Strategic Management Journal
Strat. Mgmt. J., **32**: 55–75 (2010)
Published online EarlyView in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.866
Received 16 January 2008; *Final revision received 5 May 2010*

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

LIN JIANG,[1,2] JUSTIN TAN,[3]* and MARIE THURSBY[1]
[1] *College of Management, Georgia Institute of Technology, Atlanta, Georgia, U.S.A*
[2] *Robert J. Trulaske, Sr. College of Business, University of Missouri, Columbia, Missouri, U.S.A*
[3] *Schulich School of Business, York University, Toronto, Ontario Canada*

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. We argue, however, that incumbent firms have many reasons to proactively invent early in cycles of technological change. Our 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, we 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. We find support for our hypotheses using data from the global semiconductor industry between 1989 and 2002. Copyright © 2010 John Wiley & Sons, Ltd.

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., Christensen and Rosenbloom, 1995; Hill and Rothaermel, 2003; Mitchell, 1989; Rothaermel, 2001; Sinha and Noble, 2005; Teece, 1986; Tripsas, 1997; Tushman and Anderson, 1986). 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, 1993; Henderson and Clark, 1990), 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 (Day and Schoemaker, 2000; Gans, Hsu, and Stern, 2002; Hill and Rothaermel, 2003; Sinha and Noble, 2005; Teece, 1986). For instance, incumbents may enter niche markets and serve lead users to avoid cannibalizing

Keywords: emerging technology; nanotechnology; incumbent firm; technological change; public science; inventive output
* Correspondence to: Justin Tan, Schulich School of Business, York University, Toronto, Ontario, Canada M3J 1P3.
E-mail: jtan@schulich.yorku.ca

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 (Anderson and Tushman, 1990; Christensen and Rosenbloom, 1995; Martin and Mitchell, 1998; Mitchell, 1989; Tripsas, 1997). 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 (Christensen and Bower, 1996; Tushman and Anderson, 1986). 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 (Ahuja and Lampert, 2001; Darby and Zucker, 2003; Fleming, 2001; Fleming and Sorenson, 2001; Fleming and Sorenson, 2004; Henderson and Cockburn, 1994) and the types of search activities that contribute to the incumbents' active role.

THEORY AND HYPOTHESES

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, these emerging fields expand opportunities for existing firms and industries, but on the other hand, they challenge existing product designs and methods of production (Mitchell, 1989; Tushman and Anderson, 1986). 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

DOI: 10.1002/smj

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., Hill and Rothaermel, 2003; Tripsas, 1997; Tushman and Anderson, 1986), our focus is *not* on this eventual competition, but rather on the incumbent firms' inventive performance in 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.

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, 1998a). 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 (cf., 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 materials 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' (O'Reilly and Tushman, 2004: 74; Tushman and O'Reilly, 1996). 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

DOI: 10.1002/smj

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.

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, 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

[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).

DOI: 10.1002/smj

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).

Learning from collaborating organizations

Invention is one of the key motivations for organizations to collaborate (Ahuja, 2000; Hagedoorn and Duysters, 2002; Nicholls–Nixon and Woo, 2003; Rothaermel and Thursby, 2007; Sampson, 2007; Stuart, 2000). 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 (Tan and Peng, 2003; Thompson, 1967). 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; Lane and Lubatkin, 1998; Mowery *et al*., 1996). 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

DOI: 10.1002/smj

diversity of its learning alliance partners in terms of technological distance.

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 (Darby and Zucker, 2003; Henderson and Cockburn, 1994; Narin, Hamilton, and Olivastro, 1997; Thursby and Thursby, 2006; Zucker, Darby, and Armstrong, 2002). 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 (Darby and Zucker, 2003; Zucker, Darby, