. I hypothesize that the effect of asset cospecialization on licensing is moderated by the factors that affect the buyers' productivity in developing external technology. Additionally, factors that reduce the buyers' development productivity and hence returns on licensing can be mitigated by the supplier's knowledge transfer capability. I derive these hypotheses from a stylized bargaining model. I find empirical supports for these predictions using an unbalanced cross-industry panel dataset of a sample of 345 U.S. small technology-based firms for the 1996-2007 period, with information on the licensing strategies and market performance. The findings provide guidance for both the suppliers and buyers in the market for technology.

In the third essay, I analyze how research competition from academic researchers affects firms' openness in disclosing intermediate R&D outcomes. To address this question, I develop two game theoretical models. In these models, a focal firm competes with academic researchers and another firm during the research stage of an R&D project and competes with this other firm during the development stage. Both models predict that research competition from academic researchers working in the same area as a firm's research increases the firm's incentive to publish research findings, even though the firm would not have had such an incentive without the presence of the competition. The models also imply several conditions under which the effect takes place, such as strong belief about the research strength of the competing academic researchers (and/or their labs), high potential returns on developing the research into marketable innovations, as well as importance of earning scientific credit for the firm. I then discuss the implications of phenomena that may stifle the competition among academic researchers for priority: ownership fragmentation for research materials within the scientific community and academic researchers' engagement in entrepreneurial activities. As implied by my models, these phenomena might instigate withholding of research findings by firms.

CHAPTER I

INTRODUCTION

Recent advances such as in biotechnology and nanotechnology brought an unprecedented regime of technological development. Sources of innovation are broadly distributed among organizations in different industries and sectors (Powell, Koput and Smith-Doerr 1996). As a result, no single firm has all necessary internal resources to undertake knowledge-intensive endeavor. A new paradigm of relationship among organizations has thus emerged, constituting numerous global communities of R&D organizations and individuals pursuing common targets. As an example, the development of a new approach for malaria drug discovery which appeared in a recent article (Guiguemde et al. 2010) involved at least 35 researchers affiliated with one established pharmaceutical firm, eight universities in two countries, three hospitals/medical centers, and one non-for-profit foundation. Another example is the human genome community which also involves R&D organizations from both private and public sectors. One of theses organizations was Novartis Institute for Biomedical Research, whose president commented that to translate their genome analysis study's identification of diabetes-related genes into the invention of new medicines, a global effort is required (Murray and O'Mahony 2007).

The rise of R&D communities across organizational boundaries has attracted an enormous wave of research on the dynamics of firms within an R&D community. One stream of research focuses on collaborations among firms; this research emphasizes inter-firm collaboration as a locus of innovation since it provides access to knowledge and resources not available in house (e.g., Stuart 1998, Gulati 1999, Stuart, Hoang and Hybels 1999, Ahuja 2000, Stuart 2000, Rothaermel 2001, Vanhaverbeke, Duysters and Noorderhaven 2002, Lei 2003, Owen-Smith and Powell 2004, Rothaermel and Deeds 2004, Lavie 2007, Rothaermel and Hess 2007, Stuart, Ozdemir and Ding 2007, Rothaermeli and Boeker 2008). The emphasis traces back to Powell, Koput and Smith-Doerr Powell's point that when knowledge is broadly distributed and brings a competitive advantage, companies must be expert not only at in-house but also at cooperative research and development. Another stream of research focuses on R&D competition among firms developing similar innovations (e.g., Loury 1979, Dasgupta and Stiglitz 1980, Fudenberg, Gilbert, Stiglitz and Tirole 1983, Grossman and Shapiro 1987, Harris and Vickers 1987, Cockburn and Henderson 1994, Lerner 1997, Zizzo 2002, Gill 2008). Inevitably, many groups of organizations are likely to be competing for the same targets with the rewards go to the swiftest (Powell, et al. 1996).

Although these studies have greatly improved our understanding of the dynamics within an R&D community, they tend to emphasize relationship among firms and/or within a single industry. However, as indicated by previous examples, many innovations are not always developed in one sector alone but in a broader community across industries and sectors (Tushman and Anderson 1986, Powell, et al. 1996, Woolley 2009). Innovation in many cases really requires efforts beyond firms in a single industry, demanding efforts also from the public sector, suppliers and customers. As firms move towards this new paradigm of innovation, many questions remain to be addressed for the relationship among actors within this broad R&D community.

In this dissertation, I ask the following question: what can we suggest to firms about how to manage and benefit from their R&D communities? The question is examined in greater detail in the following three essays.

1.1 Essay I

The first essay identifies how established firms can leverage a broad R&D community to invent successfully during the early stage of a technological change. Prior literature has traditionally regarded incumbent firms as focusing on incremental innovations and only responding to a major technological change once its impact on established markets and/or dominant designs becomes clear. Such a passive view of incumbents was either implicit or explicit in many case studies (e.g., EMI's CT scanning technique) and studies of pharmaceutical companies in the biotechnology revolution. Our evidence, however, counters this stereotypical view and shows significant inventions by incumbents outside the existing dominant designs early in cycles of technological change. Specifically, we relate incumbents' success in inventing to their willingness to search scientific knowledge in the public domain, collaborate with academic researchers, and learn from both organizations working in the same technological areas and those having very different expertise.

To test these hypotheses, I collected a novel dataset that includes a sample of 68 global semiconductor incumbents, over 10,000 journal publications in which the sample firms coauthored with university researchers, 631 learning alliances formed by these firms in the semiconductor business as well as over 140,000 semiconductor patents applied for by the sample firms and their partners. I also conducted interviews to better understand the industry context. For instance, in order to identify which emerging field has recently threatened the current dominant design of the semiconductor industry, I contacted an industrial expert whose opinion led me to the field of nanotechnology. This formed the basis of my collecting data on nanotechnology inventions for a measure of our dependent variable.

The findings of this study make two main contributions. First, the study identifies the R&D community which an incumbent firm can benefit from during the early stage of a technological change. As argued in the study, the boundary of such a community is expanded to include academic researchers as well as partnering organizations that have either proximal and distant knowledge. Caveats of leveraging this community are also suggested in the essay. Another contribution of this study is that it adds to the strategy research on the role of incumbents in technological change. What we find is significant inventions by incumbents early in cycles of technological change. These incumbents proactively explore an emerging field and start accumulating relevant technical expertise long before a product based on this field is commercialized. We relate this success partly to their R&D communities.

1.2 Essay II

In the second essay, I examine a classical choice within an R&D community: cooperation or competition with other firms along a technology supply chain. This question has been examined by various studies either from a technology supplier's point of view (e.g., Teece 1986, Bresnahan and Gambardella 1998, Gans and Stern 2003, Arora and Merges 2004) (whether to collaborate with downstream users or to compete with them through forward integration) or from a technology buyer's point of view (e.g., Pisano 1990, Ceccagnoli, Graham, Higgins and Lee 2010) (whether to source a technology from an external firm or to make it in house). Prior research has mostly focused on transaction costs (Pisano 1990, Gans, Hsu and Stern 2002), intellectual property protection rights (Teece 1986, Gans, et al. 2002, Gans and Stern 2003, Arora and Merges 2004, Arora and Ceccagnoli 2006, Gans, Hsu and Stern 2008), and sunk costs of product market entry (Teece 1986, Pisano 1990, Gans, et al. 2002, Gans and Stern 2003) as determinants of a firm's R&D boundary.

The novelty of this paper is that we take both perspectives of the seller and buyer into account and integrate the role of firm capabilities (including both technology buyer and supplier) into the analysis of R&D boundary or markets for technology. We begin with a practical question: even if a small technology supplier owning an invention is willing to license it to users in the face of hard-to-acquire cospecialized assets, would buyers be willing to pay to develop and commercialize the invention?

We develop a stylized model to show that this is not necessarily the case. Note that cospecialiation between development and manfacturing/marketing assets is commonly known to increase entry costs into product markets (Teece 1986). We argue that this cospecialization also increases the cost of developing the technology. This would harm the buyers of low efficiency in developing an external technology, thereby dampening their demand for the technology. A corollary of the model is that when the buyer's efficiency in developing external inventions is low, the inventor's capabilities to transfer know-how become essential for a licensing relationship with the buyer.

The results of the theoretical model find robust support using a panel dataset. The data are partly derived from the Chi Research/Small Business Administration (SBA) database containing firm and patenting information on the population of U.S. technology-based firms with less than 500 employees that were able to sustain innovation beyond the first invention upon which the firm was founded (Hicks, Breitzman, Albert and Thomas 2003, Hicks and Hegde 2005). This dataset was integrated using multiple sources including the SDC Platinum alliances database available from Thomson Reuters, the USPTO trademarks database, the NBER patent database, the USPTO patent-industry concordance file generated in 2005, Corptech, Compustat and the Carnegie Mellon Survey on industrial R&D. The final sample includes an unbalanced cross-industry panel dataset of about 345 U.S. small technology-based firms related to the 1996-2007 period, for a total of about 3300 observations.

The potential contributions of this study follow. The study suggests to managers of a small technology supplier firm how to manage its R&D boundary and the relationship with downstream companies in the R&D community. We show that a firm's R&D boundary does not just depend on transaction costs, the appropriability concerns (e.g., strength of intellectual property rights) and the sunk costs of product market entry, but also on the capabilities of the buyers and sellers. For instance, the seller's capabilities of know-how transfer increases the returns to licensing to downstream users relative to the returns to competing with them in product markets; this is particularly the case when the buyer's capabilities of developing external technologies is low. Findings from this study contribute to a better understanding of the relationships between firm capabilities and markets for technology. The study also takes the demand-side of technology markets into consideration in analyzing a supplier's decision to cooperate versus to compete with the buyers. Practical implications as well as limitations of the study are also suggested in the paper.

1.3 Essay III

The third essay suggests that a firm take a broader view of its R&D community and take into account researchers in the public sector as well as competing firms. As in many cases, firms compete with both academic researchers and other firms during the research stage of an R&D project and compete with other firms during the development stage. However, prior research on R&D competition either between incumbent firms or between an incumbent and an entrant (e.g., Loury 1979, Lee and Wilde 1980, Gilbert and Newbery 1982, Fudenberg, et al. 1983, Harris and Vickers 1985, Harris and Vickers 1985, Grossman and Shapiro 1987, Harris and Vickers 1987, D'Aspremont and Jacquemin 1988, De Fraja 1993, Lerner 1997, Zizzo 2002, Gill 2008) has typically neglected research competition from academic researchers.

My particular interest is how research competition from academic researchers affects firms' openness in disclosing intermediate R&D outcomes. To address this question, I develop two game theoretical models. Both models predict that research competition from academic researchers working in the same area as a firm's research increases the firm's incentive to publish research findings, even though the firm would not have had such an incentive in the absence of academic competition. The models also imply several conditions under which the effect takes place, such as strong belief about the research strength of the competing academic researchers (and/or their labs), high potential returns on developing the research into marketable innovations, as well as the importance of earning scientific credit for the firm. I then discuss the implications of the phenomena that may stifle the competition among academic researchers for priority: ownership fragmentation for research materials within the scientific community and academic researchers' engagement in entrepreneurial activities. As implied by my models, these phenomena would instigate withholding of research findings by firms.

This study improves our understanding of how open disclosure by industries could be driven by competing academic researchers and an increase in overlapping research areas of academia and industries. The rising activities of academic researchers and universities in industrial innovations have been a bright spot in the past few decades, especially since the Bayh-Dole Act in 1980 (see Rothaermel, Agung and Jiang 2007). A significant number of researchers conduct applied research directly relevant to industry innovations (Rosenberg and Nelson 1994, Van Looy, Ranga, Callaert, Debackere and Zimmermann 2004, Sauermann and Stephan 2009, Sauermann, Cohen and Stephan 2010). As a result, it is inevitable that academic researchers and industrial researchers may compete in the same research areas. This study suggests that considering such interaction is highly relevant for both R&D managers and policy makers. Moreover, this study provides a theoretical guidance to help us better understand what drives firms to produce social outputs, such as knowledge in the public domain.

Overall, these three essays improve our understanding of how firms can manage and benefit from their R&D communities. For instance, the second essay suggests when a small technology supplier benefits from cooperation as supposed to competition with downstream buyers within the R&D community. The first and third essays highlight expanding the boundary of an R&D community to the upstream source of innovation - researchers in the public sector. While the first essay emphasizes how this part of the R&D community can improve a firm's inventive productivity through collaboration, the third essay shows the implication of competition with them. Both essays indicate academic research affects industrial R&D and commercialization. In summary, this dissertation suggests important implications for various participants in an R&D community, including technology suppliers, technology buyers, researchers in the public sector as well as policy makers.

CHAPTER II

INCUMBENT FIRM INVENTION IN EMERGING FIELDS: EVIDENCE FROM THE SEMICONDUCTOR INDUSTRY

2.1 Introduction

The role of incumbent firms in technological change is an important topic in strategy. Major changes in technology are often thought to begin with technological advances that threaten incumbent firms' core products or process designs. The birth of these advances is followed by an era of ferment in which firms introduce products with competing designs, and the cycle ends with the establishment of new dominant designs (Anderson and Tushman 1990). A wealth of literature has addressed the question of why incumbent firms fail to respond to this drastic transition (e.g., Teece 1986, Tushman and Anderson 1986, Mitchell 1989, Christensen and Rosenbloom 1995, Tripsas 1997, Rothaermel 2001, Hill and Rothaermel 2003, Sinha and Noble 2005). In many cases, the underlying technical advances come from outside the incumbent's industry, putting incumbents at a disadvantage in adapting products to the new technology (Kline and Rosenberg 1986). In other cases, incumbents ignore the advances in a new technological field because of organizational rigidities (Henderson and Clark 1990, Henderson 1993), or because the advances do not support the existing value chain and complementary assets (Christensen and Rosenbloom 1995, Tripsas 1997). Yet, there is also a growing literature on ways in which incumbents can overcome commercialization hurdles (Teece 1986, Day and Schoemaker 2000, Gans, et al. 2002, Hill and Rothaermel 2003, Sinha and Noble 2005). For instance, incumbents may enter niche markets and serve lead users to avoid cannibalizing their existing value chain

(Day and Schoemaker 2000).

Much of the literature has focused on incumbents' commercialization of products once an emerging field clearly threatens the existing dominant design and product (Mitchell 1989, Anderson and Tushman 1990, Christensen and Rosenbloom 1995, Tripsas 1997, Martin and Mitchell 1998). In contrast, there is little research revealing the role of incumbent firms during the lengthy period before an emerging field becomes a threat (Libaers, Meyer and Geuna 2006, Rothaermel and Thursby 2007). Note that emerging fields take decades to evolve; in the case of biotechnology and nanotechnology, revolutionary products are not introduced until after a lengthy period of continued technological invention and refinement (Rothaermel and Thursby 2007). The role of incumbents in these technical advances has received limited attention in large part because incumbents are generally thought to neglect emerging fields during their infancy and concentrate on improving the current dominant design (Tushman and Anderson 1986, Christensen and Bower 1996). Nevertheless, the initial breakthrough for nanotechnology, an emerging field that impacts various industries today, came out of IBM's Zurich lab, and incumbent firms have invested considerable resources in the area (Rothaermel and Thursby 2007). This study aims to explain why some incumbent firms are successful at inventing in an emerging field even before it compromises the current dominant design.

In this paper, we view incumbent success at invention in the infancy of an emerging field as a result of overcoming two challenges. First, the incumbent needs to recognize how an emerging field will impact the existing dominant design and which lines of inquiry will pay off. Second, an incumbent needs to keep up with the emerging field's developments while continuing current core activities. We contend that some firms are better able to overcome these challenges and thus to productively invent in the emerging field because they search for knowledge in novel technology areas, for knowledge from partners diverse in terms of technological distance, and for scientific knowledge in the public domain (e.g., by working closely with university scientists, and reading academic publications). We also suggest that the positive effects of exploring novel areas and scientific knowledge exhibit diminishing marginal returns.

We find broad support for the hypotheses with a novel dataset from the global semiconductor industry between 1989 and 2002, the period before nanotechnology had a significant impact on the industry's dominant design. The results expand the understanding of the role of incumbent firms in technological change (Henderson and Cockburn 1994, Ahuja and Lampert 2001, Fleming 2001, Fleming and Sorenson 2001, Darby and Zucker 2003, Fleming and Sorenson 2004) and the types of search activities that contribute to the incumbents' active role.

2.2 Theory and Hypotheses

2.2.1 Inventing in an Emerging Technological Field

An emerging field often refers to a recently developed body of leading–edge technological knowledge (Ahuja and Lampert 2001). Our interest is in the emerging fields that eventually overturn the dominant designs in existing industries. These emerging fields are often spawned by new methods of invention (Darby and Zucker 2003). For example, Herbert Boyer and Stanley Cohen's method for cloning genetically engineered molecules enabled the development of biotechnology. More recently, the scanning tunneling microscope (STM) and atomic force microscope (AFM) enabled subsequent development in nanotechnology (technological inventions at the atomic, molecular, or macromolecular range of approximately 1–100 nanometers). On the one hand, emerging fields expand opportunities for existing firms and industries, but on the other hand, they challenge existing product designs and methods of production (Tushman and Anderson 1986, Mitchell 1989). For instance, nanotechnology has not only enabled improvements in products and processes in a number of industries but also threatened the dominant designs of other industries, such as the semiconductor industry.

The focus of this study differs from prior research in two important ways. First, for the purpose of our study an invention is a new process, composition of matter, or design that solves technical problems in an emerging field. These inventions go beyond simply adding to the scope and precision of current dominant design. A flurry of them in combination can lead to a paradigmatic shift in an industry. Thus, what distinguishes the inventions we consider from others is their role in challenging and potentially overturning existing dominant product or process designs. Accordingly, our analysis differs from the general literature on the invention process (Fleming 2001, Fleming and Sorenson 2001, Fleming and Sorenson 2004) as well as the literature on breakthrough inventions (Ahuja and Lampert 2001, Fleming 2002, Phene, Fladmoe-Lindquist and Marsh 2006), which, in many cases, overcome important hurdles in refining an existing dominant design.

Second, we define the infancy of an emerging field as the period before it is clear that it will overturn an industry's dominant design. Initially, knowledge from the emerging field is neither critical for the performance of existing products and processes nor is it clear how the current dominant design will be affected. Gradually, the threat to the design, as well as the opportunities for the next dominant design, become increasingly visible. Industry incumbents then begin to compete for a new design using knowledge from the emerging field (Martin and Mitchell 1998). Unlike prior literature on technological change (e.g., Tushman and Anderson 1986, Tripsas 1997, Hill and Rothaermel 2003), our focus is not on this eventual competition, but rather on the incumbent firms' inventive performance in the infancy of an emerging field prior to the realization of a paradigmatic shift. Inventive performance in any period is the inventive output or number of inventions. As noted by Ahuja and Lampert (2001), the creation of inventions in emerging fields is understudied.

2.2.2 Incentives and Challenges to Invention

There are clear incentives for incumbent firms to create inventions in an emerging field before it compromises the current dominant design. In particular, such inventions provide opportunities to earn long-term profits from the next dominant design. By inventing early, an incumbent firm may avoid being preempted by competitors and can develop the capacity to exploit knowledge in the field. This capacity is critical in the subsequent competition because working with new technology often requires tacit knowledge that is difficult to acquire without prior related experience (Zucker, Darby and Armstrong 2002). Additionally, an emerging field presents opportunities for an incumbent firm to increase its strength in product market competition (Mitchell 1989). For instance, according to our interviews, semiconductor firms experimented with nanotechnology early on in attempts to extend the value of their existing fabrication facilities for as long as possible. Finally, in an emerging field's infancy, technical hurdles may increase the cost and risk of introducing products based on the emerging field. Invention allows firms to experiment while they continue to earn profit from the existing dominant design, and postpone major investments in commercialization of products based on the emerging technology until major technical hurdles are resolved or the market is less uncertain. Inventions in emerging fields are thus options for future commercialization (Garud and Nayyar 1994) or out licensing (Arora and Fosfuri 2003). In industries where standards are important, broadly licensing inventions is a common strategy for establishing incumbent products as the industry standard (Arora, Fosfuri and Gambardella 2001).

Nonetheless, inventing early in the emerging field is challenging. The field continues to evolve as new knowledge components are added and obsolete ones are withdrawn or updated. The relationship of these knowledge components to existing knowledge components is likely to require further discovery. For instance, the effect of newly discovered properties of materials at nanometer scales on existing product designs that were developed based on properties of material at normal scales is not well understood. As a result, it is difficult to predict whether and how an emerging field will eventually give rise to the next dominant design. Inventing in an emerging field demands that inventors understand the changing knowledge landscape they search (Fleming and Sorenson 2004). Even firms that take a 'wait–and–see' attitude toward a new field can benefit from paying attention to the changing landscape.

Additionally, incumbents face a long-standing trade-off between exploiting existing capabilities and preparing for 'the innovations that will define the future' (Tushman and O'Reilly 1996, O'Reilly and Tushman 2004). Specifically, inventing in the emerging field increases an incumbent's expected long-term returns, but it could also distract the firm from improving products based on the current dominant design. When the firm is still able to exploit and profit from the existing design, investing in the emerging field has substantial opportunity costs. Thus, for incumbent firms there is a strong tension between improving the current design and inventing in the emerging field. This tension is embedded in the hypotheses we develop in the next sections.

2.2.3 Search in Novel Technological Areas

Search in areas that are new to the firm increases the firm's inventive performance by improving its understanding of emerging fields. Invention is the result of searching for and combining knowledge in order to discover new possibilities (Fleming and Sorenson 2001). There is a tendency for firms to recombine knowledge gained from prior experiences because of the increased ease of learning in specialized and competent areas (Levitt and March 1988, March 1991). But if a firm repeatedly exploits familiar areas as new technological fields are emerging, the firm's knowledge about this ongoing development would quickly converge to an inferior, inaccurate state (March 1991). By contrast, experimenting in many novel areas allows the firm to expand and update its knowledge scope and thus increase the likelihood of observing the direction of emerging fields. Take semiconductor incumbents as an example. Some firms experimented with different materials (e.g., GaAs, polymers, carbon nanotubes) and techniques using components at smaller scales (e.g., MEMS), and as a result, were aware of recent directions of technological developments ahead of competitors.

Search in novel areas also increases the firm's inventive performance in the emerging field by increasing the number of possible knowledge combinations (Fleming and Sorenson 2001) and exposing research and development (R&D) staff to new problem-solving techniques (Ahuja and Lampert 2001, Katila and Ahuja 2002). These add to the 'toolbox' that R&D staff can use to solve new problems in the emerging field and likely provide more effective solutions to these problems (Ahuja and Lampert 2001). Learning to use new tools is important because an emerging field that threatens an existing dominant design is often supported by different disciplines. As an example, nanotechnology draws knowledge from outside semiconductor firms' expertise in solid state physics, including material science and chemistry. In this case, the tools R&D personnel gain in exploring areas within these other disciplines allow the firm to invent more productively.

Nevertheless, the positive effect of search in novel areas is likely to exhibit diminishing marginal returns as the firm increases the number of novel areas explored. This is because there are limits to the number of ways knowledge from these areas can be combined with existing knowledge. There also are limits to the cognitive ability of R&D personnel to integrate knowledge from many novel areas (Fleming and Sorenson 2001). At some point, search may lead to information overload and impede cumulative learning within each new area so that the return would fall with excessive search (Ahuja and Lampert 2001, Katila and Ahuja 2002, Phene, et al. 2006). However, excessive search is unlikely to occur for two reasons. First, it is a gain for firms to optimize their search behavior–a firm should search an additional novel area only if it expects the return, in terms of output, to outweigh the associated cost.[1] Search in novel areas has an increasing opportunity cost. As the explorative search expands, it will eventually cannibalize resources used for current core activities and distract incumbents from competing in products based on current dominant design. Thus, it is optimal for firms to stop searching novel areas before inventive performance decreases. Second, there is evidence that firms avoid excessive search in novel areas as a result of process management practices. Prior studies (Benner and Tushman 2002, Benner and Tushman 2003) find that process management practices such as total quality control, ISO programs, and six sigma tend to increase exploitation and crowd out exploration in a firm's upstream innovation activities. This happens because process management focuses on incremental learning and influences the selection of innovation projects. With widespread use of process management, one would not expect firms to explore novel areas to the point where inventive performance suffers. Indeed, when an industry's existing dominant design can still be improved incrementally, operational efficiency and product quality enabled by process management is a critical element of firm performance (Benner and Tushman 2003). Therefore, during the emerging field's infancy, incumbents would avoid excessive exploration. Following this line of reasoning, we propose:

Hypothesis 1: When an emerging field is in its infancy, an incumbent firm's inventive performance in the field is a positive and nonlinear function of the number of new technological areas searched (i.e., the inventive performance increases at a decreasing rate until it levels off).

[1] Alternatively put, firms should conduct an activity until its marginal benefit outweighs its marginal cost, which is an important premise in managerial economics. For how firms can conduct cost/benefit analysis and evaluate the value of an investment under uncertainty, see Roberts and Weitzman (1981) and Chan, Nickerson, and Owan (2007) for theoretical models; for a review of practical methods, see Higgins (2008); and for a classical case (Merck) in practice, see Nichols (1994).

2.2.4 Learning from Collaborating Organizations

Invention is one of the key motivations for organizations to collaborate (Ahuja 2000, Stuart 2000, Hagedoorn and Duysters 2002, Nicholls-Nixon and Woo 2003, Rothaermel and Thursby 2007, Sampson 2007). Learning alliances, in particular, allow firms to acquire partners' technological capabilities (Mowery, Oxley and Silverman 1996). Much of the literature examines the role of alliances after an emerging field has become the strategic focus of an industry. For instance, the incumbents may adapt to the major change by acquiring inventions and expertise directly from new entrants (Rothaermel 2001). However, the role of alliances in inventing prior to the paradigmatic shift has not received adequate scholarly attention (Rothaermel and Thursby 2007).

The fact that incumbents must compete based on both current and future designs makes alliances particularly useful. We contend that learning alliances increases an incumbent's inventive performance in the emerging field when the partners are diverse in terms of technological distance. By interacting with a broad range of partners, from proximal partners working in areas close to the firm's own areas of expertise to distal partners working in areas further away, the incumbent can be better informed about how the field will impact the entire industry. Distal partners augment the firm's search for novel knowledge through the interactions with partnering firms' inventors, who introduce new insights and expertise. These novel knowledge contributions help the firm keep up with the changing field, develop new techniques, and avoid being left behind. Following the reasoning outlined for Hypothesis 1, exploring knowledge from distal partners helps improve inventive performance in the emerging field.

Nonetheless, an alliance with distal partners is not sufficient for building an advantage in the emerging field. Exploring knowledge from distal partners is difficult because of the lack of a common knowledge base. Hence, the gains from such alliances would be low with insufficient resources and managerial attention. To ameliorate this problem, firms may need to increase resources available for distal partnerships. Indeed, exploring a new field often needs to be supported by slack resources that are not committed to existing strategies. In organization theory, these unabsorbed slack resources allow the firm to experiment with new strategies such as introducing new products and entering new markets (Thompson 1967, Tan and Peng 2003). For example, Intel's entry into microprocessor and chipset businesses, as well as the introduction of Centrino, would not have occurred without slack resources to fund exploration of new technologies and businesses (Burgelman and Grove 2007). One way to free up existing resources and obtain more resources is allying with proximal partners. Integrating knowledge from proximal partners speeds up a firm's cumulative learning within the existing dominant design (Rosenkopf and Nerkar 2001). Knowledge sharing and transfer as well as communication and coordination are relatively easy among partners with a common knowledge base (Cohen and Levinthal 1989, Mowery, et al. 1996, Lane and Lubatkin 1998). More importantly, because they facilitate the firm's cumulative learning in the current design, proximal partners allow firms to improve their competitive position under current technology standards. This continuous improvement is particularly important for short-term financial profitability in highly competitive product markets (Jansen, Van den Bosch and Volberda 2006). The resulting short-term profitability in existing fields allows for additional slack resources that managers can allocate for distal partnerships in order to keep up with a new field.

As a result, incumbents may form learning alliances with firms at varying technological distances in order to improve inventive performance in the emerging field. With this in mind, we propose the following:

Hypothesis 2: When an emerging field is in its infancy, an incumbent firm's inventive performance in the field is positively related to the diversity of its learning alliance partners in terms of technological distance.

2.2.5 Search in Public Science

Another important input to invention is scientific knowledge. Scientific knowledge may be gained by collaborating with university scientists or reading academic publications. There is considerable evidence that industrial breakthroughs are related to both knowledge in the public domain and participation in scientific research (Henderson and Cockburn 1994, Narin, Hamilton and Olivastro 1997, Zucker, et al. 2002, Darby and Zucker 2003, Thursby and Thursby 2006). We argue that searching scientific knowledge will facilitate inventing in the emerging field, but as with the search of novel areas (Hypothesis 1) the returns are expected to be nonlinear.

Much of the knowledge in an emerging field that subsequently has a profound impact initially originates in scientific research from academia (Zucker, Darby and Brewer 1998, Darby and Zucker 2003). The main reason is that unlike for-profit organizations, academic institutions are not constrained by the threat that the emerging field poses for existing industry practices. Because university scientists have relatively more freedom to choose their own research agenda, they are more likely to develop foresight on the emerging field's most fruitful research directions. By drawing from academic publications and working with university scientists, firms are better able to learn the impact of the emerging field and increase productivity in pursuing the most important inquiries. Working with university scientists is particularly important since much of the knowledge in an emerging field is tacit during its infancy and the acquisition of such knowledge requires intensive interactions (Zucker, Darby and Armstrong 1998).

Scientific knowledge also increases inventive performance in the emerging field by providing cognitive guidance and mitigating uncertainty. Science helps inventors to reduce unproductive learning-by-doing and to predict the effects of specific knowledge combinations (Pisano 1994, Fleming and Sorenson 2004). When a combination works serendipitously, science also helps explain why it works and whether it is a replicable invention or an unpredictable random error. Furthermore, uncertainty in the emerging field can lead to frustration and inhibit inventing. Guidance from science can motivate inventors to continue looking for alternatives and avoid being trapped in a local optimum (Fleming and Sorenson 2004).

There will be limits to the cognitive ability of R&D staff to combine scientific information as well as to combine scientific knowledge with existing knowledge. There will also be a limit to which an incumbent can effectively collaborate with university scientists. While university scientists value academic freedom and disseminating knowledge, their industrial collaborators value economic returns and often keep R&D results secret (Gans, Murray and Stern 2008). Thus scientific search will be subject to diminishing marginal returns so that inventive output from scientific knowledge searched increases at a decreasing rate.

At some point, the incumbent's inventive performance might fall because of the need to coordinate value and goal conflicts as well as information overload from excessive search of scientific knowledge. But as in Hypothesis 1, the prescriptions of optimal search would prevent such a decline. Particularly at a time when incumbents face pressures to generate returns from the current dominant design and improve efficiency and quality, overly emphasizing scientific standards would undermine short-term profits. Additionally, searching scientific knowledge through collaborating with university scientists increases the risk of knowledge leakage to competitors through the scientists' academic activities. In summary, we predict the following.

Hypothesis 3: When an emerging field is in its infancy, an incumbent firm's inventive performance in the field is a positive and nonlinear function of its exploration of scientific knowledge in the public domain (i.e., the inventive performance increases at a decreasing rate until it levels off).

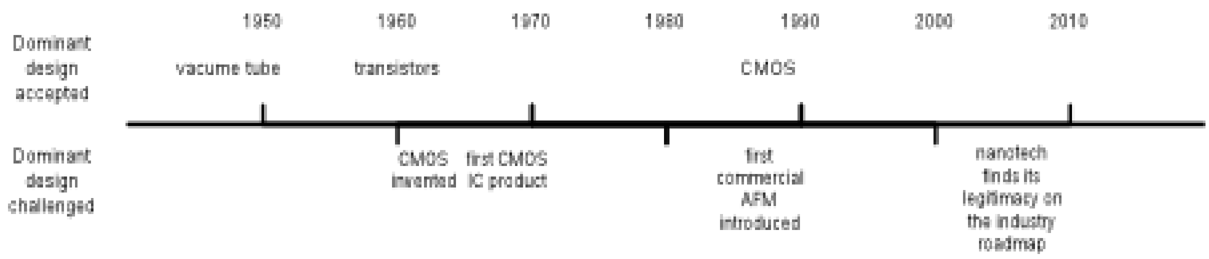

Figure 1: A timeline of dominant designs in the semiconductor industry

2.3 Data and Measures

2.3.1 Setting

We tested our hypotheses in the semiconductor industry where the current dominant design, the complementary metal-oxide semiconductor (CMOS) technology, replaced bipolar technology (which replaced vacuum tubes) and now nanotechnology threatens CMOS (see Figure 1).[2] CMOS was invented in 1963 by Frank Wanlass at Fairchild Semiconductor who worked under Gordon Moore (Riezenman 1991), cofounder of Intel and author of Moore's Law, which states that the number of transistors that can be inexpensively placed on a chip doubles every two years (Moore 1965). The first CMOS product was introduced in 1967 while bipolar technology was still vital. Gradually, bipolar transistors consumed too much power, generated too much heat, and became less reliable as more components were added to chips. CMOS answered these challenges and, in the late 1980s, became the dominant design widely used in microprocessors, microcontrollers, random access memory (RAM), and other digital or analog logic circuits.

Today CMOS faces the same challenges, in part, because the limitations of solid state physics prevent this structure from approaching the performance implied by

[2]Strictly speaking, a vacuum tube is not a semiconductor, but the term 'semiconductor industry' usually broadly covers those products that were antecedents of semiconductors, starting with the vacuum tube.

Moore's Law (McCray 2007). More importantly, as the scale of manufacturing processes goes below 100 nanometers, the properties of materials change substantially. Some materials conduct electricity better, some (e.g., carbon nanotubes) are substantially stronger; some have different magnetic properties; and some (e.g., gold) reflect light better. These properties profoundly challenge design and manufacturing throughout the industry. As a result, competency in nanotechnology becomes essential for firms to be able to compete for the design of the next dominant products/processes. Indeed, the Semiconductor Industry Association's 2005 International Technology Roadmap for Semiconductors (Roadmap)[3], predicts that alternatives such as carbon nanotubes, nanowires, and other high transport channel materials at the nanoscale will be required for Moore's Law to continue to hold. The use of these nanoscale materials, because of their unique properties, would demand significant changes to the CMOS from product designs to manufacturing. Unlike other new technologies that merely replaced components of CMOS-based designs, nanotechnology ultimately changes the CMOS in terms of both production and material platforms (Gasman 2004).

Nevertheless, nanotechnology was hardly a strategic focus for semiconductor firms during the 1990s. Our interviews revealed that although some semiconductor firms used nanotechnology, it was not critical for product performance. Nanotechnology did not show up in leading semiconductor firms' annual reports until the early 2000s. Indeed, the scale of process technology at AMD, one of the leading semiconductor companies, was still at a 'bulk' rather than 'nano' scale (350(Cassiman and Veugelers)250 nanometers [nm]) from 1994 to 1999. The R&D in nanotechnology was more of a pursuit by alert inventors than senior managers. The majority of nanotechnology inventions were, in fact, created outside the semiconductor industry (Rothaermel and Thursby 2007) (see Figure 2).

[3] Available at http://www.itrs.net/links/2005itrs/PIDS2005.pdf

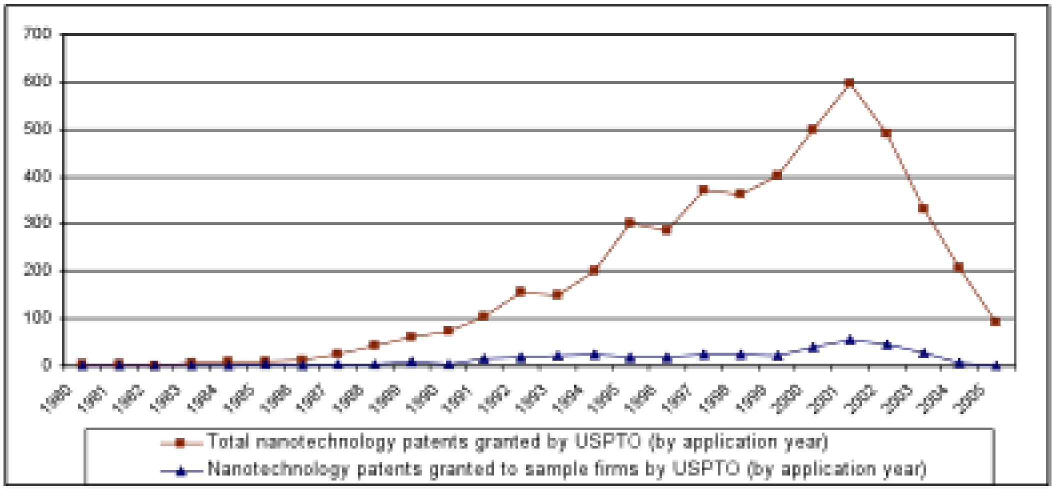

Figure 2: A contrast between all nanotechnology patents granted by USPTO and those granted to a cohort of incumbent firms (established before 1990) in the global semiconductor industry between 1980 and 2005

The period between 1989 (when the first atomic force microscopy [AFM] was commercially available) and 2002 meets our criterion for the infancy of an emerging field. After CMOS replaced bipolar technology in the late 1980s, industry incumbents elaborated on the CMOS design incrementally and competed with more reliable and better performing CMOS-based products. While there was potential for inventions enabled by the AFM to replace CMOS, the threat of nanotechnology to CMOS and the necessity for a new dominant design was far from clear. Interestingly, some incumbents seemed to be better able to assess the importance of nanotechnology during its infancy and be more productive in generating inventions in the field than others (see Figure 3). Thus the semiconductor industry during this period is ideal for testing our hypotheses.

2.3.2 Sample

First, we identified a cohort of firms that were active in the global semiconductor industry by 1989. This process began with 1,130 firms that had at least one

Firm name	Number of nano patents 1989–2002
HITACHI	59
ADVANCED MICRO DEVICES	50
MATSUSHITA ELECTRIC	29
TOSHIBA	25
MICRON TECHNOLOGY	24
MITSUBISHI ELECTRIC	22
NEC	22
VEECO INSTRUMENTS	19
MOTOROLA	15
INTEL	14
TEXAS INSTRUMENTS	13
FUJITSU	11
APPLIED MATERIALS	10

Figure 3: Semiconductor firms that were established before 1990 and filed more than 10 granted nanotechnology patents during the period of 1989-2002

semiconductor patent between 1980 and 1985.[4] Recognizing that firms with a few semiconductor patents do not necessarily operate in the semiconductor industry, we took the following steps to identify the cohort. Among the 1,130 firms, we identified those in the semiconductor business based on the profiles of electronics firms in Moody's Industrial Manual 1986, documentation on U.S. semiconductor firms established between 1966 and 1976 (Dorfman 1987)(p.184-185), non-U.S. semiconductor firms (Braun and MacDonald 1982, Malerba 1985, Dorfman 1987, Morris 1990), as well as public records for firms that were classified as semiconductor firms (standard industrial classification [SIC] code 3674) during the 1980s in Compustat. We further identified firms that did not show up in any of the records above but had at least 20 percent of their patents between 1980 and 1985 classified as semiconductor patents. Note that a firm with 100 percent of its patents classified as semiconductor patents is supposed to be a semiconductor firm, but we choose a conservative cutoff for a broader search. For these firms, we searched news/archives on the Internet for their

[4]USPTO defines a semiconductor patent as in any one of 25 patent classes and about 1,000 subclasses, according to the USPTO Technology Profile Report for Semiconductor Device and Manufacture Patents.

history, paying special attention to their business during the 1980s, and retained only firms whose semiconductor business in the 1980s could be confirmed. Additionally, we dropped firms that lost their independence (i.e., acquired or merged) by 1989 since firms acquired may subsequently report patenting under their parent firms' names and may not have a separate financial record available to us.

This process resulted in a total of 75 firms in the semiconductor industry by 1989 that had applied for at least one semiconductor patent between 1980 and 1985. Among these firms, 68 had public financial data during 1989–2002, which allowed us to control for factors such as R&D expenditure. These 68 firms had statistically significantly (at the 0.01 level) more semiconductor and nanotechnology patents per year than the seven firms without public financial data during our study period. Thus, our analysis is confined to firms that were public during at least part of our study period. The restriction to public firms is clearly a limitation but one that we could not avoid since controlling for financial variables is critical. The final sample includes 48 U.S. firms, 12 Japanese, four Canadian, two European, one Taiwanese, and one South Korean.

2.3.3 Interviews

To gain an understanding of the transition from the bipolar to CMOS technology, we interviewed a number of experts with experience in the semiconductor industry. These experts provided valuable insight into the role of nanotechnology in the eventual threat to CMOS as a dominant design. All of the interviewed experts had industrial experience in semiconductors and many are currently associated with nanotechnology research. We also conducted follow-up interviews to explore the implications of our empirical results.

2.3.4 Dependent and Independent Variables

Inventive performance. Our interest is in incumbent firms' inventive output during the initial stages of an emerging field, which was between 1989 and 2002 in the context of this study. We measured an incumbent firm's inventive output in nanotechnology by the annual count of nanotechnology patents applied for by the firm (nano patents). The patent data comes from the United States Patent and Trademark Office (USPTO).[5]

Knowledge in novel technology areas. Hypothesis 1 depicts the relationship between a firm's inventive performance and search in novel areas. Following Ahuja and Lampert (2001), we measure the search for novel technology inputs as the number of new U.S. patent classes that a focal firm entered in the previous three years. A firm enters a new technology class when this firm applies for a patent in a class in which this firm has not patented in the previous five years. The choice of a five-year period accords both with Ahuja and Lampert (2001) and prior work on knowledge depreciation (Griliches 1984). The square of this variable allows us to test the nonlinear relationship.

Knowledge from partners diverse in technological distance. Hypothesis 2 predicts that an incumbent can increase its inventive performance by acquiring knowledge from diverse partners in terms of technological distance. We measure this diversity by the variance of technological distance between a focal firm and all its partners.[6]

[5] We identified a nanotechnology patent using the USPTO's classification number (977) (http://www.uspto.gov/go/classification/uspc977/defs977.htm). The use of this patent class to identify nanotechnology patents is validated externally, since the number of nanotechnology patents applied for by our sample firms is close to the number of nanotechnology patents applied for by semiconductor firms in another study that identifies nanotechnology patents based on a thorough keyword search (Rothaermel and Thursby, 2007).

[6] This construct cannot be measured with an average technological distance between a focal firm and all its partners. Consider a firm A having two partners (X and Y). If we measure a technological distance ranging from zero to one and assume the distance between A and X is 0.2 and between A and Y is 0.8, then the mean distance is 0.5, which is the same as the mean distance if both A–X and A–Y distances are 0.5. Hypothesis 2 indicates that firm A is better off in the first situation than in the second. We believe that the variance measure is suitable to test our Hypothesis 2. The diversity construct in this hypothesis has two aspects: 1) having more distant partners (which

To do this, we first identify this firm's learning alliance partners and then calculate a technological distance between this firm and each of its partners.

The alliance data come from Thomson SDC Platinum (SDC) (Oxley and Sampson 2004, Rothaermel and Thursby 2007). This database covers worldwide alliances, regardless of whether a participant is publicly traded. Our sample firms formed a total of 3,935 alliances from 1985 to 2005, excluding several alliances that either were terminated or rumored to be formed. We further identified 1,233 alliances associated with semiconductor technologies.[7] Because many firms operate in various industries, we excluded alliances irrelevant to the semiconductor business. Of the 1,233 semiconductor alliances, 631 were learning alliances. We classify a deal as a learning alliance if it involves acquiring technologies or knowledge from a partner. For example, in an alliance between Motorola and Mosel, Motorola gained access to Mosel's production facilities and Mosel acquired proprietary chip-making technology from Motorola. We considered this case as a learning alliance for Mosel but not Motorola. With this criterion, we read the deal descriptions provided by SDC for each of the 1,233 alliances and identified the 631 learning alliances. Among them, 524 were R&D alliances flagged by SDC.

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we argued increases a focal firm's inventive performance); and 2) avoiding having excessive distal partners (which we argued would be counterproductive) and balance the portfolio by having more proximal partners. The variance measure captures both aspects. First, the measure increases with the extent of having distal partners. For example, controlling for the number of partners, firm A, whose distances to its partners are 0.1, 0.1, 1, 1 respectively, has a variance measure of 0.23. This is 0.16 for firm B, whose distances to its partners are 0.1, 0.1, 0.9, 0.9 respectively. The variance measure of firm A is higher than that of firm B whose partners are less distal. Second, the variance measure would decrease with excessive distal partners. For example, firm C has distances 0.1, 0.8, 0.9, 0.9. Compared to firm B, firm C has excessive distal partners and C's portfolio seems to be less balanced between proximal and distal partners. Accordingly, firm C has a variance measure (0.11) lower than that of firm B (0.16). Thus, the variance measure allows us to measure a diversified and balanced portfolio of partners.

[7]The SDC database has an indicator for the 'primary industry of the alliance' and defines those alliances with an SIC code of 3674 as semiconductor alliances. But we recognized that the SIC is a poor indicator of the technologies. For instance, many alliances associated with integrated circuit designs were not categorized as SIC 3674. We manually identified those associated with semiconductor technologies based on the deal descriptions and information from online resources, a semiconductor expert familiar with design technology, and an expert in the industry familiar with manufacturing technology.

With the 631 alliances, we then constructed a focal firm's portfolio in year t-1. Identifying each sample firm's partners generated 1,316 firm-partner pairs. We included the firm's set of partners from year t-3, t–2, and t-1 in the firm's alliance portfolio for year t-1. There is not a prior theory to suggest how many years a firm should look back when considering its alliance portfolio. Thus, we assumed a three-year window, and checked robustness by running analyses with alternative assumptions.

We computed technological distances using Jaffe's (1986, 1989) measure of technological similarity, which has been used in several studies (e.g., Oxley and Sampson 2004, Galasso 2007). We calculated it longitudinally, since a firm's expertise may change over time.

Technological similarity or overlap (T_{it}, T_{jt}) = $\frac{T'_{it}T_{jt}}{\sqrt{T'_{it}T_{it}}\sqrt{T'_{jt}T_{jt}}}$.

Tit is a 470-dimension vector representing the number of semiconductor patents firm i applied for between 1980 and t, in each of the 470 USPTO patent classes. Between 1980 and 2005, there were 58,776 semiconductor patents applied for by the sample firms in the 1,316 pairs, and 81,274 patents by the 385 partners outside the sample. We used all classes of a patent to avoid a bias toward the primary class (Jaffe, Trajtenberg and Henderson 1993) (p.596). Following Rosenkopf and Almeida (2003), we used the earliest year's available data if a firm did not have patents at the time of its first alliance. Then for each year, we calculated the technological distances between a focal firm and its partners[8] in the portfolio and the variance of these values.

Knowledge from public science. Hypothesis 3 predicts a nonlinear effect of exploring scientific knowledge gained either by working with university scientists or reading scientific publications. We measured the first mechanism by the number of

[8]For a partner without semiconductor patents during the entire period, we used the average proximity of those pairs in which the partners had the same SIC code as the one with the missing patents. If a partner belonged to a SIC code that no other partners shared, we used the average proximity of all pairs in which the partner's SIC code was not 3674.

scientific articles published by the firm along with at least one university scientist in year t-1 (designated 'scientific pubs with univ scientists' in tables), using data from the Thomson Reuters ISI Web of Science. To measure the second, we computed the number of semiconductor patents citing scientific articles applied for by the focal firm in year t-1, assuming that each such prior patent indicates prior exploration of scientific knowledge. The publication measure can be interpreted as tacit knowledge search, while the citation measure reflects search of codified knowledge (Zucker, et al. 1998, Zucker, et al. 2002, Rothaermel and Thursby 2007). The square of each variable allows us to test the diminishing marginal returns stated in the hypothesis.

2.3.5 Control Variables

Technological opportunities. We used a count of all nanotechnology patents granted by USPTO in year t-1 as a proxy of opportunities to invent in the field. The greater the opportunities, the greater the incentive a firm will have to invent. There were about 4,800 nanotechnology patents granted by USPTO as of November 2007.

Total technological classes. We included the number of patent classes a firm had entered over the past three years. One can think of these classes as part of the stock of knowledge the firm draws from in its search. Thus it is likely to affect inventive output in general.

Alliance portfolio content and size. We controlled for the mean technological overlap between a focal firm and the partners in its alliance portfolio (Sampson 2007). Since having more partners increases the potential sources of knowledge, we included the number of partners a firm had in its alliance portfolio in year t-1 (Rothaermel 2001). The maximum number of partners a firm had was 47 in any year. Out of 68 sample firms, 22 had no semiconductor learning alliances.

Exploring knowledge from other firms outside or within the industry domains. Rosenkopf and Nerkar (2001) suggest that searching for other firms' knowledge outside (inside) the firm's industry domain is associated with inventions of higher overall (within-domain) impact than other search strategies. To allow for this effect, we included citing non-semiconductor patents (the number of non-semiconductor patents granted to other firms and cited by the focal firm's semiconductor patents applied for in year t) and citing semiconductor patents.

Other controls. To control for unobserved effects of firm heterogeneity, we incorporated a pre-sample dependent variable, which is the number of nanotechnology patents applied for by a focal firm during the nine-year period before 1989. We also used the number of semiconductor patents a focal firm applied for in year t-1, which embodies unobserved inputs such as R&D effectiveness and other intangible assets dedicated to inventing activities in the semiconductor business. Larger or more profitable firms, as measured by annual R&D expenditure, total assets, number of employees (in thousands), and net income should have more slack resources available for invention. All financial data was taken from Compustat and are stated in 2005 U.S. dollars (in millions). For non-U.S. firms, currencies were converted using the corresponding year's real exchange rate. To capture other country-specific effects, we add U.S. incorporated with a value of one if a firm is headquartered in the United States. Finally, we use a set of year dummies to control for time-specific factors not otherwise captured.

2.4 Statistical Analyses and Results

2.4.1 Statistical Methods

We used a negative binomial maximum likelihood estimation model in which the expected count of the dependent variable (nanotechnology inventions) $E(y|X)$ equals the exponential of Xβ, where X is a vector of all independent variables and β is a vector of their coefficients. The rationale for this method is well known when the dependent variable is a count. An alternative to the negative binomial would be the

Poisson specification, which assumes that the conditional mean of the outcome is the same as the conditional variance. A higher variance than the mean of the dependent variable shown in Table 1 indicates that the Poisson model would not be appropriate (Cameron and Trivedi 1998).

Table 1: Summary statistics

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Nano patents																		
2	Novel technology areas	0.43																	
3	Variance of technological distance	0.22	0.45																
4	Scientific pubs with univ scientists	0.45	0.49	0.27															
5	Patents citing scientific articles	0.60	0.67	0.35	0.50														
6	Technological opportunities	0.15	0.13	-0.09	0.17	0.17													
7	Total technological classes	0.54	0.70	0.44	0.79	0.67	0.13												
8	Number of partners	0.31	0.49	0.44	0.63	0.48	0.08	0.71											
9	Mean technological overlap	0.31	0.48	0.44	0.44	0.42	0.04	0.57	0.60										
10	Citing semiconductor patents	0.49	0.55	0.25	0.25	0.90	0.21	0.42	0.25	0.30									
11	Citing non-semiconductor patents	0.46	0.52	0.21	0.29	0.85	0.22	0.44	0.26	0.29	0.95								
12	Pre-sample dependent variable	0.27	0.17	0.11	0.30	0.30	0.04	0.45	0.29	0.26	0.12	0.12							
13	Semiconductor patents	0.62	0.70	0.36	0.55	0.96	0.22	0.69	0.52	0.45	0.86	0.79	0.31						
14	R&D expenditure	0.46	0.49	0.32	0.80	0.44	0.05	0.89	0.56	0.44	0.19	0.24	0.29	0.43					
15	Total assets	0.49	0.45	0.28	0.73	0.42	0.03	0.86	0.52	0.41	0.17	0.21	0.35	0.42	0.96				
16	Number of employees	0.40	0.45	0.28	0.78	0.39	0.06	0.86	0.55	0.41	0.15	0.20	0.31	0.39	0.95	0.91			
17	Net income	0.15	0.31	0.23	0.24	0.14	0.02	0.30	0.15	0.14	0.07	0.09	0.06	0.14	0.36	0.33	0.3		
18	U.S. incorporated	-0.23	-0.31	-0.15	-0.49	-0.25	-0.17	-0.57	-0.40	-0.27	-0.07	-0.06	-0.25	-0.29	-0.61	-0.63	-0.61	-0.10	
	Mean	0.32	12.56	0.05	12.04	21.60	289.79	93.12	3	0.29	309.73	79.63	0.13	49.25	794.93	12021.92	35.61	237.95	0.71
	Standard deviation	1.17	13.68	0.07	32.33	54.22	165.43	148.95	6.51	0.37	1089.16	278.94	0.66	116.16	1761.10	28629.67	81.95	1044.96	0.46
	Min	0	0	0	0	0	62	0	0	0	0	0	0	0	0.00	1.77	0.03	-4491.7	0
	Max	13	72	0.41	256	611	597	611	39	0.97	17854	4589	5	1154	9662.77	179729.00	484	11947.7	1

Note. All correlation coefficients above 0.07 are significant at p<0.05. Monetary terms are in million U.S. dollars.

To account for unobserved firm-level differences in nanotechnology patenting, we use the random-effects (RE) estimation. In addition to the RE, the literature has suggested fixed-effects (FE) estimation models to control for the unobserved heterogeneity (e.g., including a set of firm dummy variables or transforming estimated equations to eliminate firm-specific effects) . We did not adopt the FE estimation for several reasons. First, including firm dummy variables would significantly reduce the degrees of freedom. Second, the FE method would drop any subject that lacks within-subject variation in the dependent variable. Twenty-five firms in our sample did not generate any nanotechnology patents during our study period. Thus, the FE estimation would omit all of these unproductive firms, which not only reduces our observations by over one-third but also leads to selection bias, biasing the results toward the more productive firms. Third, the FE model does not allow estimation of the coefficients for time-invariant regressors, such as firm nationality, which might interest international scholars. [9] In addition to the FE, scholars suggest that the pre-sample dependent variable averaged over a long, pre-sample time period can capture the unobserved firm-specific effects (Blundell, Griffith and Van Reenen 1995, Blundell, Griffith and Van Reenen 1999). Following this method and recent practices (Dushnitsky and Lenox 2005, O'Shea, Allen, Chevalier and Roche 2005, Schilling and Phelps 2007), we include the pre-sample dependent variable into an RE estimation.

2.4.2 Results

Tables 1 and 2 provide the descriptive statistics and estimates. In Model 1, we entered the control variables. The three sets of independent variables were added in Models 2, 3, 4a, and 4b, respectively. We find an improvement in the model fit for Models 2, 4a, and 4b in comparison to Model 1. Note that the number of observations in Model 3 falls below that in the other models because not all firms formed a learning alliance. In order for the variable variance of technological distance to partners to be meaningful, we limited the firm-year observations to those having at least one partner. This resulted in a subset of 348 observations across 46 firms. These 46 firms applied for 99.22 percent (55,096) of the semiconductor patents and all nanotechnology patents (335) among the 68 sample firms between 1989 and 2002. We then entered all the variables in Models 5a and 5b.

[9]'Random effects' and 'fixed effects' apply to the distribution of the unobserved firm-specific effect (Cameron and Trivedi, 1998). The unobserved firm-specific effect is assumed to be fixed in the FE estimation and randomly drawn from the population in the RE estimation. We found the FE estimation results similar to the RE estimation results, except for the decline in statistical significance, which can result from the significant drop of sample size.

Hypothesis 1 predicts that an incumbent firm's inventive performance in the emerging field increases with novel technological areas explored and this impact is nonlinear. Table 2 shows that the estimated coefficient for novel technology areas is statistically significant and positive, whereas the estimated coefficient for novel technology areas2 is statistically significant and negative in Models 2, 5a, and 5b. Thus, as we hypothesized, a positive impact of novel technological areas searched has diminishing marginal returns. Moreover, we expected that firms would stop searching for novel knowledge before inventive performance began to fall. Had we found that most firms undertook excessive search, we would need to admit the possibility that these firms acted in response to factors not considered in either our theory or empirics. Consistent with our expectation, we find that in most cases (97% of firm-year observations), firms searched only on the positively sloped portion of their performance curve.

Hypothesis 2 predicts that an incumbent's inventive performance will increase with partner diversity in technological distance. The effect of this variable is statistically significant in Models 3, 5a, and 5b, providing overall support for this hypothesis. Based on Model 5a, a standard deviation change in the variable increases the expected count of nanotechnology patents by a factor of 1.35 (=e 0.07* 4.3), holding other factors constant.

Hypothesis 3 predicts that exploring scientific knowledge will improve inventive performance with diminishing marginal returns. Table 2 shows that the effect of scientific pubs with univ scientists is statistically significant and positive, whereas the effect of its squared term is statistically significant and negative (Model 4a). The same pattern remains when we used patents citing scientific articles as a measure (Model 4b) and entered all other variables (Models 5a, 5b). As with Hypothesis 1, we argue that firms would not excessively search for scientific knowledge. This is indeed correct in 98 percent of the cases (firm-year observations).

Table 2: Negative binomial regression results

Independent variables	Model 1 coefficient	Model 1 s.e.	Model 2 coefficient	Model 2 s.e.	Model 3 coefficient	Model 3 s.e.	Model 4a coefficient	Model 4a s.e.	Model 4b coefficient	Model 4b s.e.
Novel technology areas			0.07 **	(0.03)						
Novel technology areas ^{2}			-6.16E-4 *	(3.66E-4)						
Variance of technological distance					4.77 **	(1.81)				
Scientific pubs with univ scientists							0.03 **	(0.01)		
Scientific pubs with univ scientists ^{2}							-8.35E-5 **	(2.93E-5)		
Patents citing scientific articles									0.01 *	(4.39E-3)
Patents citing scientific articles ^{2}									-2.74E-5 ***	(7.43E-6)
Technological opportunities	2.90E-3 *	(1.33E-3)	3.33E-3 **	(1.34E-3)	3.78E-3 **	(1.56E-3)	1.89E-3 †	(1.41E-3)	2.65E-3 *	(1.42E-3)
Total technological classes	0.01 ***	(1.98E-3)	3.99E-3 *	(2.08E-3)	4.96E-3 **	(2.10E-3)	0.01 ***	(1.96E-3)	0.01 **	(2.00E-3)
Number of partners	-7.30E-4	(0.01)	1.07E-3	(0.01)	-0.01	(0.01)	-0.01	(0.01)	-3.59E-3	(0.01)
Mean technological overlap	0.43	(0.41)	0.40	(0.41)	1.08 †	(0.70)	0.35	(0.42)	0.63 †	(0.41)
Citing semiconductor patents	7.65E-5	(1.94E-4)	1.72E-4	(1.85E-4)	-2.26E-5	(1.93E-4)	1.30E-4	(1.91E-4)	6.82E-4 **	(2.52E-4)
Citing non-semiconductor patents	-5.65E-4	(5.91E-4)	-8.05E-4 †	(5.68E-4)	-4.95E-4	(6.28E-4)	-7.37E-4	(5.76E-4)	-1.08E-3 *	(5.66E-4)
Pre-sample dependent variable	0.05	(0.24)	0.18	(0.20)	0.04	(0.12)	-0.07	(0.22)	0.03	(0.20)
Semiconductor patents	2.23E-3 *	(1.26E-3)	1.59E-3	(1.26E-3)	3.96E-3 **	(1.38E-3)	2.20E-3 *	(1.26E-3)	-3.25E-4	(1.95E-3)
R&D expenditure	1.03E-4	(1.45E-4)	2.61E-4 *	(1.47E-4)	1.36E-4	(1.46E-4)	-2.05E-5	(1.53E-4)	4.80E-5	(1.43E-4)
Total assets	2.25E-5 **	(8.20E-6)	1.89E-5 **	(7.98E-6)	2.01E-5 **	(6.89E-6)	2.18E-5 **	(8.32E-6)	2.26E-5 **	(7.91E-6)
Number of employees	-0.01 **	(3.21E-3)	-0.01 **	(2.98E-3)	-0.01 *	(2.75E-3)	-0.01 ***	(3.29E-3)	-0.01 *	(3.11E-3)
Net income	-5.57E-5	(6.15E-5)	-5.72E-5	(5.75E-5)	-6.83E-5	(5.79E-5)	-4.51E-5	(6.04E-5)	-2.70E-5	(5.88E-5)
U.S. incorporated	0.61	(0.54)	0.69	(0.50)	1.02 *	(0.49)	0.38	(0.54)	0.40	(0.50)
Year dummies (included)	(yes)		(yes)		(yes)		(yes)		(yes)	
Constant	-3.27 ***	(0.93)	-4.27 ***	(0.94)	-4.28 ***	(1.04)	-2.89 ***	(0.95)	-3.28 ***	(0.89)
Log likelihood	-339.80		-333.57		-273.24		-335.49		-333.48	
Wald chi square	190.80 ***		221.45 ***		214.26 ***		208.99 ***		216.77 ***	
N	702		702		348		702		702	

Independent variables	Model 5a coefficient	Model 5a s.e.	Model 5b coefficient	Model 5b s.e.	Model 6a (include n*ano partner*) coefficient	Model 6a s.e.	Model 6b (include n*ano partner*) coefficient	Model 6b s.e.
Novel technology areas	0.07 **	(0.03)	0.09 ***	(0.03)	0.07 **	(0.03)	0.09 ***	(0.03)
Novel technology areas ^{2}	-8.64E-4 **	(3.52E-4)	-1.15E-3 ***	(3.41E-4)	-8.71E-4 **	(3.47E-4)	-1.20E-3 ***	(3.44E-4)
Variance of technological distance	4.30 **	(1.69)	3.05 *	(1.73)	4.05 **	(1.69)	3.07 *	(1.73)
Scientific pubs with univ scientists	0.02 **	(0.01)			0.02 **	(0.01)		
Scientific pubs with univ scientists ^{2}	-6.39E-5 **	(2.55E-5)			-6.97E-5 **	(2.41E-5)		
Patents citing scientific articles			0.01 *	(4.20E-3)			0.01 **	(4.00E-3)
Patents citing scientific articles ^{2}			-3.29E-5 ***	(7.20E-6)			-3.22E-5 ***	(7.11E-6)
Nano Partner					0.15 **	(0.05)	0.07 †	(0.04)
Technological opportunities	2.55E-3 **	(1.03E-3)	2.90E-3 *	(1.52E-3)	3.38E-3 **	(1.24E-3)	1.91E-3 *	(9.56E-4)
Total technological classes	1.44E-3	(1.52E-3)	1.05E-3	(1.44E-3)	1.65E-3	(1.50E-3)	8.75E-4	(1.42E-3)
Number of partners	-0.02 †	(0.01)	-0.01	(0.01)	-0.04 **	(0.02)	-0.02 †	(0.01)
Mean technological overlap	0.88 †	(0.63)	0.90 †	(0.60)	0.70	(0.63)	0.91 †	(0.57)
Cites of semiconductor patents	2.03E-4	(2.06E-4)	6.79E-4 ***	(2.12E-4)	3.61E-5	(2.14E-4)	5.67E-4 **	(2.15E-4)
Cites of non-semiconductor patents	-1.49E-3 **	(6.18E-4)	-1.14E-3 *	(4.96E-4)	-1.07E-3 *	(6.26E-4)	-8.82E-4 *	(4.82E-4)
Pre-sample dependent variable	0.11 †	(0.08)	0.13 *	(0.07)	0.09	(0.08)	0.14 *	(0.07)
Semiconductor patents	4.77E-3 ***	(1.22E-3)	2.27E-3 †	(1.69E-3)	0.01 ***	(1.28E-3)	2.78E-3 *	(1.58E-3)
R&D expenditure	1.78E-4 †	(1.37E-4)	1.92E-4 *	(1.13E-4)	1.45E-4	(1.38E-4)	2.10E-4 *	(1.11E-4)
Total assets	2.24E-5 ***	(5.74E-6)	2.08E-5 ***	(5.34E-6)	2.28E-5 ***	(5.64E-6)	2.20E-5 ***	(5.48E-6)
Number of employees	-0.01 **	(2.10E-3)	-3.77E-3 *	(2.05E-3)	-4.71E-3 *	(2.09E-3)	-4.17E-3 *	(2.08E-3)
Net income	-1.11E-4 *	(5.33E-5)	-4.59E-5	(4.97E-5)	-1.39E-4 **	(5.29E-5)	-9.35E-5 *	(4.89E-5)
U.S. incorporated	1.22 ***	(0.30)	0.96 ***	(0.31)	1.39 ***	(0.30)	1.17 ***	(0.32)
Year dummies (included)	(yes)		(yes)		(yes)		(yes)	
Constant	-4.93 ***	(0.88)	-4.82 ***	(1.12)	-4.99 ***	(1.00)	-4.61 ***	(1.09)
Log likelihood	-266.70		-259.63		-261.91		-258.56	
Wald chi square	292.31 ***		312.58 ***		312.22 ***		320.26 ***	
N	348.00		348.00		348		348	

One-tail test: *** significant at 0.001, ** significant at 0.01, * significant at 0.05, † significant at 0.1.

As for the control variables, the variable technological opportunities is statistically significant. Firms seem to act upon the growing opportunities of a field. The variable total technological classes is not statistically significant once all key independent variables are included. The overall weak effect of the number of partners, consistent with the findings of Rothaermel and Thursby (2007), indicates that creating emerging technologies is a more subtle function of alliances. For the variables examined in Rosenkopf and Nerkar (2001), we do not find consistent and expected effects. Finally, total assets have consistently positive effects whereas the number of employees has consistently negative effects. This indicates that established firms with fewer employees and more physical assets invent more in an emerging field.

2.4.3 Robustness

As noted earlier, we used real exchange rates to convert non–U.S. financial data to U.S. dollars, taking account of differences in inflation rates in our sample firms' home countries. Because these firms tend to be multinationals with significant operations in the United States, one could also argue that the nominal exchange would be appropriate. We estimated the model using the financials converted both ways and the results were virtually identical. We also estimated the model for different periods (e.g., from 1989 to 2003 or 2004) and our results continued to hold.

As previously mentioned, we ran robustness analyses with different assumed lengths of time during which an alliance is taken into account. The main result continued to hold when we included alliances formed in the past four and five years, for each firm's alliance portfolio in year t. When a portfolio included only alliances formed in the past two years, the coefficient for variance of technological distance lacked statistical significance. It is likely that the more inventive firms may take a longer (three to five years) perspective when managing diversity in alliances.

Additional alliance control. While alliances for the purpose of transferring nanotechnology per se were uncommon during our sample period, we added a control for the strength of alliance partners in the emerging field. It is not surprising that there were few formal knowledge transfer agreements since the impact of nanotechnology for the industry was unclear at the time. Nonetheless, informal knowledge spillovers could well occur in alliances with partners with strength in the area. Models 6a and 6b of Table 2 add a variable for the count of the focal firm's learning alliance partners in year t-1 that had applied for at least one nanotechnology patent in year t-1. This variable is statistically significant and positive in Model 6a, but it does not qualitatively affect our main results.

2.5 Discussion and Conclusion

This study addresses why some incumbents perform better than others in creating new technologies during the infancy of an emerging field. We find that some firms invent more because they invest in exploring novel technological areas, knowledge from diverse partners in terms of technological distance, and scientific knowledge. Knowledge gained from these activities increases incumbent firms' understanding of how an emerging field could impact the industry and suggests fruitful avenues for inventors to pursue. Additionally, the diversity in alliance partners allows the firms to keep up with developments in the emerging field while continuing current core activities. This gives firms a competitive edge in inventive performance.

2.5.1 Implications for Research and Practice

Our empirical results contribute to the existing literature in several ways. First, we contribute to alliance research by suggesting how alliances could be leveraged for creating emerging technologies. As observed in this and a prior study, simply increasing the number of learning alliances does not help (Rothaermel and Thursby 2007). To improve inventive performance, alliances should not only enable the firm to keep up with the importance of technological developments, but also to balance invention in the emerging field with continuous improvement in the current design. This finding adds to recent research on ambidexterity approach in alliance formation by large firms and firms in the environment that demands both efficiency and flexibility (Lin, Yang and Demirkan 2007). Second, this study refines the classical finding in the search literature that firms engaging in more exploration are better able to create knowledge outside their core focus (March 1991, Stuart and Podolny 1996, Rosenkopf and Nerkar 2001). Our findings imply that this relationship is likely to depend on the areas that firms explore and the extent to which they also profit from areas outside their core. For instance, although we find that semiconductor incumbent exploration of scientific knowledge increases their knowledge creation in nanotechnology, we did not find the same effect for their search of non-semiconductor patents. This does not rule out, however, the potential for search of non-semiconductor patents to facilitate knowledge creation for these firms in fields other than nanotechnology. Third, the result on the collaboration of firms with university scientists adds to the management literature that increasingly recognizes the role of scientific knowledge from the public domain (Zucker, et al. 2002, Fleming and Sorenson 2004). This is consistent with our interviews with industry experts who indicated that the semiconductor companies that ventured into nanotechnology in the early years took advantage of intensive interaction with university scientists.

Our work also contributes to the literature on technological change. First, it provides new insight into the role of incumbent firms. Much of this literature has focused on incumbent responses to technological advances once their impact on product markets is clear (e.g., Teece 1986, Tushman and Anderson 1986, Mitchell 1989, Tripsas 1997, Rothaermel 2001, Hill and Rothaermel 2003, Sinha and Noble 2005). In contrast, we argue that incumbent firms have strong incentives to proactively create knowledge in an emerging field before the field challenges existing products. By examining factors that affect inventive performance in the emerging field's infancy, we show how incumbent firms can be a source of technological change.

Second, the results add to our understanding of the incremental phase of technology cycles. Technology cycles have been characterized as alternating periods of ferment (caused by major technological discontinuities) and periods of incremental improvements (following dominant design) (Anderson and Tushman 1990). A growing body of research has focused on incumbent adaptation to a new dominant design during the ferment and incremental phase (Tushman and Anderson 1986, Tripsas 1997, Hill and Rothaermel 2003, Rothaermel and Hill 2005). Once this transition is made, an incumbent is viewed as focusing on incremental improvements until the next discontinuity arises. In contrast, we find incumbent firms in the semiconductor industry invented technologies in the emerging field from the beginning of the industry's incremental period.

Overall, invention early in the emerging field provides entrepreneurial opportunities and can be viewed as a necessity for surviving technological changes. Nevertheless, we have noted that returns to inventing in emerging fields are highly uncertain and there are high opportunity costs for such an entrepreneurial activity. Firms must foresee the impact of the emerging field and at the same time compete in product markets through relentless improvement to existing dominant designs. To achieve this balance, this study implies that managers should encourage R&D staff to search in novel areas, balance alliance partners in terms of technological distance as well as collaborate with university scientists. Additionally, managers need to effectively monitor expected benefits and costs of these activities to avoid the negative consequences of excessive search.

2.5.2 Limitations and Implications for Future Research

A hallmark of provocative research is that it raises more questions for future research than the answers it generates (Walsh and Kosnik 1993). Our study is not without limitations, and we note them as possible future research opportunities. First, our results may or may not generalize to other contexts in which incumbent firms face less pressure to prepare for technological change. A future research direction would be to study whether our theoretical relationships will hold in other industries, or to compare our findings across contexts that vary in dynamism or competitiveness.

The finding that nano partner has a statistically significant effect indicates another future research avenue. Early on nanotechnology was not a strategic focus of semiconductor companies so that few alliances were formally targeted to transfer knowledge of nanotechnology. However, firms may engage in informal knowledge transfer through collaboration between their scientists and engineers. We found that a focal firm's inventive performance in nanotechnology improves after alliances involving partners with expertise in nanotechnology. This suggests the role of informal knowledge transfer in the infancy of an emerging field as a future research direction.

The limited qualitative data do not allow us to more fully uncover how the strategies we examine were implemented by the most productive companies. For our curiosity, we examined data for Intel Corp. In 2000 and 2001, Intel applied for its first seven nanotechnology patents despite the fact that nanotechnology was not Intel's strategic focus. It was not until 2002 that Intel officially reported that it would dedicate R&D spending for next-generation manufacturing technology, including development of a 90-nanometer process. Presumably, Intel might have practiced the strategies we identified through autonomous actions outside the company's strategic focus. Indeed, several major moves of Intel (e.g., focusing on microprocessors, chipsets and low-power microprocessors) all originated from engineers and middle-level managers' autonomous efforts (Burgelman and Grove 2007). This suggests the merits of empirical analysis of the role of autonomous inventive activities during an emerging field's infancy phase.

Finally, the connection between the early stages of invention and commercialization in an innovation process remains an important research area. Among others, it would be interesting to know how incumbents' transition to a new dominant design (e.g., coordinating the use of existing complementary assets for the new technology) (Taylor and Helfat 2009) and market performance in later stages of technological change, benefit from their inventing activities during the early stage. Certain pioneering activities, for example, exploring science and new technological fields collaboratively, might help incumbents to update their understanding of the promise of an emerging field as well as which complementary assets are needed (and when). This knowledge would greatly aid incumbents in subsequent development of the inventions. For instance, Hitachi, benefiting from its pioneering research in nanotechnology, had begun to commercialize a low-cost 'nanostamp' technology for biochips in medical applications by the end of 2003. Insiders believe that Hitachi has a considerable competitive advantage over potential competitors commercializing competing technologies.[10] Nevertheless, available data do not allow us to systematically verify the long-run performance of these inventing firms since nanotechnology has not yet replaced current dominant design in semiconductor products. More complete data is necessary to address whether early stage inventive activities in the emerging field leads to a sustainable competitive advantage. Research in this line would improve our understanding of the dynamics of innovation process and technological change.

In conclusion, this study has taken the literature one step further. Prior research

[10] http://www.smalltimes.com/articles/article_display.cfm?Section=ARCHI &C=Manuf&ARTICLE_ID=269177&p=109, retrieved on 23 May, 2009.

has emphasized incumbents' responses to major technological changes in which they base new products on techniques in an emerging field, once the field clearly threatens the industry's existing dominant design. Such reactions, for example, were frequently seen in the studies of pharmaceutical companies in the biotech revolution. However, the existing literature provides little analysis of the role of incumbents during the infancy of the emerging field. This study suggests that incumbent firms might proactively explore the field and start accumulating relevant technical expertise long before a product based on this field is commercialized. Certainly, inventing early in the emerging field is challenging since the field is continuing to evolve and the existing dominant design can still be exploited and improved. We suggest three approaches with which incumbents can overcome these challenges and enhance inventive performance in the emerging field during its infancy and hope our effort will inspire future research to offer more insights.

CHAPTER III

MARKETS FOR TECHNOLOGY AND THE RETURNS TO LICENSING: THE ROLE OF COSPECIALIZED ASSETS AND FIRM CAPABILITIES IN DEVELOPMENT

3.1 Introduction

In the recent decades, the grounding of technologies in science, a strengthening of appropriability, and advances in computer software, among other factors, together have facilitated the expansion of markets for technology and the contract-based strategies of a firm, such as licensing (Oxley 1999, Arora, et al. 2001, Arora and Ceccagnoli 2006, Gans, et al. 2008, Arora and Gambardella 2009, Dechenaux, Goldfarb, Shane and Thursby 2009). The result is an improved division of labor between the production and use of technology across firms, as well as the substantial growth of markets in which these firms trade the technology through licensing and other forms of cooperative alliances. Indeed, between 1996 and 2006 the value of technology exchanges as a percentage of world GDP has increased by 63% (OECD 2009).

Despite its importance for technology development and commercialization, technology licensing is still not a central activity in corporate strategy and limited to certain industries such as bio-pharmaceuticals. Understanding what facilitates and limits technology licensing and the extent of its market has been an important objective of recent strategy research (Bresnahan and Gambardella 1998, Arora, et al. 2001, Gans and Stern 2003, Arora and Ceccagnoli 2006, Gambardella, Giuri and Luzzi 2007, Lichtenthaler 2007, Arora and Gambardella 2009, Ceccagnoli, et al. 2010). The primary focus of the literature has been on the supply-side factors that lead companies to out-license or sell their technology, including the costs of reaching downstream assets, the strength of intellectual property rights protection, and various types of transaction costs (Arora and Gambardella 2009). Among these factors, the role played by the nature of the complementary assets required to commercialize a technology is still not clearly understood and with unsurprisingly ambiguous empirical findings. Moreover, there is an increasing need to integrate the role of capabilities in the explanation of the vertical boundary of firms (Argyres 1996, Leiblein and Miller 2003, Jacobides and Hitt 2005, Mayer and Salomon 2006, Parmigiani and Mitchell 2009, Qian, Agarwal and Hoetker 2010). Nevertheless, few studies have examined the capabilities of both sides of the trade - the supplier and potential buyers.

The main objective of our study is to bridge these gaps. We first examine the role of cospecialized complementary assets in facilitating (or hindering) technology licensing as well as conditioning its impact on firm performance. Cospecialization reflects a bilateral dependence between the invention and downstream activities such as manufacturing and marketing, typically originating from the relationship-specific investments that are required from both the upstream and downstream activities of the value chain (Teece 1986). When complementary assets are cospecialized to the invention, they are also hard to acquire, typically because established firms tend to gain control over them to avoid potential bargaining problems. In light of these challenges, it is especially expensive for a small innovative firm to acquire such cospecialized assets. Consistent with this idea, Gans et al. (2002) find that high-tech entrepreneurial firms are more likely to ally with incumbents in sectors where complementary assets are costly to acquire. The sustained licensing activity in the biopharmaceutical industry between biotech start-ups (which lack complementary assets) and large pharmaceutical companies that already possess the cospecialized assets supports this view (Gans and Stern 2003). Thus, a conventional wisdom seems to emerge suggesting that when complementary assets are cospecialized to the innovation, the division of labor between small and large firms will be sustained.

At least two studies, however, help refine the view outlined above. First, the work of Arora and Ceccagnoli (2006) imply that a division of labor between small and large firms in the face of cospecialized complementary assets is more likely when the technology is effectively protected by patent protection. In other words, and from the point of view of the small technology supplier, it is the interaction of weak complementary assets and strong patent protection to stimulate the propensity to out-license. Second, the study of Ceccagnoli et al. (2010), which takes a demand perspective, suggests that it is the interaction of poor internal R&D productivity of the buyer and the cospecialization between innovation and the downstream complementary assets to push the buyer into the markets for technology. Indeed, ownership of cospecialized assets by itself is not sufficient to stimulate demand, since cospecialization actually implies potential bargaining risks from the buyer's side as well, which should decrease its willingness to pay for an external technology. Taken together, these studies suggest that the division of labor is most likely to thrive between small research productive suppliers of technology that are well protected by patent rights but lack the complementary commercialization assets, and large firms with cospecialized downstream assets and weak internal R&D productivity.

Nevertheless, such view of the markets for technology is still incomplete, since it neglects some critical factors for successful technology commercialization: the nature of knowledge and the role of firm capabilities in transferring knowledge outside firm boundaries (beyond issues of appropriability) as well absorbing external knowledge (Cohen and Levinthal 1989, Arora, Ceccagnoli and Cohen 2007, Arora and Gambardella 2009). Although the causality links among all these factors may be subtle, we argue that the above factors have one common effect on the division of labor: they all affect the productivity of the buyer in developing external technology.

From this perspective, the main contribution of this paper is to better integrate the role of firm capabilities, including productivity in development, knowledge transfer and learning into the analysis of the drivers of the markets for technology. To do so, we adopt a holistic view of technology licensing by developing and estimating a stylized theoretical model that incorporates incentives to commercialize technology from both the demand and the supply side, in the spirit of Gans et al. (2002) and Arora et al. (2007). Relative to this previous literature, however, we allow for research and development to take place at different stages and condition our analysis on the technology having been generated by the supplier (ex-post technology trade). This theoretical approach fits well with the empirical setting, since we will examine the licensing strategies of small firms conditional on holding a portfolio of patents, which better proxies for a firm's knowledge stock and ideas (yet only those protected by patents) rather than developed technologies (e.g. innovations), especially since most patents tend to be applied for relatively early in the life of an R&D project (Griliches 1990). Within this setting, we focus on the interplay between the nature of assets required to commercialize a technology and the buyers' productivity in developing external inventions as a determinant of licensing, as well as the effect of licensing on firm performance.

In a nutshell, we find that even though a small firm is willing to out-license its invention in the face of hard-to-acquire cospecialized assets, potential buyers may not be willing to pay to develop and commercialize the invention when certain factors are present and undermine the productivity of buyers in developing an externally generated invention. We suggest two such factors: 1) the extent to which the invention is general-purpose and thus is less directly dedicated to specific applications in the buyers' industries, 2) the buyer's limited learning capabilities, e.g., a poor absorptive capacity. Again, these factors undermine the buyer's productivity in developing the external invention. Given a low such productivity, the buyer's incentive to buy an external invention would reduce if the invention requires substantial investment in the development stage. We argue it is costly to develop an invention into a marketable innovation when cospecialization between development and manufacturing/marketing of an innovation is high. As a result, the effect of asset cospecialization on the likelihood of licensing as well as its marginal effect on firm performance is conditioned on the buyer's productivity in developing external inventions. Our model also shows that when such productivity is low, the technology supplier's capability to transfer knowledge across firm boundaries become essential for the expansion of technology markets. Indeed, we find that this supplier-side capability, typically developed over time through co-development alliances with other organizations, mitigate the factors that reduce the buyer's development productivity.

We test our theory using data partly derived from the Chi Research/Small Business Administration (SBA) database containing firm and patenting information on the population of U.S. technology-based firms with less than 500 employees that were able to sustain innovation beyond the first invention upon which the firm was founded (Hicks, et al. 2003, Hicks and Hegde 2005). We integrated this dataset with data from multiple additional sources including the SDC Platinum alliances database available from Thomson Reuters, the USPTO trademarks database, the NBER patent database, the USPTO patent-industry concordance file generated in 2005, Corptech, Compustat and the Carnegie Mellon Survey on industrial R&D. The final sample includes an unbalanced cross-industry panel dataset of about 345 U.S. small technology-based firms related to the 1996-2007 period, for a total of about 3300 observations. Our empirical findings based on this dataset lend robust support to our hypotheses.

The paper is organized as follows. In the next section, we describe a stylized model of technology commercialization that considers both buyer's and seller's perspectives, as discussed above. In the main text of the paper, we develop our hypotheses and intuitions, whereas we formalize the model in the Appendix. In section 3 we test our theoretical predictions using above panel-data. Section 4 contains the discussion of the results, the study's limitations, and the conclusions.

3.2 Model and Hypotheses

In this section we describe our simple model of technology licensing based on which we formalize our hypotheses. We analyze the classic decision of a small technology-based firm ("supplier" or "seller" or "licensor") lacking downstream capabilities to compete in the product market with an industry incumbent ("buyer" or "licensee"), as opposed to cooperate with the incumbent. The former entails the investment of forward integration, while the latter entails the transfer of the rights to develop and commercialize the technology to the buyer. The choice of commercialization strategy is determined jointly by the supplier and the buyer.

As such, our approach is similar to Gans et al.'s (2002) model of commercialization strategy, except that we add the following important aspects. First, we incorporate the basic development challenge that the invention may not be directly and immediately applicable to the practical problems of the buyer and thus needs to be localized to the buyer's needs. In other words, we relax the assumption that the invention has been developed and focus on the factors facilitating the markets for technology by reducing the cost of localizing the technology to the industry of application. To this end, our analysis explicitly breaks up the innovation value chain into distinct activities of invention (the "R" of R&D), development (the "D" of R&D), and commercialization (e.g., manufacturing, marketing, service and distribution). Second, unlike the standard technology commercialization models, in which incumbents typically imitate a start-up's innovation (Teece 1986, Gans, et al. 2002, Gans and Stern 2003), we consider that the incumbent firm may invent without infringing the inventive firm's property right. This stylized setting reflects the possibility that, even beyond the issue of imitation, incumbents do invent internally and can secure their own property rights (Gilbert and Newbery 1982, Cohen and Levinthal 1994, Garud and Nayyar 1994, Ahuja and Lampert 2001, Fleming 2002, Arora and Fosfuri 2003, Burgelman and Grove 2007, Jiang, Tan and Thursby 2009, Ceccagnoli, et al. 2010), and thus face a "make or buy" decision for their technological needs. Finally, we incorporate and analyze the supplier and buyer's productivity in technology development, which we will elaborate in the next section.

In our simplified framework, licensing will take place if the gains from the trade outweigh the transaction costs. The gains from trade are due to the avoidance of product market competition in the industry of application of technology, as well as the avoidance of duplicative research costs (for the licensee) and duplicative costs of development and commercialization (for the licensor). Indeed, if the licensing negotiations are successful, the licensee and licensor share the gains from trade; otherwise they will compete in the product market. In the latter case, the buyer needs to invent a substitute technology in-house followed by development and production, whereas the supplier vertically integrates by developing the invention as well as acquiring the complementary assets (manufacturing, sale, and service capabilities).

For our purposes, a critical component of the gains from trade is the buyer's costs of developing the supplier's invention, which in turn is a function of the buyer's productivity in developing external technologies and the extent to which the seller is capable in technology transfer, among other factors. In particular, since the development costs are also affected by the nature of complementary assets required for technology commercialization, the model predicts the existence of important interaction effects between all of these factors in driving the gains of trade and licensing. In the following sections we develop the hypotheses and underlying intuition, whereas the propositions are formalized in the Appendix A.

3.2.1 Asset Cospecialization and Productivity in Developing Externally Generated Inventions

The cospecialization between development and downstream activities required to commercialize an innovation mainly affects the payoffs from licensing trough two channels. First, technology commercialization may require specialized production facilities or marketing channels that are hard to acquire for a small firm and increase the cost of building the downstream commercialization assets to compete in the product market; licensing would avoid the duplication of such assets, increase the gains from trade, and thus increase the incentives to license for a small technology-based firm that is poorly positioned relative to the acquisition of such assets (Teece 1986, Gans and Stern 2003).

Second, cospecialization between development and manufacturing/marketing of an innovation also tends to increase the cost of developing the innovation, not just the cost of manufacturing or marketing. To illustrate this point, we use examples of such cospecialization from the pharmaceutical industry. For instance, the manufacturing and marketing of a new drug typically requires clinical data on how this specific drug works, knowledge acquired during the development of this drug. Drug development may also involve the introduction of new processes that entail a great deal of trial-and-error activities which generate specialized knowledge for the subsequent manufacturing process. In these examples of cospecialization, product development incurs the cost of generating knowledge specialized to the downstream assets used to manufacture or market the new product. This cost is sunk because these cospecialized assets would lose value if leveraged in the context of a different innovation or if commercialized by a different company. Moreover, when the development and downstream activities are cospecialized, it will require intensive interactions between these activities in order to successfully introduce a new product. These interactions, as in the case of face-to-face communications of individuals developing a new drug and those marketing it, can be costly. The cost would be reflected as sunk investments applying to both activities. In summary, development costs are increased by the cospecialized nature of the complementary assets required to commercialize an invention. [1]

The key point of our analysis is that the cospecialized complementary assets required to commercialize an invention have an ambiguous effect on the gains from cooperative commercialization strategies. The direction of the effect, as formalized in our model in the Appendix A, depends on the internal development capabilities of the buyer and supplier, as well as the productivity of the buyer in developing external inventions. The intuition of the former is consistent with what is suggested in the existing literature: firms (either the buyer or the seller) contract for activities that they do not have strong internal capabilities and advantage (e.g., Mayer and Salomon 2006). What we focus on is the latter: the effect of asset cospecialization on the gains from trade depends on the buyer's productivity in internalizing external inventions. Intuitively, asset cospecialization increases the cost of development and the gains from licensing, which would avoid the duplication of such increased development costs. But when the buyer's productivity in developing externally generated inventions is low, such increased gains from trade are mitigated, thus reducing the marginal effect of cospecialized assets on the returns on licensing. The following proposition summarizes this prediction:

Proposition 1: The marginal effect of complementary assets cospecialization in the potential buyer's industry on the incentives to license of a small technology supplier is lower when the buyer's productivity in developing external inventions is low.

[1] When complementary assets are cospecialized, the transaction costs of contractual commercialization modes such as licensing can also increase (Williamson 1981). When the licensor or licensee need to invest in relation-specific assets, such assets are likely to lose value when deployed in other applications. The result is potential risk of hold-up and opportunism during licensing, increasing the expected costs of the ongoing transaction and thus reducing the incentive to license (Teece 1986). In our model, we suppose for simplicity that the transaction cost of licensing are fixed, although specifying it as a function of asset cospecialization does not affect our main predictions.

From this proposition we develop two testable hypotheses by focusing on two key drivers of the buyer's productivity in localizing external technology, that is the generality of the technology and the learning ability of the buyer.

We argue that the efficiency in developing external inventions is lower when they are not developed but have potential application in multiple distinct industries (e.g., both chemicals and electronics). Such inventions are sometime defined as general-purpose or platform technologies (Bresnahan and Gambardella 1998, Shane 2004, Goldfarb 2005, Thoma 2008). Despite the fact that these inventions have potential in multiple application sectors, it is typically difficult for buyers to assess how the inventions can fit in their industry-specific products/processes (Shane 2004). Moreover, unlike inventions that are targeted to a single sector, general technologies are more likely to be created in an environment different from where the users would actually use the technology. Since much of the knowledge that the inventors have about how to reproduce and develop them in different contexts is tacit and context-specific, technology transfer will be challenging (Arora 1995, Agrawal 2006). Therefore, generality of the inventions reduces the buyer's productivity in developing them.

Recall that when the productivity of the buyer in developing external inventions is low, gains from licensing and avoiding the duplication of development costs in the presence of asset cospecialization are mitigated. Since generality tends to lower buyers' development productivity, we expect the following hypothesis.

Hypothesis 1a: The marginal effect of complementary assets cospecialization in the potential buyer's industry on the incentives to license of a small technology supplier is lower when its invention is more general.

A second common determinant of the buyer's efficiency in localizing the external technology is its ability to learn new external knowledge (Cohen and Levinthal 1989). When the buyer firm is less able to integrate and exploit external inventions, the firm faces a lower productivity in developing technologies licensed from the markets for technology. This lack of efficiency from the perspective of the buyer, as we have argued in Proposition 1, will reduce the technology supplier's gain from licensing in industries where development is costly due to the use of cospecialized assets in innovation. We therefore formulate the following hypothesis:

Hypothesis 1b: The marginal effect of complementary assets cospecialization in the potential buyer's industry on the incentives to license of a small technology supplier is lower when the learning capability of the potential buyers is low.

3.2.2 Knowledge Transfer Capabilities and the Potential Buyer's Productivity in Localizing External Technology

In this section, we focus on the factor that increases the buyer's efficiency in localizing external technology, thereby mitigating the challenges of markets for technology. In particular, the technology supplier's ability to transmit knowledge to users is critical for successful technology transfer (Teece 1977). This capability goes beyond the intrinsic nature of knowledge, and entails organizational processes and resources that effectively facilitate knowledge sharing and the transfer of know-how between the firm and the buyer of the technology (Kogut and Zander 1993). The technology supplier's knowledge transfer capability may also allow the firm to better identify the conditions under which its knowledge can be used effectively (Nelson and Winter 1982, Martin and Salomon 2003). To the extent that developing external inventions requires knowledge sharing and technical assistance from the inventors, the buyer's development cost would be lowered when the supplier has a higher knowledge transfer capability. Thus the knowledge transfer capability of the supplier should increase the gains from licensing.

Moreover, our model predicts that this knowledge transfer capability of the supplier and the buyer's productivity in developing external inventions act as substitutes in stimulating the incentive to license. After all, both types of capabilities facilitate necessary knowledge flow from the supplier to the buyer. If one side of the trade can not initiate the knowledge flow efficiently, the other side's ability to do so is especially essential for the trade. In other words, the supplier's efficiency of transferring knowledge to the buyer would partly supplement the buyer's lack of functions in internalizing necessary knowledge from the supplier. We thus propose the following.

I delete this part (Since our model suggests that both the knowledge transfer capability of the supplier and the buyer's productivity in developing external inventions reduce the costs of technology development in a cooperative setting, thereby increasing the gains from licensing, an increase in one of the two factors will reduce the marginal effect of the other on the incentives to license) because this language would easily lead people to ask why if A and B both reduces Y, A and B should be substitutes.

Proposition 2: The potential buyer's productivity in developing external inventions and the technology supplier's knowledge transfer capability act as substitutes in stimulating the incentives to license. In other words, the supplier's knowledge transfer capability is more important for licensing in the presence of the buyer's low productivity in developing external inventions than when this productivity is high.

Since the efficiency in localizing external technology critically depends on technology generality and the learning ability of the buyer, among other factors, we derive two hypotheses from the above proposition that will be subject to empirical testing. First, when the focal invention is general, the inventing firm's knowledge transfer capability is especially essential. The buyer's relative inability to assess and evaluate the general technology (Shane 2004) means the know-how and assistance from the inventors are particularly important. On the other hand, when the invention is targeted to a single use and industry and thus most likely created in an environment similar to the industry of use, the buyer is more capable of learning and assessing this invention without the assistance from the inventing firm. We thus formulate the following hypothesis:

Hypothesis 2a: The technology holder's knowledge transfer capability is more likely to facilitate licensing when the invention to be commercialized is more general.

Additionally, when the buyer firm is less able to integrate and exploit external inventions, the inventing firm's transfer of know-how as well as its technical assistance becomes more essential for the user firm to successfully develop and commercialize the invention. That is, the buyer is more likely to rely on the inventing firm's knowledge transfer capability. In contrast, if the buyer's learning ability is high, the inventing firm's skills in knowledge transfer and technical assistance matters less. We therefore formulate the following hypothesis:

Hypothesis 2b: The technology holder's knowledge transfer capability is more likely to facilitate licensing when the potential buyer's learning capability is low.

As a final note aimed at introducing our empirical strategy, it is important to stress that our theory and hypotheses are based on the assumption that the technology supplier aims to maximize the returns on its licensing decisions. Therefore, any factor facilitating –or hindering– licensing, is also expected to influence the returns on licensing or the marginal value of licensing. In other words, given that the supplier is most likely to choose licensing under the conditions summarized by our hypotheses presented above, we also expect these conditions to influence the marginal effect of licensing on the supplier's economic performance. For instance, since a supplier is more likely to enter licensing when complementary assets in the potential buyer's industry are cospecialized and when the buyer firm's productivity in developing the technology is high, we expect under these conditions the marginal effect of licensing on economic performance to be higher. Similarly, we expect the marginal effect of licensing on economic performance to increase with the supplier's knowledge transfer capabilities when there is lack of development productivity among potential buyers.

Therefore, our empirical strategy aims to provide evidence for both of the following: whether a firm enters licensing under our proposed conditions, and whether these conditions indeed complement the firm's licensing choice and have a performance effect. Combining both evidences, we should provide more robust normative rules for a company's vertical integration strategy in high-tech industries.

3.3 Data and Measures

3.3.1 Data

To test our hypotheses, we construct our sample and variables based on multiple data sources. We first provide a brief overview of the breath of our sources relating to our key measures. In particular, patents and trademarks data are taken from the small firm patent database constructed by Diana Hicks and Chi Research Inc. and sponsored by the Office of Advocacy of the Small Business Administration (SBA); Bronwyn Hall's NBER patent database; the USPTO patent-industry concordance file generated in 2005; the USPTO trademarks database. One of our key dependent variables, the licensing agreements of our focal firms, comes from the SDC Platinum alliances database available from Thomson Reuters. From this database we also gathered longitudinal information on each firm codevelopment alliances and industry-level licensing data. Industry level measures of absorptive capacity, patent effectiveness, and cospecialized complementary assets, some of which are used to test the robustness of our results, were obtained using the Carnegie Mellon Survey on industrial R&D (1994) (Cohen, Nelson and Walsh 2000). Longitudinal information on firm size was obtained from Corptech for the private firms and Compustat for the public ones. We used Compustat to measure a firm's market value for the public firms, used as an alternative to licensing to test the substitution and complementarity effects hypothesized in the paper.

The Chi Research-SBA patent database, in particular, defines our sample. This dataset contains detailed patent information on the population of over 1,200 private and public U.S. companies that generated at least 15 patents between 1998 and 2002. The strength of this database is that in identifying these companies, all establishments and subsidiaries were unified to the ultimate parent company and their patents counted towards the parent firm patent count.[2] Scholars have defined this set of firms as the population of U.S. "serial innovators," e.g. technology-based firms that were able to sustain innovation beyond the first great idea upon which the firm was founded (CHI_Research 2003, Hicks, et al. 2003, Hicks and Hegde 2005). From this database we selected the small firms (e.g. those with less than 500 employees) for which we could obtain longitudinal information for at least 3 years on employees either from Corptech or Compustat during the 1996-2007 period. Our final sample is based on an unbalanced panel dataset of 347 technology-based small firms with primary industry within and outside manufacturing, for a total of 3269 firm-year observations.[3] Among the top innovators in our database there are several pharmaceutical and information technology firms that vary in their emphasis on licensing.[4]

[2]Obtaining 15 patents in a 5-year window for a small firm reflects a strong inventive performance. The 15 patent threshold was necessary to ensure accurate firm identification for, essentially, the entire population of inventive firms in the U.S. (Hicks 2002). This is due to both the challenges of name-matching patenting entities to the ultimate parent and the high volatility among small firms, which are acquired or disappear regularly. In other words, substantial work must be done to ensure that the patenting entities are currently in business and independent, etc. Ignoring this point will compromise the integrity of the results (Tether, Smith and Thwaites 1997).

[3]The distribution of sample firms using the 2-digit SIC industry of primary activity of each sample firm is the following: Chemicals and Allied Products (SIC 28; No. of obs.=84); Primary Metal (SIC 33; No. of obs.=10); Fabricated Metal Products (SIC 34; No. of obs.=5); Industrial Machinery And Equipment (SIC 35; No. of obs.=36); Electronic & Other Electric Equipment (SIC 36; No. of obs.=73); Instruments and Related Products (SIC 38; No. of obs.=74); Other manufacturing (various SICs; No. of obs.=12); Automotive Dealers & Service Stations (SIC 55; No. of obs.=7); Holding And Other Investment Offices (SIC 67; No. of obs.=5); Business Services and Software (SIC 73; No. of obs.=12); Engineering & Management Services (SIC 87; No. of obs.=18); Other non manufacturing (various SICs; No. of obs.=11).

[4]Among the top innovating firms in our database we find pharmaceutical firms such as Isis, Alliance, Neurogen and NPS. These are small (less than 500 employees) public companies with a sustained record of innovation. Each has a core technology around which their research and development is focused. Alliance has perfluorochemical technology; Isis has antisense RNA based technology; NPS has calcium receptor technology, and Neurogen has a technology it calls the Accelerated Intelligent Drug Discovery platform. These companies enter into alliances with big pharmaceutical firms both for R&D and for commercialization and marketing purposes. There are also small information technology companies figure among the top patentees in our dataset. For example Candescent and Tessera. Candescent owns patents on thin cathode ray tube technology and focuses on a licensing

3.3.2 Licensing

For the measure of a firm's out-licensing activity, we count the number of out-licensing agreements made by the focal firm each year during our study period (1996-2007). The data comes from the SDC Platinum alliances database available from Thomson Reuters. We first identified the technology-based licensing agreements of our sample firms and used the deal synopsis to select only those in which the sample firms were the technology suppliers.[5] In the market value regression as explained in the next section, we also include the licensing count, using the log(1+x) transformation, along with an industry-level instrumental variable. Summary of statistics and correlations for this variable (as well as the remaining variables detailed below) are presented in Table 3.

business model. Tessera has semiconductor chip-scale packaging technology for demanding applications that finds its way into advanced consumer electronics devices. It earns money licensing its technology and has successfully litigated its patents against big firms (Chi Research Inc. 2003).

[5] Whenever the deal description was not clear, we searched archival news online to identify the out-licensing agreements of our sample firms.

Table 3: Correlation matrix and descriptive statistics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Out-licensing														
2	Market value	*0.04*													
3	Asset cospecialization	0.02	*0.09*												
4	Codevelopment experience	*0.24*	*0.09*	*0.15*											
5	Tot. sales potential ind. of use	*0.03*	0.02	*0.08*	*0.10*										
6	Patents	*0.09*	*0.12*	*-0.20*	*0.12*	*-0.04*									
7	Trademarks	0.01	*0.17*	0.02	*-0.03*	*0.03*	-0.01								
8	Employees	0.00	*0.27*	0.02	*0.07*	*0.08*	*0.09*	*0.12*							
9	Firm age	*-0.03*	*-0.04*	*-0.03*	*-0.05*	*0.09*	*-0.08*	*0.05*	*0.08*						
10	R&D	*0.06*	*0.66*	*0.13*	*0.17*	*0.04*	*0.08*	*0.08*	*0.27*	*-0.04*					
11	Cash Flow	*0.05*	*0.74*	*0.11*	*0.10*	*0.03*	*0.09*	*0.13*	*0.24*	*-0.05*	*0.56*				
12	Cash burn rate	-0.01	-0.02	*-0.05*	-0.02	-0.02	-0.01	-0.01	-0.02	0.04	0.01	-0.03			
13	Total assets	*0.06*	*0.73*	*0.13*	*0.18*	*0.03*	*0.12*	*0.14*	*0.59*	*-0.05*	*0.67*	*0.74*	-0.03		
14	Capital expenditure	*0.05*	*0.44*	*0.05*	*0.17*	*0.03*	*0.11*	*0.07*	*0.43*	*-0.06*	*0.41*	*0.50*	0.00	*0.65*	
	Mean	0.02	102.14	3871.02	0.19	1718648	4.75	0.71	216.69	20.85	7.04	9.76	12.13	40.83	1.40
	Standard Deviation	0.18	583.16	2864.28	0.77	809366	9.65	1.90	320.01	20.59	37	40.01	232.18	141.76	5.69
	Min	0	0	0	0	0.003	0	0	0	0	0	0	0	0	0
	Max	5	23378	14722	17.74	7634845	245	32	5000	148	2460	1399	5000	4094	182

Notes:
1) Correlations in italics are significant (p < 0:05).
2) N varies from 6834 observations in the case of variables available for both private and public firms to a minimum of 1853 for the case of public firms.
3) All US dollars are all in real terms deflated by the corresponding year's GDP deflator with the base year in 2005.

3.3.3 Market Value

In an alternative way to test our propositions for the subset of public firms in our study, we employ the focal firm's yearly financial market value obtained from Compustat. This variable is computed as the common shares outstanding multiplied by their year-end price measured in millions of U.S. dollars. We convert this variable in real terms using the corresponding year's U.S. GDP deflator with 2005 as the base year and transform the variable using natural logs. All financial variables in the paper have been deflated and transformed using the same methodology.

3.3.4 Cospecialized Complementary Assets

The measure of cospecialized complementary assets is computed using a two-step procedure. As a first step, we identify the industries where the firm's invention can be potentially used. The invention data (patents) comes from the Chi Research-SBA database covering the 1998-2002 period. Application industries of these patents are identified by matching the technological classes of each firm's patents into 2-digit Standard Industry Classification codes (SIC), using patent-industry concordance developed and maintained by the U.S. Patent and Trademarks Office's (USPTO).[6] The USPTO concordance links each patent class to one or more of the 57 industries/sectors (two- to four-digit SIC) that belong to twelve two-digit SIC sectors that are expected to produce the product designed by the patent or to use the new patented processes in the manufacture of their products. For example, the concordance links the patents of Maxigen, a biopharmaceutical company that has out-licensed its technology only to pharmaceutical firms, to three potential industries: industrial organic chemistry, pharmaceuticals, and professional/scientific instruments. This methodology to identify potential user industries is clearly broader than the method based on the industries in which a focal firm has actually licensed its technologies.

Once we identify the total number of application industries of the focal firm's invention through the sample firms' patent portfolios, we compute the natural logarithm of the average of the total number of new registered trademarks in each 2-digit SIC application industry and each year between 1996-2007 as our measure of Asset Cospecialization. We collect these data from the USPTO CASSIS Trademarks BIB database and match them to each 2-digit SIC industry.[7] According to the USPTO,

[6] An excerpt of this report is available at http://www.uspto.gov/go/taf/brochure.htm. Paul Harrison from the USPTO (Paul.Harrison@uspto.gov) provided us with the decision rules used by the USPTO for assigning USPCS classifications to a SIC classification: "1. Determine if patents in a USPCS subclass are product, apparatus and/or process. 2. If product - determine, type of establishment that would be engaged in producing that type of product. 3. If apparatus- determine, type of establishment that would be engaged in producing that type of apparatus. 4. If process - determine, whether process more closely related to the product of that process or apparatus used in the process then classify accordingly. 5. If unable to determine- then place in all possible SIC categories."

[7] Goods and services protected by trademarks are classified into forty-two international classes (http://www.uspto.gov/faq/trademarks.jsp#Application018). Most of these classes can be easily linked to the SIC industry classification system, at least at the 2-digit SIC level. For example, the first 3 classes are "Chemicals," "Paints," and "Cosmetics and cleaning preparations," which can be easily assigned to SIC 28 ("Chemicals And Allied Products.") For the trademark classes that can be assigned to multiple 2-digit SICs we used a "fractional count" method analogous to the

a trademark "identifies and distinguishes the source of the goods or services of one party from those of others". Trademarks can be conceived as an important measure of marketing capabilities (Fosfuri, Giarratana and Luzzi 2008, Gambardella and Giarratana 2008, Huang, Ceccagnoli, Forman and Wu 2009, Ceccagnoli, et al. 2010). Indeed, firms would not be able to sustain a trademark without being able to build the firm's distinctive identity in the product markets (Mendonca, Pereira and Godinho 2004, Fosfuri, et al. 2008, Fosfuri and Giarratana 2009). Prior research has also identified marketing capabilities as important specialized assets for commercialization in the sense that the capabilities are not readily accessed through the market (Chan, et al. 2007). By capturing a firm's brand-capital, trademarks are also characterized by a certain degree of asset-specificity, since such intangible asset is difficult to be re-deployed by alternative users (Williamson 1981).

As an alternative to trademarks, we also use a variable derived from the Carnegie Mellon survey on industrial R&D (CMS) (Cohen, et al. 2000) based on the frequency of face-to-face interaction between personnel from R&D and marketing or manufacturing units to measure cospecialized complementary assets at the industry-level, as in Arora and Ceccagnoli (2006). This measure is based on the idea that when complementary assets are cospecialized, an innovation and its subsequent commercialization are intertwined requiring ongoing mutual adjustments between the two (Kline and Rosenberg 1986, Teece 1992). Although the survey was conducted in the pre-sample period (e.g. in 1994), the importance of complementary assets in profiting from innovation has been shown to change slowly over time (Cohen, et al. 2000, Ceccagnoli and Rothaermel 2008). About 1,477 business units from a broad range of industries

way the USPTO counts patents by SIC codes for their "Patenting Trends in the United States" reports (http://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_pat_tr.htm#PATR), when a patent class can be assigned to multiple SIC industries. So for example since class 9 of the trademark classification system, "Electrical and scientific apparatus", can be assigned to two different 2-digit SIC industries, SIC in 36 ("Electronic & Other Electric Equipment") and SIC 38 ("Instruments And Related Products"), we assigned 50% of new trademarks registrations with a class code of 9 to each of the two SICs. The full concordance is available from the authors upon request.

responded to the CMU survey. We computed the share of business units in which R&D and marketing/manufacturing personnel interacted daily (the median frequency was weekly) for each industry defined at the 2-digit SIC level.[8] Then we used the average of this measure across the 2-digit SIC application industries listed in the focal firm patents. Since this survey-based measure is time-invariant, we only include it in our robustness analysis using a panel data random-effect estimation model.

3.3.5 Technology Generality and the Learning Capability of Potential Buyers

To test our first two hypotheses we split our sample firms into two groups based on factors that are expected to affect the buyer's efficiency in developing the seller's inventions: the generality of the invention to be commercialized, which decreases such efficiency, and the potential buyers' learning capability, which increases it. Below we detail how we measure these two constructs.

Technology Generality. We create a measure that indicates the extent to which an invention can be applied to multiple industries:

$Generality_i = 1 - \sum_{j}^{n_j} s_{ij}^2$, where s_{ij} represents the share of firm i's patents that can potentially be used in industry j. Here an industry is measured at the 2-digit SIC level, and the patents are granted to the firm between 1998 and 2002, the central portion of our sample period, consistent with the treatments for our measure for asset cospecialization.

Our generality measure differs from the patent generality indices suggested by Hall, Jaffe and Trajtenberg (2001) and widely used in the literature (Hall and Trajtenberg 2004, Hicks and Hegde 2005, Powers and McDougall 2005, Gambardella and Giarratana 2008, Ceccagnoli, et al. 2010). A major difference with our preferred index is that their measure for an invention's generality is computed using the share

[8]Respondents were asked: "How frequently do your R&D personnel talk face-to-face with personnel from the 'Production,' 'Marketing or Sales,' and 'Other R&D units' functions?". Responses were coded utilizing a 4-point Likert scale corresponding to daily, weekly, monthly, rarely or never.

of a firm's forward citations in its patents' technology classes. However, the use of forward citations could be in principle problematic in our study because our dependent variable may affect forward citations and thus the way we split the sample. More specifically, when a firm out-licenses a patented technology to a buyer, subsequent development by the latter can result in new patents that cite the licensed patent. As such, our sampling would not be independent of our dependent variable. Moreover, our notion of generality only requires a technology to have multiple application industries, as opposed to be dedicated to a specific user sector. In other words, a general technology, in our setting, does not necessarily have to be subject to continual technical advance, or induce improvement in the productivity of innovation in the user sectors, as per the classic definition of general purpose technologies a la Helpman (Helpman 1998), characteristics that are better captured by generality measures based on forward citations. Nonetheless, we also use this widely utilized measure to test the sensitivity of our results, which remain qualitatively unchanged.

Learning Capability of Potential Users. We also split the sample based on the buyers' capabilities in learning external inventions. Research on the incentives to innovate has suggested that a firm's ability to integrate and exploit external knowledge often correlates with a firm's R&D intensity (Cohen and Levinthal 1989). This is because R&D has two roles: the first serves to introduce new or improved products and processes; the second allows the firm to better exploit external knowledge flows (Cohen and Levinthal 1989). To better capture the latter, e.g. the learning capabilities of the buyers, we use both the average R&D intensity of the potential buyers and the percentage of R&D that is devoted to learning external knowledge. We compute the former using R&D expenditures and sales data from Compustat and use survey data to measure the concept of learning. In particular, we first calculate the average firm R&D intensity weighted by sales during the sample period for each 2-digit SIC industry using the total population of U.S. public firms.[9] We then weight the R&D intensity of the typical potential buyer using responses from the following question administered through the CMU survey (Cohen, et al. 2000): "Approximately what % of R&D projects in your unit were initiated to keep up-to-date with new developments?" We computed 2-digit SIC averages of this survey-based measure and multiplied them by the corresponding R&D intensity of the typical firm in each industry. In the case in which the inventions of a sample firm could be applied to more than one 2-digit SIC industry, we took the simple average of the 2-digit learning-based R&D intensities, and obtained our final measure of a Buyer's Learning Capability.

3.3.6 Knowledge Transfer Capability

We hypothesize that when potential buyers suffer from inefficiencies in developing external technologies, the supplier's knowledge transfer capability is especially important. Such capability reflects the supplier firm's skills to manage alliances, e.g. ability to coordinate and communicate with partners and to develop mutual trust and reciprocity to facilitate knowledge sharing (Schreiner, Kale and Corsten 2009), as well as its ability to transfer technology across firm boundaries and provide technical assistance. Empirically, we measure this construct with the natural logarithm of the number of times a sample firm participated in R&D alliances with other firms in the past, in which the focal firm's inventions are to be developed, which we label co-development experience. The stock of co-development alliances allows us to better capture the notion of technology transfer capability than the annual counts of these alliances. We compute the stock of these alliances using an 85% discount rate. Again, the alliance data comes from the SDC database which provides an indicator for the deals with R&D agreements. We then read through the deal synopsis to only select

[9] Note that a limitation of this measure is that it is only available for public firms. However, potential buyers in our theory are industry incumbents with downstream capabilities, which indeed are very likely to be both large and public.

deals aiming at developing the focal firm's technology.

The logic underlying this measure is that firms gain efficiency and capability in an action simply by repeating it over time, like in many other types of alliances and activities (Teece, Pisano and Shuen 1997, Zott 2003). Co-development activities related to basic information sharing, technical assistance, and trust/reputation building can therefore improve a firm ability to transfer its technology to partners more efficiently. Note, however, that the ability to transfer knowledge could also depend on the nature of knowledge, for example its codifiability (Teece 1977, Arora and Gambardella 1994, Hippel 1994, Arora 1995). Since the previous effect has been already established in the literature and the source of our measure is firm specific, we examine the robustness of our results to the inclusion of a common proxy for knowledge codifiability, based on backward references to science publications. As reported in the robustness section, the results are qualitatively unchanged.

3.3.7 Control Variables

Patents. We control for the time-variant amount of inventions available for commercialization to each firm with the number of successful U.S. patent applications in the licensing equation. In the market value regressions, we instead use the standard approach of including the depreciated stock of patents (Hall, Jaffe and Trajtenberg 2005).

Trademarks. We also control for the firm's own holding of complementary assets by counting the number of new registered trademarks the firm has in year t. Controlling for this firm-level variable, an increase in the importance of complementary assets in the industries where the inventions of the focal firms can be applied –e.g. our measure of cospecialized assets– represents a greater challenge for the commercialization of these inventions. As for the case of patents, we include the depreciated stock of a firm's trademarks in the market value regression, to better capture the intangible nature of marketing related assets.

Sales-weighted Number of Potential User Sectors. Our model focuses on the challenges of licensing a technology in a representative user sector. With reference to a general technology we thus only highlight the demand-side development challenges due to the localization of the focal invention. However, Bresnahan and Gambardella (1998), among others, show that licensing of general inventions is conditioned by the number of potential users and their average size. In particular, the division of labor is positively affected by an increase in the number of users. To control for these effects, we compute the number of potential user sectors weighted by each sector's product market size. Application sectors are identified using the patent-industry concordance developed by the USPTO, as explained in previous sections. We compute the yearly total market size in the potential user sectors based on the deflated 2-digit SIC sum of sales derived from the total population of Compustat firms.

Employees and Firm age. We control for firm size and age in all estimated models. Size is measured using the number of employees. For the private firms we collect this information from CorpTech, a large database that compiles technology companies' yearly information including employees and sales; whereas, we use Compustat for the employees of public firms. We obtain the age of a firm from the Chi Research/SBA database.

Cash burn ratio. Our theoretical model predicts that the weaker the bargaining power of the technology supplier, the less likely it will enter a successful licensing agreement (see Appendix A). Some entrepreneurial firms may have weak bargaining power typically when they have cash constraint, or a weaker financial position relative to buyers that are industry incumbents. We thus control for the focal firm's bargaining power by including in the right-hand-side of the market value regression a firm's annual Cash burn ratio, following the methodology of Lerner, Shane and Tsai (2003). This is computed as the ratio of the absolute value of the net income in year t to cash reserve (including cash and short-term liquidable investment such as letters of credit and marketable securities), for firms that have a negative net income. Firms that are profitable or running on a breakeven basis have a cash burn ratio of zero. Since this variable, as for other financial information explained below, is only available for public firms, we only use it in the benchmark estimation of the market value equation.

Other Financial Variables. In the market value regressions, where we focus on the subset of public firms, we also include standard financial variables such a firm's total assets, cash flow, capital investment and R&D investment. The latter is cumulated and depreciated using a 15% rate. All the financial variables used in the paper are collected from Compustat and converted in real terms using the corresponding year's U.S. GDP deflator with 2005 as the base year and transformed using natural logs.

Firm and Year Fixed Effect. A key feature of our benchmark estimation is the use of firm fixed-effects, which allows us to control for unobserved firm heterogeneity that is time-invariant. We also include a set of time fixed effects to control for time varying unobserved variables that have a common effect on firms' licensing and market value during the 1996-2007 period.

3.4 Statistical Analyses and Results

3.4.1 Statistical Methods

Because of the count and longitudinal nature of our licensing dependent variable, we estimate the Poisson individual-specific effects model. This model assumes that the number of out-licensing agreements of each firm in each year is Poisson distributed with a mean of $E(y_{it}|\alpha_i,\, x_{it}) = \alpha_i\, exp(x'_{it}\beta)$, where x_{it} is the vector of independent variables, β is a vector of parameters to be estimated, and α_i is the unobserved firm-specific effect possibly correlated with x_{it}. The latter is eliminated estimating the model using the conditional maximum likelihood estimator. Since our dependent variable has a higher variance than its mean, as shown in Table 3, we correct the standard error for over-dispersion when estimating the Poisson fixed effects model (Wooldridge 1999). We also estimate a random effects specification, as explained in the robustness section (Cameron and Trivedi 1986). The Poisson model implies that the estimated coefficients also have an elasticity interpretation, representing the percentage change in the expected count of the dependent variable for a unit change of the related independent variable. Since we use the natural log of the two main independent variables of interest, complementary assets and codevelopment experience, the estimated coefficients can be interpreted as standard elasticities and, therefore, provide information about the magnitude of the effects of interest.

As an alternative test of our hypotheses we also use a firm's performance approach. Since a firm's market value is determined by the current and future profitability of the firm, estimating a market value equation allows us to test the conditions under which a firm's out-licensing strategy and its knowledge transfer capability (as well as the cospecialized nature of downstream assets) are complements or substitutes. In particular, based on our model and hypotheses, we expect that downstream asset cospecialization and out-licensing are less likely to be complement with each other when buyers' productivity in developing the seller's invention is relatively low; additionally when this productivity is low, we expect a complementarity between the supplier's knowledge transfer capability and its out-licensing strategy.

Note that the market value approach has two challenges. The first has to do with the lack of financial data on private firms. For a cross-industry dataset like ours, this limitation cannot be overcome other than by only focusing on the set of public firms, which is the approach taken in this study. The second challenge has to do with the fact that a firm's out-licensing decision is an endogenous variable in our model. Although the conditional fixed-effect model tends to mitigate this problem, we also instrument for out-licensing using the yearly count of all technology licensing deals in the sectors where a firm's inventions could be used, obtained from the SDC Platinum database.[10] This avoids the potential correlation of licensing with unobserved firm heterogeneity that varies over time. The proposed instrumental variable has sufficient statistical power, since the first-stage F-test statistics is greater than 10, suggesting that it is correlated with the firm-level licensing variable at conventional level. We cannot test, however, whether our instrument is uncorrelated with the unobserved error, since we lack overidentification. This implies that the key identification assumption in our fixed-effects market value regression is that the time varying component of industry-licensing does not affect a firm's market value other than through the firm-level licensing decisions.

In the licensing and market value regressions presented below, our hypotheses are tested by splitting the sample based on the degree of technology generality of each focal firm's patent portfolio and the learning capabilities of their potential buyers.

3.4.2 Benchmark Results

Out-licensing. As a first result it is worthwhile to show the effect of cospecialized complementary assets on out-licensing in our full sample (e.g., the population of U.S. small technology-based firms). The effect is negative and significant at the 1% significance level (Table 4, column 1), against what would be expected according to the conventional wisdom. Using our model, this could be due to either the negative effect of cospecialized assets on the cost of developing the technology for the buyer or to their positive effect on transaction costs. These two latter effects tend to empirically offset the positive effect on the incentive to out-license due to an increase in the sunk investments needed to compete downstream, which licensing would instead avoid.

The benchmark estimates of the licensing and market value equations are shown

[10] Due to the interactions of out-licensing with asset cospecialization and co-development experience, we also include the interaction of the instrumental variable with the latter two explanatory variables as instruments.

in Tables 4 and 5. To test our hypotheses 1a and 1b, we split our sample of small technology-based firms into groups based on the median values of our measures of technology generality and the typical Buyer's Learning Capability in the application industries. Recall that, as we have argued, the buyers' productivity in developing the seller's invention is lower for the group of firms with more general technologies and for which the potential buyers are characterized by lower learning capabilities. As predicted by our Hypothesis 1a, table 4 shows that the effect of cospecialized assets is reduced for small firms with more general technologies. The difference in the coefficients, which represent elasticities, is large (going from -1.24 to -2.29) and significant at the 1% confidence level (two sample t-test statistics = -12.77). The elasticity of cospecialized assets is instead substantially increased in the group of firms with higher learning capabilities going from -2.8 to -1.8 (two sample t-test statistics = -10.94), as predicted by Hypothesis 1b. In other words, when the buyers are characterized by a low productivity in developing external technologies (e.g. the case of High G and Low L), the importance of asset cospecialization as a limiting factor in the markets for technology tends to increase.

Table 4: Benchmark results: licensing

Dependent variable: Annual number of outlicensing deals (Poisson Fixed Effects)

Independent Variables	**Full Sample**	**Generality** Low	High	*Difference ‡*	**Buyer's Learning Capability** Low	High	*Difference ‡*
Asset cospecialization	-1.44 ***	-1.24	-2.29 ***	-12.77 ***	-2.80 **	-1.76 **	-10.94 ***
	(0.59)	*(1.04)*	*-0.97*	(H1a)	*(1.28)*	*(0.79)*	(H1b)
Codevelopment experience	1.25 ***	0.42	2.30 ***	38.79 ***	3.34 ***	0.69 **	28.09 ***
	(0.49)	*(0.50)*	*(0.66)*	(H2a)	*(1.37)*	*(0.41)*	(H2b)
Sales-weighted number of potential user sectors	1.43	2.83	-1.85		4.57	1.43	
	(2.07)	*(2.21)*	*(5.02)*		*(4.95)*	*(2.61)*	
Patents	-0.03	0.13	-0.02		-0.30 *	-0.05	
	(0.11)	*(0.24)*	*(0.15)*		*(0.23)*	*(0.20)*	
Trademarks	0.02	-0.20	0.10		0.40	0.07	
	(0.23)	*(0.36)*	*(0.34)*		*(0.56)*	*(0.26)*	
Employees	-0.32 *	0.11	-0.50 *		1.03 *	-0.53 ***	
	(0.20)	*(0.32)*	*(0.38)*		*(0.69)*	*(0.23)*	
Firm age	0.85	1.43	2.10 *		-0.65	1.84 *	
	(1.02)	*(1.87)*	*(1.56)*		*(2.07)*	*(1.40)*	
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Firm fixed effect	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Number of obs.	*599*	*322*	*277*		*222*	*377*	
Number of groups	*54*	*29*	*25*		*20*	*34*	

- Robust standard errors in parentheses

‡ Two sample t-test statistics

*** significant at 0.01; ** significant at 0.05; * significant at 0.1

All independent variables are transformed using natural logs, i.e., log(1+variable), except for sales-weighted number of potential user sectors which is transformed using log (variable).

The buyer's inefficiencies in localizing external technology are in turn critically mitigated by the inventing firms' knowledge transfer capabilities. We test the related Hypotheses 2a and 2b by evaluating the effect of co-development experience within the samples split based on our measure of technology generality and the potential buyers' learning capabilities. As shown in Table 4, the estimated coefficient for co-development experience, which represents a standard elasticity, is much higher for firms holding more general technologies, going from 0.4 to 2.3 (two sample t-test statistics = 38.79), and much lower for firms facing buyers with strong learning capabilities, going from 3.3 to 0.7 (two sample t-test statistics = 28.09). These results indicate that the inventive firms' knowledge transfer capabilities are more valuable

Table 5: Benchmark results: market value

Dependent variable: log of Market value (Linear fixed effects with instrumental variables)

	Full sample	Generality			Buyer's Learning Capability		
Independent Variables		Low	High	*Difference ‡*	Low	High	*Difference ‡*
Asset cospecialization X out-licensing	-0.56	1.05	-1.36	-10.83 ***	-9.22 *	-0.04	-29.63 ***
	(1.71)	*(1.58)*	*(5.73)*	*(H1a)*	*(6.84)*	*(1.21)*	*(H1b)*
Codeveloment experience X out-licensing	5.75	-3.21	1.08	11.59 ***	2.54	1.78	2.24 **
	(6.38)	*(8.43)*	*(5.52)*	*(H2a)*	*(6.85)*	*(4.43)*	*(H2b)*
Outlicensing	-5.69	-0.17	9.03		72.07 *	-4.96	
	(7.78)	*(6.89)*	*(54.49)*		*(50.93)*	*(6.12)*	
Asset cospecialization	-1.43	-1.39 *	-1.64		-0.07	-1.89 **	
	(1.17)	*(0.92)*	*(1.78)*		*(4.47)*	*(0.81)*	
Codevelopment experience	-0.34	0.09	-0.04		0.09	-0.16	
	(0.48)	*(0.58)*	*(0.86)*		*(0.51)*	*(0.47)*	
Sales-weighted number of potential user sectors	-0.00	0.00	0.00		0.00	-0.00	
	(0.00)	*(0.00)*	*(0.00)*		*(0.00)*	*(0.00)*	
Patent (cumulative)	-0.13	-0.02	0.09		0.19	-0.32 ***	
	(0.14)	*(0.34)*	*(0.16)*		*(0.18)*	*(0.13)*	
Trademarks (cumulative)	0.11	-0.19	0.20 **		-0.07	0.09	
	(0.11)	*(0.26)*	*(0.13)*		*(0.23)*	*(0.16)*	
R&D investment (cumulative)	-0.09	-0.12	-0.18		-0.15	0.03	
	(0.18)	*(0.24)*	*(0.17)*		*(0.28)*	*(0.18)*	
Cash flow	0.00	-0.04	0.04		0.08	-0.00	
	(0.05)	*(0.08)*	*(0.08)*		*(0.07)*	*(0.05)*	
Cash burn ratio	-0.20 *	0.01	-0.10 *		-0.12	-0.27 **	
	(0.13)	*(0.21)*	*(0.10)*		*(0.19)*	*(0.13)*	
Total assets	0.27 ***	0.30 **	0.30 **		-0.07	0.34 ***	
	(0.10)	*(0.18)*	*(0.17)*		*(0.12)*	*(0.11)*	
Capital investment	-0.04	0.18	0.01		-0.08	-0.02	
	(0.10)	*(0.28)*	*(0.07)*		*(0.20)*	*(0.09)*	
Employees	0.00	-0.12	-0.02		0.32	-0.00	
	(0.18)	*(0.42)*	*(0.21)*		*(0.47)*	*(0.27)*	
Firm age	0.39	-0.70	-0.04		-0.47	0.26	
	(0.56)	*(1.09)*	*(0.74)*		*(0.94)*	*(0.57)*	
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Firm fixed effect	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Number of obs.	1467	755	711		495	990	
Number of groups	164	84	81		56	109	

- Robust standard errors in parentheses

‡ Two sample t-test statistics

*** significant at 0.01; ** significant at 0.05; * significant at 0.1

All independent variables are transformed using natural logs, i.e., log(1+variable), except for sales-weighted number of potential user sectors, cash flow, total assets, which are transformed using log (variable).

in the presence of low productivity in developing external technologies from the perspective of the technology buyer.

Market value. The results of the fixed-effects market value regressions with an instrumental variable, presented in Table 5, equally support our hypotheses. Although most of the coefficients of the interaction terms in each sub-sample are not statistically significant, the differences of these coefficients across the two groups are statistically significant with the expected signs, as predicted by our hypothesis. In term of the magnitude of the coefficients, note that since market value, asset cospecialization, and out-licensing are all transformed using the natural log of these variables in the performance regressions, and the estimated equations are linear, the magnitude of the effects of the interactions can be directly inferred from Table 3. With respect to the interpretation of the estimates, the coefficients of the interactions reflect the impact of asset cospecialization (and the seller's knowledge transfer capabilities) on the marginal benefit of the out-licensing strategy with reference to the market value of the firm.

Specifically, Table 5 shows that an increase in asset cospecialization tends to increase the marginal benefits of licensing when technology generality is low and to decrease such benefits when generality is high, supporting Hypothesis 1a. Indeed, a one percent increase in asset cospecialization would result in an increase of 0.011 on the elasticity of market value w.r.t. out-licensing when generality is low and a decrease of 0.014 on the elasticity when generality is high. When the sample is split using the buyer's learning capability, a one percent increase in asset cospecialization would result in a decrease on the elasticity of market value w.r.t. out-licensing by 0.092 when learning capability is low but the effect is null when learning capability is high, supporting Hypothesis 1b. With reference to the hypotheses on the knowledge transfer capabilities of the technology supplier, Hypothesis 2a and 2b, our estimates indicate that a one-percentage increase in our measure of codevelopment experience would result in a decrease of 0.032 on the elasticity of market value w.r.t. out-licensing when generality is low, but an increase of 0.011 on the elasticity when technology is more general. When the sample is split using the learning capability of buyers, a one-percentage increase in asset cospecialization would result in an increase of 0.025 on the elasticity of market value w.r.t. licensing when the buyer's learning capability is low, but the change in elasticity significantly decreases to 0.018 when the buyer's learning capability is high.

3.4.3 Robustness

Random effects panel data models and alternative measure of cospecialized complementary assets . Since the Poisson FE estimator does not use the observations when the dependent variable lacks the within-firm variation (i.e., firms that did not license over the 1996-2007 study period), we also adopt a random-effects (RE) specification to control for unobserved firm-specific differences in out-licensing, where the unobserved firm-specific effect is assumed to be randomly drawn from the population. Despite the disadvantage of relying on such strong assumption, the RE specification also allows us to examine the effect of an alternative time-invariant industry-level measure of cospecialized complementary assets derived from the CMU survey, which provides information on the degree of interdependency between R&D and downstream activities, as explained in a previous section.

The random effects model is estimated by including additional control variables that are time invariant, such as the Patent effectiveness in potential industries of use. Indeed, the strength of intellectual property rights protection is a key determinant of a firm's technology commercialization strategy (Teece 1986, Gans and Stern 2003, Arora and Ceccagnoli 2006). We measure this variable using the average patent effectiveness in the industries where a firm's inventions could be applied. The data comes from the CMU survey which asked R&D executives to report the percentage of their product and process innovations for which patent protection had effectively protected their firm's competitive advantage (Cohen, et al. 2000). This measure can vary across firms with similar primary business focus, since their inventions typically differ with respect to the industries of potential use. In addition, we include six dummy variables associated with a focal firm's primary industry defined at the 2-digit SIC level in the random effect estimation, to control for unobserved industry drivers of a firm's propensity to commercialize technologies through licensing.[11]

As a time invariant variable we also control for whether the firm is Public, to reflect differential access to finance. The results of the Poisson random effect model, presented in Table 6, show that all our hypotheses are again strongly supported.

[11] Eighty-five percent of the primary business of our focal firms has one of the following six SIC codes, which correspond to the industry fixed-effects: SIC 28, 35, 36, 38, 73, and 87.

Table 6: Alternative measure of cospecialized assets

Dependent variable: Annual number of outlicensing deals (Poisson Random Effects)

	Full Sample	**Generality**			**Buyer's Learning Capability**		
Independent Variables		Low	High	*Difference ‡*	Low	High	*Difference ‡*
Asset cospecialization (CMU)	-3.88	-3.26	-7.84	-17.19 ***	-4.65	3.34	-33.98 ***
	4.35	*5.61*	*9.28*	*(H1a)*	*5.34*	*8.02*	*(H1b)*
Codevelopment experiencea[a]	1.48 ***	0.92 ***	2.30 ***	117.59 ***	2.74 ***	1.01 ***	125.92 ***
	0.23	*0.30*	*0.37*	*(H2a)*	*0.45*	*0.31*	*(H2b)*
Sales-weighted number of potential user sectors[b]	0.32	0.89	-0.59		-0.84	1.57 **	
	0.43	*0.57*	*0.79*		*0.71*	*0.72*	
Patents[a]	0.23 **	0.33 **	0.46 **		0.48 ***	0.30	
	0.11	*0.16*	*0.18*		*0.18*	*0.16*	
Trademarks[a]	0.13	0.08	0.23		0.47	0.05	
	0.20	*0.29*	*0.31*		*0.36*	*0.26*	
Employees[a]	-0.22 *	-0.18	-0.32 *		-0.31	-0.23	
	0.13	*0.20*	*0.20*		*0.21*	*0.18*	
Firm age[a]	-0.33	-0.39	-0.03		-0.07	-0.34	
	0.23	*0.29*	*0.37*		*0.30*	*0.34*	
Public Firm dummy	*1.35* ***	*1.95* ***	*1.04* *		*1.56* ***	*1.23* **	
	0.38	*0.62*	*0.55*		*0.56*	*0.61*	
Patent effectiveness in potential industries of use (CMU)	*2.79*	*0.22*	*5.28*		*17.71* ***	*-1.71*	
	2.65	*3.58*	*4.28*		*5.48*	*4.39*	
Industry fixed effects	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Year dummies (1997-2007)	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Firm fixed effect (Random)	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Constant	(Yes)	(Yes)	(Yes)		(Yes)	(Yes)	
Number of obs.	*3253*	*1558*	*1695*		*1459*	*1794*	
Number of groups	*345*	*170*	*175*		*153*	*192*	

- Robust standard errors in parentheses

‡ Two sample t-test statistics

*** significant at 0.01; ** significant at 0.05; * significant at 0.1

[a]: transformed using natural log, log(1+variable). [b] : transformed using natural log, log (variable)

Finally, Table 7 presents a summary of tests of hypotheses using the licensing equation. In addition to the Poisson FE approach reported above, we estimate a negative binomial panel data model with fixed and random effects (whose coefficient estimates are not shown), as well as using the trademark-based or the survey-based measure of cospecialized assets. Our main conclusions remain unchanged.

Table 7: The summary of two-sample T-test statistics across estimation methods

	Poisson with corrected standard errors		Negative binomial		Negative binomial		Negative binomial with CMU measure of asset cospecialization	
	Fixed effects		Fixed effects		Random effects		Random effects	
	(H1a)	(H1b)	(H1a)	(H1b)	(H1a)	(H1b)	(H1a)	(H1b)
Asset cospecialization	-12.77	-10.94	-11.69	-11.44	-34.65	-24.54	-11.20	-17.31
	(H1a)	(H1b)	(H1a)	(H1b)	(H1a)	(H1b)	(H1a)	(H1b)
Codevelopment experience	38.79	28.09	38.65	33.67	176.63	104.22	195.09	142.28
	(H2a)	(H2b)	(H2a)	(H2b)	(H2a)	(H2b)	(H2a)	(H2b)

All numbers are two sample t-test statistics, significant at the 0.01 level.

Nature of knowledge. Our variable, the stock of prior codevelopment alliances of the supplier, should be interpreted as reflecting the technology supplier capability in knowledge transfer. However, it can be argued that the primitive driver of codevelopment is the nature of knowledge itself. Indeed, technology licensing transactions tend to be more effective when technologies are more easily codified (Teece 1977, Hippel 1994, Arora 1995). From this perspective, codevelopment may facilitate licensing by facilitating the transfer of tacit knowledge. To test the sensititivity of our result to the inclusion of a control for the nature of knowledge, we add the counts of references to scientific papers by the typical patent of the focal firm (Narin, et al. 1997) on the right hand side of the licensing equation. Our results, presented in Table 8, remain qualitatively unchanged.[12]

[12] We also included the science linkages variable on the right-hand-side of the market value equation, with similar results, which we do not include in the paper to save on space.

Alternative measure of generality. To test the sensitivity of the results related to our hypotheses 1a and 2a to the measure of generality used, we re-estimated the benchmark Poisson fixed-effects specification splitting our sample into two groups based on the median values of the standard measure of generality. Generality is typically measured based on forward citations, introduced by Hall, Jaffe and Trajtenberg (2001), computed as $Generality_i = 1 - \sum_{j}^{n_j} s_{ij}^2$, where s_{ij} = share of patent i's forward citations in patent class j. In their later work, Hall and Trajtenberg (2004) argue that this measure may bias towards patents that receive more citations because having more citations implies that more technology classes would be observed to have forward citations. To overcome this possible bias, they propose an adjusted generality index, $Generality_i' = Generality_i \frac{N_i}{N_i - 1}$, where N_i is the number of citations received by patent i. Using this measure, our conclusions based on the results presented in Table 9 are qualitatively unchanged.

Table 8: Adding a control for the importance of science

Dependent variable: Annual number of outlicensing deals (Poisson fixed-effects)

	Generality			Buyer's Learning Capability		
Independent Variables	Low	High	*Difference ‡*	Low	High	*Difference ‡*
Asset cospecialization	-1.26	-2.34 ***	-13.00 ***	-2.99 **	-1.80 ***	-14.07 ***
	(1.03)	*(1.00)*	(H1a)	*(1.31)*	*(0.76)*	(H1b)
Codevelopment experience	0.43	2.37 ***	38.84 ***	3.39 ***	0.69 **	35.31 ***
	(0.50)	*(0.69)*	(H2a)	*(1.39)*	*(0.40)*	(H2b)
Sales-weighted number of potential user sectors	2.68	-1.32		4.73	1.28	
	(2.25)	*(5.31)*		*(5.11)*	*(2.66)*	
Patents	0.09	0.05		-0.18	-0.1	
	(0.30)	*(0.15)*		*(0.28)*	*(0.23)*	
Trademarks	-0.20	-0.01		0.38	0.07	
	(0.36)	*(0.36)*		*(0.57)*	*(0.27)*	
Employees	0.11	-0.48		1.06 *	-0.5 ***	
	(0.33)	*(0.39)*		*(0.68)*	*(0.23)*	
Firm age	1.45	1.74		-0.17	1.93 *	
	(1.87)	*(1.51)*		*(2.10)*	*(1.37)*	
Linkage to science	0.03	-0.11		-0.11	0.02	
	(0.11)	*(0.10)*		*(0.16)*	*(0.07)*	
Year dummies (1997-2007)	(Yes)	(Yes)		(Yes)	(Yes)	
Firm fixed effect	(Yes)	(Yes)		(Yes)	(Yes)	
Number of obs.	322	277		377	222	
Number of groups	29	25		34	20	

- Robust standard errors in parentheses

‡ Two sample t-test statistics

*** significant at 0.01; ** significant at 0.05; * significant at 0.1

All independent variables are transformed using natural logs, i.e., log(1+variable), except for sales-weighted number of potential user sectors which is transformed using log (variable).

Table 9: Alternative measure of generality

Poisson (fixed effect): Licensing

Independent Variables	Generality: Low	Generality: High	*Difference ‡*
Asset cospecialization	-1.09 **	-4.01 ***	-34.97 ***
	(0.64)	(1.21)	*(H1a)*
Codevelopment experiences	0.96 *	1.64 ***	12.01 ***
	(0.69)	(0.68)	*(H2a)*
	4.72 *	-0.06	
Sales-weighted number of potential user sectors	-3.17	(0.09)	
Patents	0.04	-0.14	
	-0.13	(0.21)	
Trademarks	-0.10	0.33	
	-0.27	(0.44)	
Employees	-0.34 **	0.17	
	-0.18	(0.71)	
Firm age	0.08	2.43	
	-1.19	(2.32)	
Year dummies (1997-2007)	(Yes)	(Yes)	
Firm fixed effect	(Yes)	(Yes)	
Number of obs.	346	253	
Number of groups	31	23	

Linear (fixed effect and IV): Market value (log)

Independent Variables	Generality: Low	Generality: High	*Difference ‡*
	28.41	0.99	-12.99 ***
Asset cospecialization X out-licensing	(58.16)	(1.33)	*(H1a)*
	-8.27	5.46 *	12.94 ***
Codeveloment experiences X out-licensing	(28.91)	(4.24)	*(H2a)*
Outlicensing	-220.86	-10.61	
	460.56)	(10.79)	
Asset cospecialization	-6.90	-2.22 **	
	(9.88)	(1.12)	
Codevelopment experiences	-0.82	-1.00 *	
	(2.57)	(0.69)	
	-0.00	-0.00	
Sales-weighted number of potential user sectors	(0.00)	(0.00)	
Patent (cumulative)	-1.07	0.03	
	(1.63)	(0.14)	
Trademarks (cumulative)	-0.05	0.05 **	
	(1.27)	(0.08)	
R&D expenses (cumulative)	-0.71	-0.13	
	(1.36)	(0.18)	
Cash	-0.11	-0.00	
	(0.31)	(0.06)	
Cash burn ratio	0.01	-0.10 *	
	(0.39)	(0.10)	
Total assets	0.14	0.28 ***	
	(0.25)	(0.10)	
Capital expenditure	0.06	0.10 *	
	(0.77)	(0.07)	
Employee	0.66	-0.05	
	(1.39)	(0.12)	
Firm age	0.43	-0.18	
	(2.33)	(0.54)	
Year dummies (1997-2007)	(Yes)	(Yes)	
Firm fixed effect	(Yes)	(Yes)	
Number of obs.	759	708	
Number of groups	86	78	

- Robust standard errors in parentheses
‡ Two sample t-test statistics
*** significant at 0.01; ** significant at 0.05; * significant at 0.1
All independent variables are transformed using natural logs, i.e., log(1+variable), except for sales-weighted number of potential user sectors, cash flow, total assets, which are transformed using log (variable).

3.5 Discussion and Conclusion

We investigate some of the critical challenges and facilitating factors in the licensing of small firms' inventions. An important characteristic of commercializing these inventions is the need for further development and adaptation to the buyer's product market. When such development and adaptation is costly, such as when asset cospecialization in the buyer's industry is high, and when the buyer is inefficient in such endeavors, the buyer may be less willing to in-license and the small technology-based firm is more likely to integrate downstream. We thus explicitly incorporate the buyer's incentives to in-license into our theoretical discussion and view licensing as a bargaining problem in which both the inventing firm and the buyer determine whether to reach the licensing agreement based on their respective net gain from the deal and their respective outside options. Indeed, we find that when the buyer is less efficient in developing an external invention, asset cospecialization (although driving up the inventing firm's incentive to out-license) can deter licensing. This finding receives robust empirical support using a comprehensive panel dataset of small technology-based firms partly obtained from the U.S. Small Business Administration. We also find that the challenges to the licensing of small firms caused by the buyer's inefficiency in localizing external inventions can be mitigated by the inventing firm's knowledge transfer capabilities, such as those developed over time through co-development alliances.

This study bridges an important gap in the literature of markets for technology. Most of the literature has focused on the supply side of the market, i.e., the inventing firms' incentive to cooperate or to compete with established firms in the potential industries of use (Arora and Gambardella 2009). We contribute to this literature by examining the buyers' disincentives to in-license and point to factors that would allow sellers to overcome these challenges. A fuller consideration of the demand-side of the market also requires to relax the assumption that firms out-license an "innovation", as opposed to an "invention." Key limiting factors of the markets for technology are indeed represented by the development of the ideas owned by small technology-based firms.

Our consideration of the demand side extends and qualifies the predictions of Teece (1986) and Gans et al. (2002), who suggest that higher asset cospecialization, ceteris paribus, increases a small firm cost of acquiring downstream assets and thus its incentives to out-license. In contrast, our theory suggests that the sign of the marginal effect of an increase in asset cospecialization on the decision to license is ambiguous. In other words, due to the bilateral dependence between the upstream and downstream activities required to develop and commercialize technology, higher assets cospecialization does not necessarily ensure an increase in licensing of the start-up firm. For one, both the development cost and the cost of acquiring downstream assets are expected to increase with the level of asset cospecialization in the industry, with offsetting effects on the likelihood of licensing agreement. Secondly, we find that the effect of asset cospecialization depends on the buyer's efficiency in developing external technologies.

Recent research in the markets for technology has focused focus on the challenges of technology licensing related to the threat of expropriation by established firms of the proprietary knowledge of the technology supplier and the role of IPR in facilitating technology transactions (Arora, et al. 2001, Gans, et al. 2002, Gans and Stern 2003, Arora and Ceccagnoli 2006). It is worthwhile to point out that although our theoretical setting does not focus on such issues, the predictions of our model are robust to the possibility of knowledge spillovers and IP enforcement.[13]

This study also points out the role of firm capabilities in firms' R&D boundaries and the use of market for technology. We show that the R&D boundary of a firm does not just depend on transaction costs (Pisano 1990, Gans, et al. 2002), the appropriability concerns (e.g., strength of intellectual property rights) (Teece 1986, Gans, et al. 2002, Gans and Stern 2003, Arora and Merges 2004, Arora and Ceccagnoli 2006, Gans, et al. 2008), and the sunk costs of product market entry (Teece 1986, Pisano 1990, Gans, et al. 2002, Gans and Stern 2003), but also the learning capabilities of the buyers and sellers' knowledge transfer capabilities. Thus, the findings of this study contribute to a better understanding of the relationships between firm capabilities and boundary choice (Argyres 1996, Leiblein and Miller 2003, Jacobides and Hitt 2005, Mayer and Salomon 2006, Parmigiani and Mitchell 2009, Ceccagnoli,

[13] A more general model that allows for the incumbent to imitate the technology supplier and for the latter to enforce its IPR is contained in Appendix B.

et al. 2010, Qian, et al. 2010). Particularly, we suggest the capabilities of both sides of the trade matter.

Our study complements recent research highlighting the importance of technology generality as a key driver of markets for technology. Outlicensing a general technology to a broad set of industries should allow the start-up business to diversify its investments risk across applications and capitalize on a larger set of profit opportunities (Shane 2004). However, empirical evidence on the effectiveness of this commercialization strategy provides mixed results. Case studies focusing only on a few set of firms holding general-purpose technologies support the idea that generality stimulates licensing and firm performance (Shane 2004, Maine and Garnsey 2006). Gambardella et al. (2007) provide large scale empirical evidence suggesting that firms holding general-purpose patented technologies have a greater willingness to out-license, but conditional on the propensity to license of the technology supplier, the likelihood of licensing is unchanged. Scholars have therefore focused on factors that might condition the actual probability of licensing. In particular, the work of Gambardella and Giarratana (2008) focuses on the incentives to license a technology for an incumbent outside its product market based on the generality of its technology and industry fragmentation. They find that in more fragmented industries, incentives to out-license a general technology are higher, partly due to the fact that fragmentation tends to reduce the typical rent-dissipation effect of licensing by an incumbent with downstream capabilities to competitors. We complement this line of research work by focusing on the incentives to license general technologies to incumbents from the point of view of a small firm lacking downstream capabilities in the product market as well as providing systematic cross-industry empirical evidence.

We would also like to point out some limitations of our study. First, our analysis does not account for a third outside option faced by a small technology-based firm facing the commercialization decision: neither out-license the invention nor forward integrate, but rather shelve the invention for one industry and license it to another. This option is relevant for firms owning general technologies. Research on general-purpose technologies has shown that they can be potentially used in different industries (Bresnahan and Gambardella 1998, Hall and Trajtenberg 2004, Maine and Garnsey 2006), so the owners may choose which industry to license to. Thus, while considering these different choices and when to license to what industry is beyond our scope, we might not rule out the explanation that the finding that asset cospecialization reduces out-licensing when the technology is general is because firms of such technology can afford to shelve the invention (rather than compete) for the industries where the asset cospecialization is high. Nevertheless, our control for the number of potential user sectors may to some extent eliminate such a concern. Second, readers are cautioned that our measure of buyers' efficiency in developing external inventions is an average measure across all potential buyers, distinguished by the sector of use of the inventions. This may not be an accurate measure when buyers are highly heterogeneous within those industries (Klein and Kozlowski 2000). This suggests the merits of future research that empirically tests the likelihood of licensing at the buyer-supplier dyad level based on more fine-grained information about each potential buyer.

This study provides practical managerial guidance for small firms with a sustained record of inventiveness but with limited downstream capabilities. There are numerous examples of such firms: the specialist engineering firms in the second half of the 20th century designing chemical plants and related engineering services for large firms; the fabless semiconductor firms designing the software for the functioning of semiconductor chips; the biotech start-ups specializing in drug discovery for large pharmaceutical companies (Arora, et al. 2001). In these firms, licensing is often a vital component of the firm corporate strategy. Our study suggests that these firms should manage the licensing negotiation process paying sufficient attention to their buyers' capabilities in localizing external inventions to their specific needs and to the fact that buyers have an option to 'make' substitute technologies using internal R&D. In other word, managers of small inventive firms need to recognize under what circumstances they may face a challenge from the buyers in the market for technology, and more importantly, what factor may mitigate the buyers' disincentives in order to reach a successful licensing deal. As we have suggested, the inventing firm's capabilities in technology transfer and technical assistance, typically developed over time through past co-development alliances, facilitate licensing especially when the invention to be licensed is general and when the buyer has weak capabilities in learning externally generated inventions (e.g., a low absorptive capacity).

This study also provides guidance to managers from established firms who are increasingly in charge of commercializing inventions generated outside firm boundaries. Depending on the type of the invention and their capability of exploiting external knowledge, established firms may want to avoid relying on external inventions when commercialization requires cospecialized assets. Our results also imply that established firms should look for licensors with a strong knowledge transfer capability, identifiable by their past co-development alliances. The importance of licensor's knowledge transfer capability is highlighted in a recent survey by Zuniga and Guellec (Zuniga and Guellec 2009). They show that, in a representative sample of European patenting firms in 2007, 41% of respondents report that know-how transfer is involved in more than 20% of the out-licensing deals. In light of today's frequent demand for know-how transfer in licensing, inventors who are able to accomplish this transfer efficiently add critical value to their buyers.

CHAPTER IV

COMPETITION FROM ACADEMIC RESEARCHERS: HOW DOES IT AFFECT THE OPENNESS OF RESEARCH DISCLOSURE IN INDUSTRIES

4.1 Introduction

Corporate publishing has been a significant activity in many areas. According to a survey by ScienceWatch, IBM and AT&T were the most active publishers in computer science between 1991 and 2001, exceeding Stanford and MIT who are ranked third and fourth; in 'Pharmacology and toxicology', GlaxoWellcome and Merck were among the five most active publishing institutions based on citations (Penin 2007). The phenomenon has seemed to spread to companies that used to publish infrequently. Intel produced 64 scientific publications per year from 1980 to 1999, but the number increased to 302 per year in the last ten years according to ISI Web of Science. Similarly, Eli Lilly published an average of less than 30 papers per year prior to 1980, and the number jumped to 227 between 1980 and 1999 and to 433 during the past decade.

The significance of corporate publishing is surprising given that we traditionally consider industries as maintaining their scientific discoveries as trade secrets and the source of patenting (Gans, et al. 2008). Publications, however, offer valuable and unprotected knowledge to competitors without the assurance of any direct reward (Penin 2007). In fact, over three quarters of the users of IBM's ideas published in its Bulletin between 1996 and 2001 were other companies such as Apple Computers, Compaq Computer Corporation, Intel, Hewlett-Packard, Sun Microsystems, Texas Instruments, indicating that IBM's disclosures were very relevant to its competitors' research (Baker and Mezzetti 2005, Bar 2006). While glorifying increasing openness of firms towards innovation (Chesbrough 2003), many scholars have been intrigued by why firms voluntarily disclose important information in the public domain (Hicks 1995, Parchomovsky 2000, Eisenberg and Nelson 2002, Bar-Gill and Parchomovsky 2003, Baker and Mezzetti 2005, Bar 2006, Gans, et al. 2008, Gill 2008, Jansen 2008, Henkel and Jell 2009). Some studies suggest that publishing allows firms to attract research employees, investors and partners (Nelson 1990, Henderson and Cockburn 1994, Hicks 1995, Cockburn and Henderson 1998, Eisenberg and Nelson 2002); others suggest it increases the value of the research projects by encouraging complementary innovations (Bar-Gill and Parchomovsky 2003, Yang, Steensma and Phelps 2009). A recent review can be found in Penin (2007) about mechanisms through which firms may gain from publishing research findings.

Nevertheless, little research has examined how industrial publishing could have been driven by competing academic researchers and an increase in overlapping research areas of academia and industries. The traditional wisdom is that academic researchers focus on basic research, whereas industrial R&D labs conduct applied research. However, this distinction has become to blur in the past decades, especially since the Bayh-Dole Act in 1980 (see Rothaermel, et al. 2007). A significant number of researchers, especially in engineering departments, conduct applied research directly relevant to industry innovations (Rosenberg and Nelson 1994, Van Looy, et al. 2004, Sauermann and Stephan 2009, Sauermann, et al. 2010). Many academic researchers strive to achieve the fundamental understanding necessary to solve practical problems that also directly interest industries (Eisenberg and Nelson 2002, Gans, et al. 2008). As a result, it is inevitable that academic and industrial researchers may compete in the same research areas. The competition between the public and private sectors to complete the DNA sequence of the human genome is a vivid example (Eisenberg and Nelson 2002). Considering such interaction is highly relevant for both R&D managers and policy makers.

This study examines how competition from academic researchers affects firms' openness in disclosing research findings. To address this question, I develop two game theoretical models. The conclusion from both models indicate that research competition from academia in the same area as a firm's R&D projects increases the firm's incentive to publish, even though the firm would not have had such an incentive in the absence of the competition. The models also imply several conditions under which the effect takes place, such as strong belief about the research strength of the competing academic researchers (and/or their labs), high potential returns to developing the research into marketable innovations, as well as importance of earning scientific credit for the firm. I then discuss the implications of phenomena that may stifle the competition among academic researchers for priority: ownership fragmentation for research materials within the scientific community and academic researchers' engagement in entrepreneurial activities. As implied by my models, these phenomena might encourage withholding of research findings by firms.

4.2 Related Literature

During an innovation project, there can be a long lag between the initiation of the project and the creation of something of marketable value (Nelson 1959). During this process, a project may produce research findings that are important inputs for development of a new product and/or process. The firm could either keep the research findings as trade secret or publish them. I define publication as open knowledge disclosure, or voluntarily revealing knowledge to the public, without direct remuneration for the disclosure or being able to prevent others from accessing the disclosed knowledge (Penin 2007). Common channels of such publication include scientific journals, conference presentation and proceedings, as well as the Internet.

While scientists have long argued for free and wide communication of research results in the academic communities (Merton 1957, Nelson 1959), doing so comes at a significant cost for a company. Publication of research results communicates information to potential competitors, which is likely to fasten their introduction of competing designs. Moreover, once the knowledge is in the public domain, it is not possible for the discloser to establish an agreement with the recipients to ensure that the discloser will be remunerated (Penin 2007). Thus, conventional wisdom suggests that firms would usually try to keep their research confidential.

On the contrary, studies suggest significant evidences of open knowledge disclosure (Penin 2007). To name a few, Bar-Gill and Parchomovsky (2003) identified more than 1,000 small and large firms engaged in publicly disclosing their R&D findings; Baker and Mezzetti (2005), examining IBM's patents issued between 1996 and July of 2001, find that during this period IBM frequently published information about projects which it was actively pursuing; similarly in the pharmaceutical industry, Swiss pharmaceutical firm Novartis released on the Internet, for anyone to use, a vast amount of gene sequence data from its genome-wide analysis of more than 3,000 type 2 diabetes patients (c.f., Murray and O'Mahony 2007).

The question is why and under what circumstances companies choose to openly disclose research findings versus keeping them secret. A stream of studies address this question (e.g., De Fraja 1993, Hicks 1995, Lichtman, Baker and Kraus 2000, Parchomovsky 2000, Bar-Gill and Parchomovsky 2003, Baker and Mezzetti 2005, Bar 2006, Gill 2008, Jansen 2008, Mukherjee and Stern 2009). In a recent review of the literature, Penin (2007) presents eight motivations, which I summarize into four major categories: to earn scientific credit, to encourage complementory innovations and reduce costs of accessing them, to increase demand, and to undercut competitors.

4.2.1 Why do Firms Publish

First, publishing allows the sponsoring firm to earn credit for scientific achievements. This credibility in turn will benefit the publishing firm in several ways. It facilitates access to top scientific researchers and graduates since they are often reluctant to work for private firms if they will not be allowed to publish and maintain their scientific reputations (Cockburn and Henderson 1998, Eisenberg 2000). Because of information asymmetries, it might be difficult for graduates and researchers to identify which firm provides a stimulating research environment. Firms may therefore encourage publication in journals and conferences, to signal what they can offer to prospective employees (Penin 2007). Additionally, a firm may use its scientific reputation as a public relationship vehicle for funding (Hicks 1995, Eisenberg 2000). Investors such as public centers responsible for the allocation of public fundings arguably do not have all the expertise to know exactly which firm that will make best use of financial support; thus, firms who has credibility for research may be better positioned to receive such funding (Penin 2007). Moreover, publication may allow a firm to build the technical reputation necessary to engage in exchange of scientific and technical knowledge with potential partners (Nelson 1990, Henderson and Cockburn 1994, Hicks 1995, Cockburn and Henderson 1998). And again, publication reduces search cost for potential partners to identify collaboration opportunities. Finally, publication lowers costs of monitoring and rewarding researchers. Monitoring and measuring efforts of firm researchers are notoriously difficult and costly, but when their research outcomes are disclosed publicly, the performance can be scrutinized by the entire scientific community (Dasgupta and David 1994).

A firm may publish research findings also to encourage complementary innovations and reduce the cost of accessing them. Several studies suggest that placing research results in the public domain rather than holding them secret can better enable follow-on researchers to access and build on the disclosed information (Eisenberg 2000, Bar-Gill and Parchomovsky 2003, Belenzon 2006, Murray and O'Mahony 2007, Stein 2008, Yang, et al. 2009). The disclosing firms can benefit by getting feedback and learning from the follow-on innovators about their approaches (Yang, et al. 2009). As a result of internalizing other innovators' follow-up work, the original firm may earn a higher profit per R&D dollar (Belenzon 2006) and increase the rate of innovation (Yang, et al. 2009). As such, the value of a line of research increases as more and more subsequent innovators contribute to it. In another study, Harhoff and colleagues suggest that firms may benefit from their disclosure through stimulating better quality and better-adapted inputs at lower prices from suppliers (Harhoff, Henkel and von Hippel 2003). Although a firm could reveal information selectively to suppliers instead of openly, open disclosure may encourage entry of more competent suppliers. Finally, open knowledge disclosure among competitors may be motivated by an attempt to build an open-exchange environment in order to access complementory knowledge from the rivals in the future (Penin 2007). The spirit of all encouraging and benefiting from complementory innovations can be observed in Novartis's release of gene sequence data from its genome analysis study and the statement of the president of the Novartis Institute for Biomedical Research: "To translate this study's provocative identification of diabetes-related genes into the invention of new medicines will require a global effort" (Murray and O'Mahony 2007).

Furthermore, firms may want to publish research findings underlying a particular innovation in order to decrease the cost of adoption of this innovation. For instance, Harhoff finds that knowledge disclosed by a firm substitutes for R&D efforts by downstream users, reducing the equilibrium sunk cost of R&D for downstream firms and thus facilitates entry; the result is an expansion of downstream output and an increase in the demand for the publishing firm's products (Harhoff 1996). Particularly when the research findings are relevant for establishing an industry standard, releasing the findings to the public early before the end of an innovation project may allow the firm's innovation to become the standard as a result of a first-mover advantage and network effect (Penin 2007).

Finally, studies suggest that firms may choose to publish certain information defensively, often in a patent race, in order to prevent other firms from patenting the disclosed innovation or to extend the patent race (Lichtman, et al. 2000, Parchomovsky 2000, Baker and Mezzetti 2005, Bar 2006). For instance, by publishing and raising the novelty bar, the firms lagging behind a race may gain time to catch up with the leader and wins a patent (Baker and Mezzetti 2005). Bar (2006) further suggests this strategy works better for laggards with a higher chance of first conceiving a patentable invention (e.g., when they are patient and research intensive). These scholars also suggest a firm leading the race may also publish results to block the laggard if an extended race raises the costs of racing and discourages the laggard from racing aggressively (Baker and Mezzetti 2005) or even continuing the race (Lichtman, et al. 2000).

Many scholars have also challenged the feasibility of defensive publication (Eisenberg 2000, Lichtman, et al. 2000, Henkel and Pangerl 2008). First, publication does not necessarily prevent others from filing for a relevant patent under the U.S. patent system that favors the "first-to-invent"; the firm that invents first can still apply for a patent (Lichtman, et al. 2000) unless the publication comes out a year prior to the patent application date (Eisenberg 2000). In reality, it is very difficult for a firm using the defensive publication strategy to time its research disclosure so that it is public a year before its competitor applies for a patent. Additionally, the publication can be dangerous for the disclosing firm since the disclosure may instead help the competitor to get a patent: If the two firms are taking different approaches toward the same inventive goal, the publication may well help the second firm to draft patent claims and distinguish its invention from the published work (Eisenberg 2000). Moreover, the research stage of an R&D project typically produces an advance or discovery and does not produce information needed to make or use the discovery. Disclosure of such research information therefore cannot defeat a subsequent patent claim for how to make and/or use the discovery (Eisenberg 2000).

4.2.2 Research Competition between the Public and Private Sectors

A missing piece in this entire literature is research conducted by academic researchers who work in the university, research institutes, government or other non-for-profit laboratories. The ignorance of academic researchers in the consideration of R&D competition among firms naturally follows from the conventional account that public science and private R&D are independent, distinctive enterprises. The former's objective is to advance fundamental knowledge about the world and follow the norm of open disclosure; the latter is to solve practical problems in the hope of generating profits, seeking intellectual property rights protection for private profits generated from their research (Dasgupta and David 1994, Eisenberg and Nelson 2002). Academic research, although may eventually diffuse into the industry, was regarded to be irrelevant for the contemporal industrial R&D.

Eisenberg and Nelson (2002) point out that this conventional account, however, leaves out the often complex ways in which basic science and applied technology frequently overlap. One of many ways that the two institutions overlap is that the work of many academic researchers work in what Donald Stokes called the "Pasteur's Quadrant", combining both objectives simultaneously. For them, the objective is to achieve the fundamental understanding necessary to solve practical problems that also directly interest industries (Eisenberg and Nelson 2002, Gans, et al. 2008). As an example, both academic and industrial researchers are attempting to improve our understanding of causes of many diseases. Today many drugs are used to treat symptoms instead of causes because there is a lack of scientific understanding behind these diseases. Take chronicle hives (a skin condition) as an example, 95% of the cases are "idiopathic" (a medical term that means there is no discernible cause).[1] A better understanding of what cause a disease would greatly help pharmaceutical companies develop more effective drugs faster and at a lower cost.

Indeed, many academic departments are established to conduct research closely related to industrial technologies, including electrical engineering, mechanical engineering, chemical engineering, life science and medical departments. A significant number of researchers in these departments conduct applied research directly relevant to industry innovations (Rosenberg and Nelson 1994, Van Looy, et al. 2004, Sauermann and Stephan 2009, Sauermann, et al. 2010). In a recent survey, Sauermann and Stephan (2009) find that among a representative sample of academic researchers with a Ph.D. Degree in a science or engineering field, [2] roughly 35% of them report applied research as their primary activity.

Therefore, academic researchers are not completely isolated from industrial R&D competition geared towards practical solutions. At least during the research (the "R" of "R&D") stage of an industrial R&D race, academic researchers are very likely part of the competition, in parallel with their industrial peers to achieve knowledge necessary to solve practical problems. Nonetheless, the effect of competition from this broader community on firms' R&D disclosure remains understudied.

4.3 Models and Propositions

In this section, I develop two models to analyze how competition from academic researchers may affect a firm's strategic incentives to publish intermediate R&D results.

[1] Retrieved from http://www.aocd.org/skin/dermatologic_diseases/urticaria.html on May 18, 2010.

[2] Draw from all individuals living in the United States in the week of October 1, 2003 who either have a degree in science or engineering (S&E) fields or who are working in a science and engineering occupation and hold a degree in a non S&E field.

The analysis follows the studies that examine a firm's decision to disclose information in a multistage R&D contest in the presence of knowledge spillovers from disclosure (e.g., Gill 2008). In my models, two firms are competing to produce innovations such as a new product design. The innovation process is two-stage. The first stage produces intermediate R&D results (e.g., a discovery) necessary for continuing in the second stage. Completion of the second stage entails the progress toward a marketable design, with the rewards W going to the first one that completes it. This set-up would apply to a more realistic competition where the first stage is research and the second is development, as long as the payoff disproportionately favors the first firm to complete the research-development cycle. As in Gill (2008), I focus on a firm's publication decision at the end of the first stage and the subsequent competition between firms in the second stage.

The novelty of my models is to introduce academic researchers to the traditionally firm-only contests. Presumably, the main mission of academic labs is research, thus they compete with industrial labs only during the research stage.

In a nutshell, the two models reach similar conclusions about the effect of competition from academia despite describing two different competitive situations. The first model describes a head-on R&D competition in which two firms more or less know each other's competitive positions. A close example is contest among semiconductor firms (such as Intel versus AMD) to introduce smaller and more powerful computer chips. Presumably, established firms have typically developed a relatively sophisticated network (e.g., formal alliances and professional ties) to monitor and detect competitors' progress. Classical R&D race models in economics lend themselves to analyzing such head-on competition. The novelty of my model is introducing uncertainty due to research competition from academic researchers which may emerge from anywhere in the world. This uncertainty, as I will show in the next section, changes the firm's disclosure behaviors.

The second model describes a situation in which one of the firms is not as well informed. The uninformed firm spot a commercial opportunity to develop an innovation based on the current state of arts in the public domain (e.g., a recently published scientific breakthrough) and decides whether to be the first to introduce the innovation. We may call this firm an "entrant". The entrant is not informed that another firm (call it an "incumbent") has recently completed a research project and advanced the current state of arts. The incumbent decides whether to publish it. The incumbent is aware of potential entry and the competitive position of the entrant, but the entrant is not aware of the private progress of the incumbent unless the it is published. This one-way information asymmetry allows the incumbent using research disclosure to deter the potential entrant from developing the innovation.[3] If that is the case, I show that firms would publish regardless of competition from academic researchers. A key contribution of this model is that it further delineates the conditions under which academic peers might affect firms' research disclosure.

4.3.1 Model I

4.3.1.1 Without Competition from Academic Researchers

In this section, I introduce and analyze the head-on competition model. The model builds upon the two-stage research disclosure model in Gill (2008) without information asymmetry but with stochastnic process of R&D process as much of the R&D race models (Fudenberg, et al. 1983, Grossman and Shapiro 1987, Harris and Vickers 1987). In this model, both firms have already paid a sunk cost to enter the research stage of the two-stage contest. The timing and specification of the game is the following.

- t_0: Leader (A) completes the first stage and makes an intermediate discovery

[3] Besides different situations the two models attempt to capture, each model has its realistic aspects in some specifications but at the expense of simplifications in other aspects. Analyzing both models allow me to corroborate the findings from both.

with scientific value of $\sigma_1 \in (0, 1)$. Publication of this discovery produces scientific credit $\sigma_1 V$ for A. This value distinguishes my model from Gill (2008) in which the first-stage research results do not have any intrinsic value to the firm. Gill's assumption may not be true in the settings where firms intensively pursue scientific credit and reputation in order to attract investors and talented researchers, as in the case of biotechnology. These firms have relatively strong taste for science or desire for scientific credit, which is parameterized as V in my models. Firm A decides simultaneously whether to publish σ_1 and how much R&D effort to invest toward achieving the second stage. Let x denote A's R&D flow rate in stage 2. The time T_1 until A completes is a random variable distributed exponentially: $Pr(T_1 < t) = 1 - e^{-h(x)t}$, if $h(x) > 0$ (i.e., the flow rate of investment is non zero). For simplicity, we suppose $h(x) = x$, $x \in [0, 1)$. If $x = 0$ then A never completes. As such, the expected completion time $E(T_1) = 1/x$, if $x > 0$. The higher the x, the faster A moves towards the final achievement. The effort rate also increases the flow development cost $\frac{cx^2}{2}$, with c indicating a typical firm's development efficiency. The above specification for the innovation process in the second stage closely resembles the classical race models in the literature (Loury 1979, Dasgupta and Stiglitz 1980, Lee and Wilde 1980, Fudenberg, et al. 1983, Grossman and Shapiro 1987, Harris and Vickers 1987, De Fraja 1993).[4] I further assume that the discovery from the first stage helps A accomplish the second stage and reduce the flow cost of this stage to $\frac{1}{2}cx^2(1-\sigma_1)$. It is not uncommon that research results reduce development costs, and this is precisely why many companies conduct research. As an example, a better understanding of what cause Parkinson's disease would dramatically reduce the cost of developing treatment and drugs for the disease.

[4] In contrast, Gill (2008) incorporates technological uncertainty by giving W a stochastic value and supposing competing firms equal probability of winning the award if they both invest in the second stage.

- t_1 : Follower (B) discovers $\sigma_2 < \sigma_1$ and decides its flow investment rate $y \in [0, 1)$ for the second stage. The time T_2 until B completes the race is also a random variable distributed exponentially $Pr(T_2 < t) = 1 - e^{-yt}$. If A publishes at t_0, spillovers increase B's progress to σ_1 and reduce B's flow cost in the second stage to $\frac{1}{2}cy^2(1 - \sigma_1)$.

- t_2: Either A or B first completes the second stage and becomes the winner. Let $T = min(T_1, T_2)$ be the time until the winner emerges. One can easily show that T is distributed exponentially with a parameter $x+y$ if $x+y > 0$, and thus $E(T) = 1/(x + y)$ (Lee and Wilde 1980, Harris and Vickers 1987).[5] As such, the probability that a firm wins the race is a stochastic function that increases with own R&D effort rate and decreases with the other firm's. The probabilities are $x/(x + y)$ for firm A and $y/(x + y)$ for firm B. Achieving the second stage gives the winner an award (e.g., a patent or a marketable new product) which has a current value of W while the loser earns zero. The value of the award increases with the importance of the award and patent exclusivity in the case of competing for a patent.

If A publishes, A and B's respective expected returns are $\pi_A = \frac{xW - \frac{1}{2}c(1-\sigma_1)x^2}{x+y} + V\sigma_1$, $\pi_B = \frac{yW - \frac{1}{2}c(1-\sigma_1)y^2}{x+y}$.

In equilibrium, A and B's optimal rate of R&D is $x^* = y^* = \frac{2W}{3c(1-\sigma_1)}$. The higher the size of award and the more A's research progress which is published, the more aggressive are the two firms competing in the second stage. But the competition softens as their development efficiency decreases. A's expected return is $\pi_A^* = \frac{1}{3}W + V\sigma_1$, which increases with the size of award and the value of A's research progress.

[5] A more straightforward proof: the probability that neither firm completes by time t is $Pr(T > t) = e^{-xt}e^{-yt}$. Then at least one firm completes by time t is $Pr(T \leq t) = 1 - e^{-xt}e^{-yt} = 1 - e^{-(x+y)t}$. Thus T follows exponential distribution with a parameter of $x + y$, which leads to $E(T) = 1/(x + y)$.

If A chooses not to publish σ_1, A and B's respective expected returns are $\hat{\pi}_A = \frac{xW - \frac{1}{2}c(1-\sigma_1)x^2}{x+y}$, $\hat{\pi}_B = \frac{yW - \frac{1}{2}c(1-\sigma_2)y^2}{x+y}$. The $\hat{x}^*$ and $\hat{y}^*$ that maximize the above returns must satisfy the following first order conditions (F.O.C.):

$c(1-\sigma_1)x^2 + 2c(1-\sigma_1)yx - 2yw = 0$

$c(1-\sigma_2)y^2 + 2c(1-\sigma_2)xy - 2xw = 0.$

Let $a \equiv \frac{\hat{y}^*}{\hat{x}^*}$ and $b \equiv (1-\sigma_1)\hat{x}^*$, then it follows $\hat{x}^* \equiv \frac{b}{1-\sigma_1}$ and $\hat{y}^* \equiv \frac{ab}{1-\sigma_1}$. Thus the above F.O.C. become

$$\begin{cases} 2ab + b = \frac{2W}{c}a & (F.O.C.1) \\ \frac{1-\sigma_2}{1-\sigma_1}ab + 2\frac{1-\sigma_2}{1-\sigma_1}b = \frac{2W}{c}\frac{1}{a} & (F.O.C.2) \end{cases} \tag{1}$$

Dividing $(F.O.C.2)$ by $(F.O.C.1)$, we get $\frac{1-\sigma_2}{1-\sigma_1} = \frac{(1+2a)}{(2+a)a^2}$ and $b = \frac{2Wa}{c(1+2a)}$.

We now can derive comparative statics by identifying the range of possible value of a.[6] First, let δ denote $\frac{1-\sigma_2}{1-\sigma_1}$, thus $\delta > 1$. As such, it is easy to see that $a < 1$, which means $\hat{y}^* < \hat{x}^*$. That is, in equilibrium, firm A is more aggressive than B. The intuition is that completing the second stage costs A less than it costs B, thus winning the second stage is more valuable to A than to B, making A to act more aggresively than B. This implies that the more A is ahead of B in terms of the first stage results, the more aggressive is A in its second stage (i.e., $\frac{\partial a}{\partial \sigma_1} < 0$, $\frac{\partial a}{\partial \sigma_2} > 0$, all else equal).

Second, we can rewrite $\hat{\pi}_A^* = \frac{W}{1+2a}$, and the incentive to publish

$$\Delta \equiv \pi_A^* - \hat{\pi}_A^* = V\sigma_1 + W\frac{2(a-1)}{3(1+2a)}. \tag{2}$$

The first item of Δ is positive while the second is negative because $a < 1$. Thus the incentive to publish in the world without competing academia increases with the desire for scientific credit V and decreases with the final award size W. A's scientific progress σ_1 has an ambiguous effect: it increases the gain from scientific credit, but on

[6]This is done even without solving the cubic function for a, which gives us complex number solutions.

the other hand reduces the gain from competition. Finally, the incentive to publish increases with B's progress from the first stage σ_2. The intuition for the positive effect of σ_2 is that as B is closer to A in the race, publication has less to help B and thus less to lose.

4.3.1.2 With Competition from Academic Researchers

In this section, I consider the situation where firm A believes there is an academic research lab working on the same area. Suppose there is a probability α that the academic lab has completed the first stage with at least as valuable results as firm A (i.e., $\sigma_r \geq \sigma_1$) and a probability of $1-\alpha$ that the research lab has not exceed A in the first stage. The higher the α, the more likely that firm A would be scooped by the lab even if A does not intend to publish. Again, I assume that the academic lab's goal is to earn scientific credit by publishing research findings and that the lab does not participate in the second stage (e.g., product development part of an innovation process). This is more or less the case in general.

As a result, firm A's expected returns are:

$$\begin{cases} \pi_A^* - V\sigma_1 & if\ A\ does\ not\ publish\ and\ the\ academic\ lab\ has\ \sigma_r \geq \sigma_1\ by\ t_0 \\ \bar{\pi}_A^* & if\ A\ does\ not\ publish\ and\ the\ academic\ lab\ has\ \sigma_r < \sigma_1\ by\ t_0 \\ \pi_A^* & if\ A\ publishes \end{cases},$$

where $\bar{\pi}_A^* = \frac{W}{1+2\bar{a}}$ and $\bar{a}$ comes from (1) with σ_2 replaced by $max\{\sigma_2, \sigma_r\}$. Note that if $\sigma_r > \sigma_2$, firm B can adopt σ_r for the second stage.

It follows that A's incentive to publish when facing possible competition from academic research labs is $\tilde{\triangle} = (\pi_A^* - \bar{\pi}_A^*)(1-\alpha) + V\sigma_1\alpha$. Using the equivalent of (2) to replace $\pi_A^* - \bar{\pi}_A^*$, we have

$$\tilde{\triangle} = V\alpha + [W\frac{2(\bar{a}-1)}{3(1+2\bar{a})}](1-\alpha). \tag{3}$$

It follows that

$$\Theta \equiv \tilde{\Delta} - \Delta = W \left[\underbrace{\frac{2(\bar{a}-1)}{3(1+2\bar{a})} - \frac{2(a-1)}{3(1+2a)}}_{+} + \alpha \underbrace{\frac{2(1-\bar{a})}{3(1+2\bar{a})}}_{+} \right] \tag{4}$$

It is not difficult to see $\bar{a} \geq a$ and thus the first item of (4)is positive, since $\bar{a} = a$ if $\sigma_r \leq \sigma_2$ and $1 > \bar{a} > a$ if $\sigma_1 > \sigma_r > \sigma_2$. The second item of (4) is also positive since $\bar{a} < 1$. Thus, the possibility that an academic research lab is working in the same area as firm A increases firm publishing and thus the openness of scientific progress in industry. The effect is stronger if α and W are higher. I summarize these results in the following proposition:

Proposition 1 *In the head-on R&D competition between firms, the existence of academic researchers working in the same research area increases the leading firm's incentive to publish intermediate R&D results during the competition. The effect increases with an increase in α and W.*

The intuition behind the proposition is that firms publish more openly when they believe there are academic researchers working in the same area who might have more advanced findings to publish (i.e., $\sigma_r \geq \sigma_1$); if the firm does not publish first, it loses the chance of earning scientific credit. I should note that if the firm does not value scientific credit ($V = 0$), it has nothing to gain from publication regardless of the competition from academic researchers (both Δ and $\tilde{\Delta}$ negative). On the other hand, as long as $V > 0$, the size of V does not change the positive effect Θ. What changes this effect is α and W. Intuitively, a stronger belief (i.e., a larger α) that the academic researchers have exceeded the firm in research findings increases the firm's pressure to get the results publish. Additionally, the publication of research progress makes competitors more aggressive in the head-on R&D competition and reduces own chance of winning the race. Thus when a firm has a strong incentive to win the race (i.e., a large W), the firm would hardly want to publish research progress unless the firm is afraid of being scooped by academic researchers.

4.3.2 Model II

In this alternative model, I analyze the competition between an incumbent and a potential entrant with one-way information asymmetry. The timing and specification of the game are as follows.

- t_0: The state of the latest scientific progress in the public domain is at σ_0. Firm A, an incumbent firm, attempting to advance the state of the art, has completed the first stage research with a discovery $\sigma_1 > \sigma_0$ and decides whether to publish it before entering the development stage. The development stage typically costs C, which can be reduced by A's scientific progress. Thus for firm A, the second stage costs $C(1 - \sigma_1)$. Again, publication gives A a scientific credit of $V\sigma_1$.

- t_1 : An entrant (B) decides whether to introduce an innovation based on available opportunities (σ_0 if A has not published σ_1 or σ_1 if A has published it). As such, the second stage would cost firm B an amount of $C(1 - \sigma_0)$ or $C(1 - \sigma_1)$ depending on whether A has published σ_1. If A does not publish σ_1, B does not know that A has already been developing the innovation. Firm B only knows it is competing with A's ongoing project if A publishes it.

- t_2: If B decides not to develop the innovation, A is the monopoly and wins the race. Otherwise, one of the two firms first completes the second stage and becomes the winner. Recall that in the previous model the probabilities of winning is determined by the rates of R&D effort of each firm. This current model, however, replaces the decisions of R&D effort rates with Firm B's decision of whether to develop the innovation. Thus I specify the probabilities of winning differently. First, which firm wins depends on whether A publishes σ_1 and whether B enters the competition. Specifically, the incumbent's probability of winning is $\sigma_1/(\sigma_1 + \sigma_0)$ if B enters the competition and 1 if B does not enter. Second, because of information incompleteness for B, B makes its entry

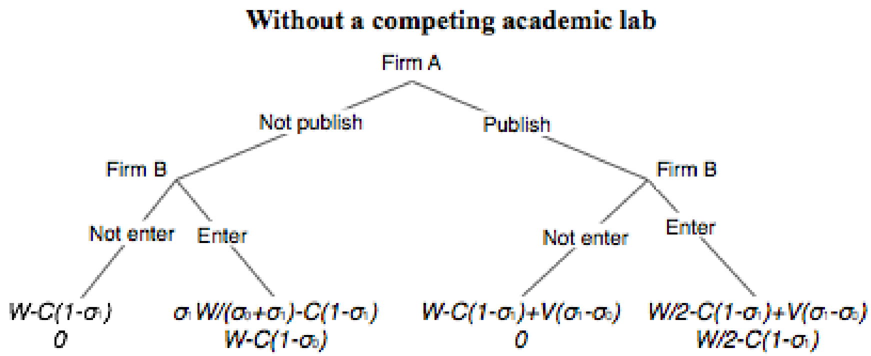


Figure 4: Game tree: without competing academic researchers

decision based on its *perceived* probability of winning. Entrant B's perceived probability of winning is $\sigma_1/(\sigma_1+\sigma_1) = 1/2$ if firm A publish σ_1 and 1 if A does not publish σ_1. Again, achieving the second stage gives the winner an award that has a current value of W.

As in the first model, if an academic research lab conducts parallel research, we assume a probability of α that by the time t_0 the lab has completed the research with σ_r that is at least as valuable as σ_1 and a probability of $1-\alpha$ that the lab has not exceeded σ_1. And as before, we assume the lab always publishes its research if nobody else has done so. Thus, if the lab has $\sigma_r \geq \sigma_1$ and publishes it at time t_0, the entrant would gain an equal footing as firm A in terms of the knowledge input for the development stage. The trade-offs and decision trees are shown here.

4.3.2.1 Cases when competition from academic researchers has no effect

Before I introduce the circumstance when firm A's publication decision is affected by competing academic researchers, I first show the two cases when the academic researchers have no effect on A's publication incentive. The first is when A's publication induces B to enter. In this case, A would not publish unless A strongly values scientific credit. The second is when A can use publication to deter B from entering. In this case, A would always find it worthwhile to publish intermediate R&D results.

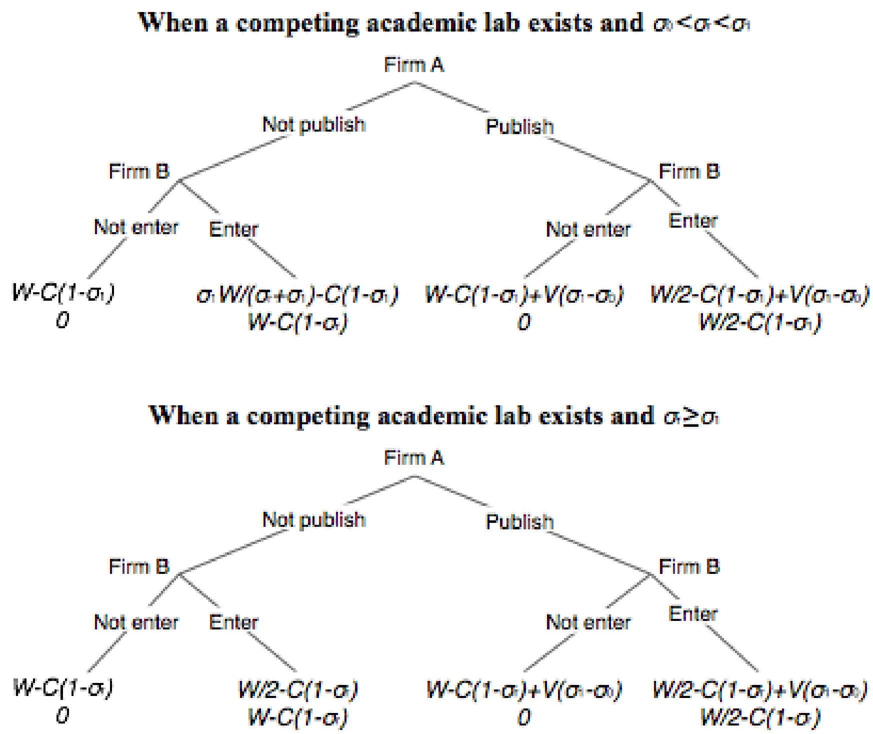


Figure 5: Game tree: with competing academic researchers

Case 1 *First consider the case when publication induces entry. This is when*

$$2C(1-\sigma_1) < W < C(1-\sigma_r) \text{ and } \sigma_1 > \frac{1+\sigma_r}{2}. \tag{5}$$

Under this condition, B would enter only if A publishes. Then absent competition from academic researchers, A would publish if and only if

$$V > \frac{W}{2(\sigma_1-\sigma_0)}. \tag{6}$$

When competition from academic researchers exists, A is better off to publish if and only if expected returns increase with publication. One can easily show that this condition is the same as (6) above. Therefore, competition from academic researchers does not make a difference in A's incentive to publish.

Case 2 *Then let us consider the case when A's publication deters entry. This occurs* *when*

$$C(1-\sigma_0) < W < 2C(1-\sigma_1) \; and \; \sigma_1 < \frac{1+\sigma_0}{2}. \tag{7}$$

Under these inequalities, B would choose to enter only if it is not aware of competition from A. In this case, if absent the competition from academic researchers, A would always publish since the returns on deterring B exceed the returns on competitng with B. The same logic also holds true when the competition from academic researchers exists.

The above analysis indicates that competition from academic researchers does not affect A's incentive to publish when publication induces entry (i.e., Condition (5)) and when publication deters entry (i.e., Condition (7)). Intuitively, the condition (5) means A would not want to publish σ_1 if it is highly valuable and gives B a large cut in entry costs. As a result, competition from academic researchers has no effect, and A would publish only if scientific credit for publishing is high enough. The condition (7) means regardless competition from academic researchers, A would always want to publish since it serves to deter B from enterring. Publication would possibly deter B if B does not expect a cost cut that is large enough to compensate the expected loss of award ($\frac{W}{2} > \frac{C(1-\sigma_0)}{2}$) due to the competition with A.

4.3.2.2 The Case When Competition from Academic Researchers Has an Effect

I will show that competition from academic researchers increases A's publication incentive only when B chooses to develop the innovation regardless whether A publishes or not. In reality, this might be the case when B is aggressive and has strong incentive to compete. Below inequalities describe this situation:

$$W > max\{C(1-\sigma_0),\ 2C(1-\sigma_1)\},\ or\ equivalently\ C < min\{\frac{W}{1-\sigma_0},\ \frac{W}{2(1-\sigma_1)}\}. \tag{8}$$

Under this condition and in the absence of competing academic researchers, firm A would publish if and only if

$$V > \frac{W}{2(\sigma_1 + \sigma_0)} \equiv \bar{V}. \tag{9}$$

In contrast, when expecting competition from academic researchers, firm Awould publish if and only if

$$V > \frac{W(1-\alpha)\frac{\sigma_1 - \sigma_r}{\sigma_1 - \sigma_0}}{2(\sigma_1 + \sigma_r)} \equiv \hat{V}. \tag{10}$$

It is easy to see that $\bar{V} > \hat{V}$. As a result, the value range of parameter V that induces firm A to publish is larger when there is competition from academic researchers. In other words, A is more likely to publish its research progress when expecting academic researchers to compete for priority. The effect is stronger if $\bar{V} - \hat{V}$ is larger, that is when α, W and σ_r are higher, and when σ_1 is smaller, conditioning on the (8) above. I summarize these results in the following proposition.

Proposition 2 *Consider the R&D competition between an entrant and incumbent, the existence of academic researchers working in the same research area increases the incumbent's incentive to publish its research progress. The effect*

(i) increases with an increase in α, σ_r, and W conditioning on $W > max\{C(1-\sigma_0),\ 2C(1-\sigma_1)\}$ or $C < min\{\frac{W}{1-\sigma_0},\ \frac{W}{2(1-\sigma_1)}\}$;

(ii) is absent if σ_1 is less than $1 - \frac{W}{2C}$; beyond this cut-off point, the effect become positive but reduces as σ_1 further increases;

(iii) is absent if V=0.

Again, the intuition in (i) and (iii) is that firms publish more openly if they expect to being scooped by academic researchers (i.e., α, σ_r) and value the chance of earning scientific credit. Also an increase in the expected return on innovation (i.e., W) increases the potential risk of publishing since it helps competition; thus without competition from academic researchers, the firm would not choose to publish. Competing academic researchers and entry-deterrence serve as substitutes, both driving firms' publication; thus the effect of competing researchers diminishes as firms use publication to deter entry (e.g., when the cost of developing an innovation C is high, and when the benefit of entry W is small). The intuition for (ii) is that an incumbent can use publication to signal competition and deter an otherwise optimistic entrant when the incumbent's research value (i.e., σ_1) is limited and hardly enables the entrant's development process. On the other hand, when the incumbent's research value is high enough to assist the entrant's development, the incumbent becomes unwilling to publish and would only publish if facing competitive pressure from academic researchers. The effect of this pressure diminishes as the value of the incumbent's research further increases, because of the counteracting effect of research disclosure on assisting entrants.

4.4 Discussion

This study argues that parallel research in academia affects a firm's research disclosure behavior in industrial R&D competition. Prior research finds a significant number of researchers in universities conducting research directly relevant to industry innovations (Rosenberg and Nelson 1994, Van Looy, et al. 2004, Sauermann and Stephan 2009, Sauermann, et al. 2010), indicating possible competition between academic and industrial research. In this competition, information asymmetry may exist since research in academic communities have no organizational or national boundaries and may emerge in many universities or countries. Certain research projects in governmental labs may even be confidential until completed and published. Thus, a firm can hardly ensure that no academic researchers somewhere in the world scoop the firm and publish similar or better results. If academic researchers claim the priority, every firm involved in the competition will be aware of the discovery and can freely access and use it. Had a firm attempted to block competitors from getting the results by keeping them secret, this attempt would fail to a large extent. Accompanying this failure is a loss of benefits associated with scientific credit, such as reputation, visibility and attractiveness to potential stakeholders. To the extent that scientific credit is important, competition from academic researchers makes the firm more aggressive in disclosing research results.

My models also imply several factors that influence the effect of competing academic researchers. These factors include the importance of earning scientific credit for solving the research problem, the research strength of the competing academic researchers, as well as the size of award for the final product of the R&D project. Additionally, the effect of competing academic researchers also increases nonlinearly with the value of the firm's solution in the case of an incumbent facing potential entry. Specifically, the effect peaks at an intermediate level of the solution value, and beyond this point, the effect decreases due to two counteracting competition effects (the competition for priority with academic researchers and the competition with other firms for a final innovation). These testable hypotheses, along with the main effect of competing academic researchers on industrial publications, are subject to empirical testing which I will conduct in a follow-up study.

4.4.1 The Assumption of Openness in Academic Communities

Note that the effect of competing academic researchers is conditioned on an assumption implicit in the models: academic researchers publish instead of withholding their research findings. Because of the importance of this assumption, I explicitly discuss its validity and the implication of violating this assumption in this section.

It is commonly known that academic researchers are fully motivated to publish their research findings promptly and extensively in order to claim priority earlier than others (Merton 1957, Merton 1973, Hagstrom 1974). Merton comments that the race to establish priority is "far from being a rare exception in science..." and has "practically become an integral part of the social relations between scientists. Indeed, the pattern is so common that the Germans have characteristically compounded a word for it." (Merton 1957) (P637). Merton's comment draws extensively from his observation of a long history of priority fights among famous scientists, including those famous disputes between Charles Darwin and Alfred Russel Wallace, and between Issaac Newton and Gottfried Wilhelm Leibniz. The root for priority fights, Merton concludes, is the institution of science that emphasizes originality as a supreme value and that rewards scientists' originality with recognition. This institutional norm, along with the moral imperative to make one's work known to others, motivates scientists to publish (Merton 1957). Publication serves two purposes. First, publication allows individual scientists to claim priority and to be known by peers. As Merton notes, recognition for priority is "socially validated testimony that one has successfully lived up to the most exacting requirements of one's role as scientist" (Merton 1957) (P640). Publication also serves as a currency for scientists to secure positions in an academic departments or society (Dasgupta and David 1994), or helps them to attract grants and students for follow-on research. Overall, priority directly links to reputation and rewards that academic researchers receive; and publications are the most important avenue towards that priority. Thus, unlike their industrial counterparts, academic researchers have strong incentive to publish their research findings promptly and extensively.

Although the assumption generally holds, there are also exceptions. An exception is when the researcher's incentive to publish is inhibited by commercial interests. For instance, the researcher might be partly funded by industries, and therefore would be constrained from publishing promptly. Nevertheless, the delay periods are normally quite short (Dasgupta and David 1994). A researcher may also be personally engaged in commercial activities, such as patenting and starting a company, and therefore refrains from publishing as companies normally do. In other cases, academic researchers may be constrained in making research progress because of difficulty of acquiring necessary materials, especially when the ownership of these materials are fragmented. In the following, I discuss the implications of these examples for publishing behavior in industries.

4.4.1.1 Entrepreneurial Activities of Academic Researchers

Scholars have observed a recent surge of university faculty involving in entrepreneurial activities including both business activities (such as patenting, developing a new firm based on their invention, a product or process in the market) and conducting research sponsored by industries (Thursby and Thursby 2004, Stuart and Ding 2006, Rothaermel, et al. 2007, Thursby, Thursby and Gupta-Mukherjee 2007, Fabrizio and Di Minin 2008). In a recent survey of a random sample of 414 academic researchers in genomics and proteomics, Walsh and colleagues find that these academic researchers spend 3% time in average on business activities and receive 4% of their funding from industries; the industry-funding percentage is higher (13%) for researchers conducting drug discovery (Walsh, Cohen and Cho 2007).

There has been an enormous debate on whether academic researchers' entrepreneurial activities affect their publication (Thursby, et al. 2007, Walsh, et al. 2007, Thursby and Thursby 2010). On one hand, their entrepreneurial activities may delay publication because they allocate less time to publication or they intend to secure patent applications (Thursby and Thursby 2002, Thursby and Thursby 2003, Murray and Stern 2007). Academic researchers may also keep research secret to ensure competitive advantage when behaving like industrial firms (Walsh, Cho and Cohen 2005, Walsh, et al. 2007). Walsh and colleagues find that academic researchers' business activities increase their tendency to keep research secret and refuse to share research materials with competing scientists, which in turn negatively affect other researchers' research outputs (Walsh, et al. 2005, Walsh, et al. 2007). There is also empirical evidence supporting delayed publication or research secrecy related to sponsored research and/or licensing, particularly exclusive licensing (Thursby and Thursby 2002, Thursby and Thursby 2003, Murray and Stern 2007). As a result, the scientific community where researchers are involved in more entrepreneurial activities may publish less promptly and fruitfully than a community where every researchers devote full-time to pure academic research. On the other hand, scholars suggest that entrepreneurial activities may instead increase researchers' overall research effort and outputs (Zucker, et al. 1998, Zucker, et al. 1998, Thursby, et al. 2007, Thursby and Thursby 2010). These studies provide two reasons. First, entrepreneurial activities may inspire and complement research (Murray 2002, Thursby and Thursby 2010). Second, faculty involved in entrepreneurial activities sacrifice their leisure time and devote more time for research (Thursby, et al. 2007, Thursby and Thursby 2010). Consistent with these argument, Zucker et al. (1998, 1998) found that the biotechnology scientists who start new enterprises are often the most productive researchers (in terms of publication) in their academic appointments. Thursby et al (2007, 2010) find that faculty licensing is followed by a flurry of publication of both basic and applied research. Nonetheless, these studies do not exclude the possibility that researchers may keep some research results secret and delay publication.

Therefore, it is likely that companies in a research community that is overwhelmed with commercial interest would be less willing to openly disclose research outcomes. To the extent that entrepreneurial activities of academic researchers encourages secrecy, we shall expect that these researchers would have limited impact on the publication decisions of companies conducting similar research.

4.4.1.2 Difficulty to Access Research Materials

Sharing of research materials such as gene sequences, cell lines, reagents, genetically modified animals, and unpublished information is critical to scientific advances (Watson 2001, Murray and Stern 2007, Walsh, et al. 2007, Haeussler, Jiang, Thursby and Thursby 2009, Huang and Murray 2009). Although academic communities have long emphasized on openness in sharing, recent data has suggested that academic researchers may refrain from sharing these research materials with competing researchers (Walsh, et al. 2005, Caulfield, Cook-Deegan, Kieff and Walsh 2006, Walsh, et al. 2007). After all, sharing would increase other researchers' chance of solving the problem first and claiming priority. Haeussler et al suggest that researchers share research inputs only when they expect reciprocity (Haeussler, et al. 2009). Individual researchers without access to needed materials suffer from lower research productivity. Take academic researchers in genomics and proteomics as an example, there is an average of one project abandoned for every nine academic researchers because of unfulfilled requests for materials (Walsh, et al. 2007). But a lack of sharing does not necessarily impede the entire academic community from generating a solution if at least some laboratories have all the necessary materials or resources to gain the materials. On the other hand, a lack of sharing does become a problem when ownership of research materials is fragmented, that is, each academic research laboratory owns some pieces of materials needed to solve the problem but not all. This would especially impedes research progress of the entire academic community when no facilitator exists to make important materials "open source", accessible at a low cost by all researchers. As a result, competition among academic researchers backfires and reduces the community's chance of solving the research problem. Therefore, we would expect that the effect of competition from academic researchers on industry publishing is reduced when sharing and accessing research materials are inhibited by competition among academic researchers, ownership fragmentation of the necessary resources or a lack of facilitators for material sharing (e.g., an open-source database of gene sequences).

4.5 Conclusion

I conclude this paper with potential contributions. First, the study adds to management research about when companies benefit or suffer from openness in innovation. Firms' decision to publish research is poorly understood in the management literature where publication is often merely an indicator of the firm's or scientists' research productivity (e.g., Henderson and Cockburn 1994, Zucker, et al. 1998, Zucker, et al. 2002, Rothaermel and Hess 2007). This study shows that publication decision is strategic and endogenous, and firms do not blindly publish research especially when facing R&D competition from other companies. Second, this study suggests that firms need to consider a broader research community and take into account of not just industrial competitors but also academic researchers working on the similar research projects. As indicated in this paper, the existence of competing academic researchers can potentially impact a firm's benefits/costs of disclosing research findings during R&D competition with other firms. I further make it clear the boundary conditions of the theory of this paper in order to enable future empirical testing.

Furthermore, the study implies the condition when it is socially desirable to have research conducted in for-profit firms as oppose to non-for-profit institutions. Nelson (Nelson 1959) suggests that in the absence of incentives of "for-profit" firms to publish research results quickly, a dollar spent on basic research in a university lab is worth more to society than a dollar spent in an industry lab. This study points out firms can also contribute to the social good if they value scientific credit and if they believe peers in academic labs may scoop them. As long as these conditions are satisfied and the industrial research productivity is comparable to those in universities, having firms conducting upstream research can still be valuable to the society. Finally, the findings that research competition from academic researchers facilitates knowledge dissemination by industry suggests an important implication for policy makers. Policies that encourage open sharing of research materials among scientists and that attempt to reduce secrecy among researchers can not only stimulate the sharing of knowledge among academic researchers, but also increase research dissemination by industrial firms and the overall scientific progress.

APPENDIX A

FOR CHAPTER III: A SIMPLE MODEL OF LICENSING

We develop a stylized model of technology commercialization through the markets for technology in the presence of asymmetries in the productivity in technology development between a small (e.g., lacking downstream capabilities) technology supplier (Firm 1) and an incumbent (Firm 2) that could potentially buy - or make - the focal technology (Gans et al 2002).[1] Within this framework, we analyze Firm 1's decision to vertically integrate and compete in the product market with Firm 2, as opposed to transfer of the rights to develop and commercialize the technology to Firm 2.

According to our setup, if a licensing agreement is reached, the buyer develops and commercializes the invention. The two firms share the monopoly profits π^m, with τ being transferred to Firm 1 and $\pi^m - \tau$ being captured by Firm 2. If negotiations break down, Firm 1 vertically integrates by developing the invention as well as acquiring the complementary assets (manufacturing, sale, and service) at a cost of A. In contrast, Firm 2 can either in-license the technology or invent a substitute technology in-house at a cost of I, followed by development and commercialization. In the latter case, the two firms compete in the product market, with each earning a profit of π^c. Note that these profits π^m and π^c do not include the investments in R&D and downstream assets. We separate out these investment costs in order to better illustrate how they affect commercialization choice.

[1] We also extended the model so that the incumbent can choose whether to imitate the entrepreneurial firm's invention, as in the model of Gans et al (2002). The model is available in appendix. Since our main results are unchanged, we choose the simplified model structure to better understand the underlying intuitions.

Since the focal technology needs development, we denote with $D(k, \cdot)$ the remaining development cost of the typical technology in this industry, which is independent of the productivity in development of the individual firms. Such costs are a function of the industry practices, standards and regulations, and the industry's cospecialization between development and downstream activities, represented by the parameter k, with $k \geq 0$. In the development cost function $D(k, \cdot)$, the notation "$\cdot$" represents other industry-related costs which we are not focusing on. For simplicity, we use $D(k)$ instead of $D(k, \cdot)$ to represent an industry's typical development cost.

Note that the buyer and supplier may be characterized by different development efficiencies and thus incur a lower development cost. To allow for this possibility, we specify the costs of development under the various options as follows:

$(1-\alpha_{11})D(k)$: the total development cost Firm 1 – the technology supplier– would incur if it develops its own invention. The parameter $\alpha_{11} \in (-\infty, 1)$ reflects Firm 1's productivity in developing its own inventions (the first subscript refers to the inventing firm, the second to the firm developing the invention). An increase in α_{11} effectively reduces the total development cost for Firm 1.

$(1-\alpha_{22})D(k)$: the total development cost that the incumbent Firm 2 would incur if it develops its own invention. The parameter $\alpha_{22} \in (-\infty, 1)$ reflects Firm 2's productivity in developing its internal inventions, e.g. an increase in α_{22} effectively reduces the total development cost for Firm 2.

$(1-\alpha_{12})D(k)$: the total development cost that the incumbent Firm 2 would incur if it develops the invention produced by Firm 1, e.g. when the markets for technology are used. Indeed, the parameter $\alpha_{12} \in (-\infty, 1)$ indicates how efficient it is for Firm 2 to develop an external technology, e.g. the invention introduced by Firm 1. In the paper, we have argued that this efficiency factor can be driven by the generality of the focal invention and the buyer's learning capability.

δ: the supplier's knowledge transfer capability, with $\delta \in (0, 1]$. Since knowledge

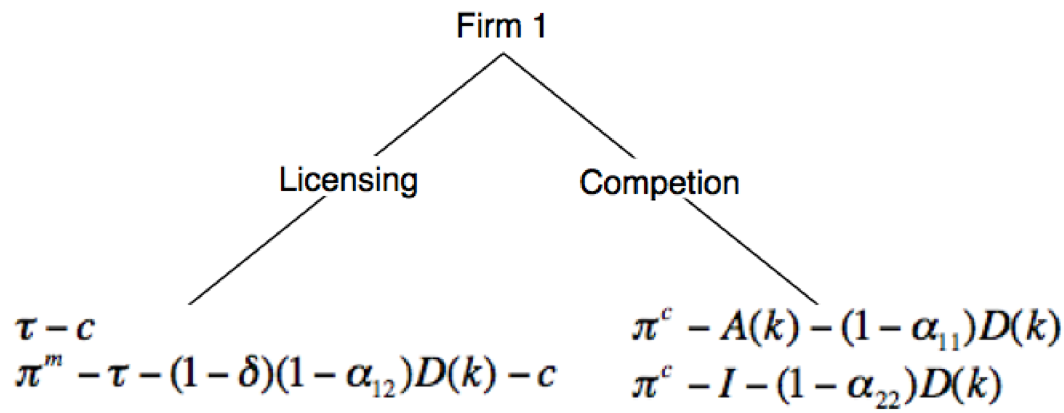


Figure 6: Game tree of a licensing negotiation between a small technology supplier and a potential buyer

sharing and technical assistance from the inventors facilitates the buyer's development efforts, Firm 2's development cost would be lower when Firm 1 has a higher knowledge transfer capability. We assume that the development cost is reduced by $1 - \delta$ and thus becomes $(1 - \alpha_{12})D(k)(1 - \delta)$.

Finally, an industry' asset cospecialization affects the commercialization costs A. In particular, if Firm 1 is to forward integrate into Firm 2's industry, and if in this industry the assets required to commercialize the technology are cospecialized, the sunk cost of vertical integration would increase (Teece 1986, Gans et al. 2002). Thus, we will denote A with $A(k)$.[2]

Figure 6 provides a summary view of the decision tree and payoff functions. The payoff with forward integration in the product market for Firm 1 is $\pi^c - A(k) - (1 - \alpha_{11})D(k)$. Meanwhile, Firm 2 earns $\pi^c - I - (1 - \alpha_{22})D(k)$. On the other hand, if the two firms reach a licensing agreement, they each incur a fixed transaction cost c, with Firm 1 earning $\tau - c$, and Firm 2 earning $\pi^m - \tau - (1 - \alpha_{12})D(k)(1 - \delta) - c$. The transfer τ from Firm 2 to Firm 1 is determined by the Nash bargaining solution

[2]In what follows, as mentioned in the main text, we suppose for simplicity that the transaction costs of licensing are fixed, although making them a function of cospecialized assets does not affect our main predictions.

(Nash 1950). Under this solution, the transfer maximizes the parties' joint net gains from the negotiation, i.e., the two parties both earn more from cooperating than from competing. In equilibrium, the transfer is:

$$\begin{aligned}\tau^* \;=\; & \max_{\tau}\{\underbrace{[\tau - c - \pi^c + A(k) + (1-\alpha_{11})D(k)]}_{1's\, net\, gains\, from\, licensing}^{b} \\ & \underbrace{[\pi^m - \tau - (1-\alpha_{12})D(k)(1-\delta) - c - \pi^c + I + (1-\alpha_{22})D(k)]}_{2's\, net\, gains\, from\, licensing}^{(1-b)}\},\end{aligned}$$

where b represents the bargaining power of Firm 1. For simplicity, we assume that the two firms have equal bargaining power in reaching a licensing agreement, and thus $b = 0.5$. Although our predictions are robust to relaxation of this assumption, the more general model suggests that a stronger bargaining power of the technology supplier increases the incentives to license. We therefore control for this factor empirically.

Solving for the value of τ that maximizes the joint returns to licensing we obtain $\tau^* = \frac{\pi^m + I - A(k) + [\alpha_{11} - \alpha_{22} - (1-\alpha_{12})(1-\delta)]D(k)}{2}$. In equilibrium, the transfer to the seller increases with several parameters such as the monopoly profit from technology commercialization under cooperation, the buyer's cost of inventing a substitute, and the seller's productivity of developing the technology in-house.

For the comparative statics analysis we compute the technology holder's gain from licensing net of transaction costs relative to vertical integration:

$\Delta = \pi^L - \pi^{NL} = \frac{\pi^m - 2\pi^c}{2} - c + \frac{A(k)+I}{2} + \frac{[(2-\alpha_{11}-\alpha_{22})-(1-\alpha_{12})(1-\delta)]D(k)}{2}$.

A licensing agreement will take place as long as $\Delta \geq 0$ or equivalently, [3]

[3] The conditions under which licensing as opposed to forward integration occurs in equilibrium are identical to the conditions under which the net returns to licensing for the technology startup are positive. This is because by assumption a higher return to licensing relative to forward integration gives Firm 1 an incentive to choose licensing. The Nash bargaining solution (the transfer of τ^*) enables both Firm 1 and Firm 2 to earn more from licensing than from their respective outside options.

$$\underbrace{(\tau * -c) + [\pi^m - \tau * -(1-\alpha_{12})D(k)(1-\delta) - c]}_{1\, and\, 2's\, net\, gains\, from\, licensing} \geq$$
$$\underbrace{[\pi^c - A(k) - (1-\alpha_{11})D(k)] + [\pi^c - I - (1-\alpha_{22})D(k)]}_{1\, and\, 2's\, net\, gains\, from\, competition}.$$

Comparative statics analysis. We start the comparative statics analysis by showing that the sign of the marginal effect of an increase in asset cospecialization on the decision to license is ambiguous. Indeed,

$$\frac{\partial \Delta}{\partial k} = \frac{1}{2}\left\{\underbrace{\frac{\partial A(k)}{\partial k}}_{+} + [\underbrace{(2-\alpha_{11}-\alpha_{22})}_{+}\underbrace{-(1-\alpha_{12})(1-\delta)}_{-}]\underbrace{\frac{\partial D(k)}{\partial k}}_{+}\right\}. \tag{11}$$

Our theory suggests that the ambiguity of the sign of (11) can be reduced by examining the interaction effects between cospecialized complementary assets and the productivity of the buyer's in developing external technology. Indeed, in the main text of the paper we state the following proposition:

Proposition 1*: The marginal effect of complementary assets cospecialization in the potential buyer's industry on the incentives to license of a small technology supplier is lower when the buyer's productivity in developing external inventions is low.*

Proof: The partial derivative of (11) with respect to α_{12} is $\frac{\partial^2 \Delta}{\partial k \partial \alpha_{12}} = \frac{1}{2}(1-\delta)\frac{\partial D(k)}{\partial k} > 0$.

Proposition 2*: The potential buyer's productivity in developing external inventions and the technology holder's knowledge transfer capability act as substitutes in stimulating the incentives to license.*

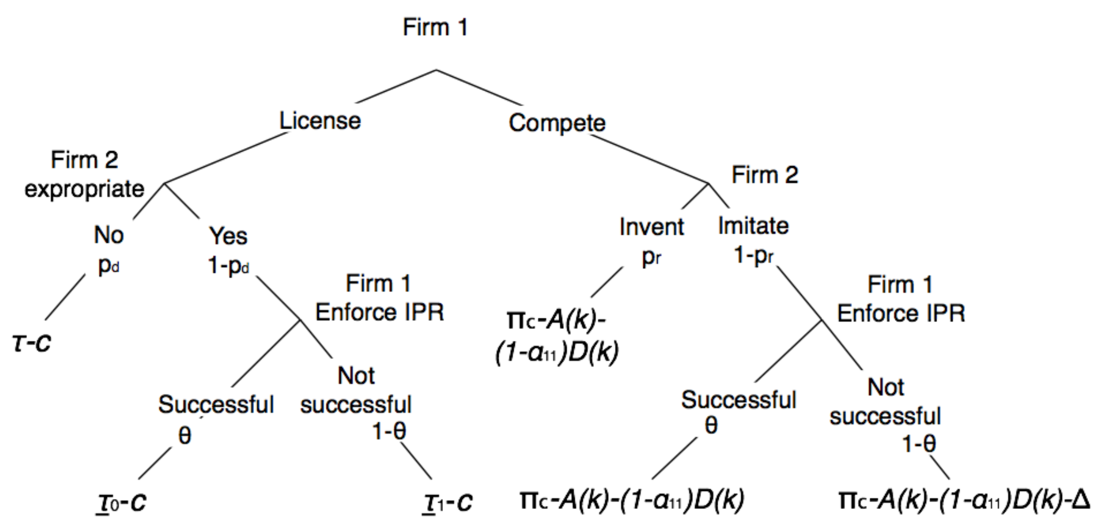
Proof: The partial derivative of Δ with respect to δ and α_{12} is $\frac{\partial^2 \Delta}{\partial \delta \partial \alpha_{12}} = -D(k) < 0$.

The four hypotheses presented in the paper follow from the above propositions, simply considering that the productivity in developing external inventions α_{12} *decreases* with technology generality and *increases* with the learning capabilities of the buyer.

APPENDIX B

FOR CHAPTER III: EXTENSIONS - THE BUYER IS ALLOWED TO IMITATE

Note that our simple model allows Firm 2 to invent an invention in-house without infringing Firm 1's inventions. In this extension, we consider the case when the infringement is possible and Firm 1 can enforce its intellectual property rights (IPR) in case of Firm 2's infringement. While our paper does not focus on the effect of IPR regime, our extension shows that the effect is consistent with prior studies (Gans et al 2002, Gans and Stern 2003) and the key conclusions above from our simple model continue to hold. The decision tree is as the following.



This set-up explicitly builds on Gans et al's (2002) model. Firm 2 can infringe in either case of licensing or competition. Specifically, when the two firms form the licensing deal, Firm 2 may expropriate Firm 1's invention disclosed to Firm 2 during the licensing deal with a probability of $1 - p_d$. And when the two firms do not form a licensing agreement, Firm 2 may imitate Firm 1's invention through reverse engineering with a probability of $1-p_r$. When Firm 2 infringes, Firm 1 may attempt to enforce its IPR with a probability of θ of success, with θ governing the strength of IPR. If Firm 1 fails to enforce its IPR, Firm 1's product market profits reduces by Δ and Firm 2's produt market profits increase by a similar amount. As such, Firm 1 faces a risk, with probability $(1-\theta)(1-p_r)$, that its profits are reducedΔ when negotiations break down.

But we depart from Gans et al's model by introducing the industry-average development cost for develping 1's invention in 2's industry, Firm 1 and 2's efficiency of developing in-house technologies (α_{11}, α_{22} respectively), Firm 2's efficiency of developing external technologies α_{12}, as well as Firm 1's knowledge transfer capability δ. As such, we replace the entry cost K for Firm 1 (Entrant) in Gans et al's model with the cost of developing the invention for Firm 2's industry as well as the cost of acquiring downstream assets to produce and sell the product: i.e., $K = A(k) + (1-\alpha_{11})D(k)$, where k is the parameter of asset cospecialization in Firm 2's industry.

The analysis is as the following. On one hand, if Firm 2 does not expropriate their cooperation, Firm 1's net returns are equal to

$$\underbrace{\tau - c - [\pi^c - \Delta(1-p_r)(1-\theta) - A(k) - (1-\alpha_{11})D(k)]}_{Firm\,1's\,Net\,Return} =$$
$$\underbrace{[\pi^m - \tau - (1-\delta)(1-\alpha_{12})D(k) - c] - [\pi^c - I + \triangle(1-p_r)(1-\theta)]}_{Firm\,2's\,Net\,Return}$$

$$\Longrightarrow \tau = \tfrac{\pi^m - A(k) - (1-\alpha_{11})D(k)}{2} - \triangle(1-p_r)(1-\theta) - \tfrac{(1-\delta)(1-\alpha_{12})D(k) - I}{2}$$

On the other hand, if Firm 2 expropriates the licensing deal, the share of the monopoly profits Firm 1 expects to receive would reduce. But Firm 1 can still threaten to reduce Firm 1's profits by competing in the product market (Anton and Yao 1994, 1995) and to enforce its IPR with probability θ. However, relative to payoffs in the absence of expropriation during licensing, the choice of licensing decreases Firm

1's potential competitive position and increases Firm 2's position. Using the same bargaining rule above, we have the following:

$$\underbrace{\underline{\tau}_0 - c - [\pi^c - A(k) - (1-\alpha_{11})D(k)]}_{Firm\,1's\,Net\,Return} =$$
$$\underbrace{[\pi^m - \underline{\tau}_0 - (1-\delta)(1-\alpha_{12})D(k) - c] - [\pi^c - I - (1-\alpha_{22})D(k)]}_{Firm\,2's\,Net\,Return} \text{ if IPR enforced;}$$

$$\underbrace{\underline{\tau}_1 - c - [\pi^c - A(k) - (1-\alpha_{11})D(k) - \triangle]}_{Firm\,1's\,Net\,Return} =$$
$$\underbrace{[\pi^m - \underline{\tau}_1 - (1-\delta)(1-\alpha_{12})D(k) - c] - [\pi^c - I - (1-\alpha_{22})D(k) + \triangle]}_{Firm\,2's\,Net\,Return} \text{ if IPR not enforced.}$$

That is, Firm 1's share will be:

$$\underline{\tau}_0 = \frac{\pi^m - A(k) - (1-\alpha_{11})D(k)}{2} - \frac{[(1-\delta)(1-\alpha_{12}) - (1-\alpha_{22})]D(k) - I}{2} \text{ if IPR enforced;}$$

$$\underline{\tau}_1 = \frac{\pi^m - A(k) - (1-\alpha_{11})D(k)}{2} - \Delta - \frac{[(1-\delta)(1-\alpha_{12}) - (1-\alpha_{22})]D(k) - I}{2} \text{ if IPR not enforced.}$$

Taken together, Firm 1's share under expropriation is $\underline{\tau} = \frac{\pi^m - A(k) - (1-\alpha_{11})D(k)}{2} - \triangle(1-\theta) - \frac{[(1-\delta)(1-\alpha_{12}) - (1-\alpha_{22})]D(k) - I}{2}$.

Therefore, Firm 1 will choose an out-licensing strategy as long as its expected profits from out-licensing is not less than the expected profits from competition:

$$p_d\tau + (1-p_d)\underline{\tau} - c \geq \pi^c - (1-p_r)(1-\theta)\triangle - A(k) - (1-\alpha_{11})D(k)$$

$$\Longrightarrow \frac{\pi^m}{2} + \frac{1}{2}[A(k) + I] + \frac{1}{2}[(1-\alpha_{11}) + (1-\alpha_{22})(1-p_d) - (1-\delta)(1-\alpha_{12})]D(k) \geq \pi^c + c + p_r(1-p_d)(1-\theta)\triangle.$$

Similar as the results from our simple model, the effect of k on the probability of licensing agreement is not necessarily positive. Asset cospecialization k has a positive effect on $A(k)$ and a negative effect on $-(1-\delta)(1-\alpha_{11})D(k)$. All else equal, the overal effect is more likely to be negative if α_{12} is lower. Additionally, the effect of δ on licensing is higher when α_{12} is lower.

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VITA

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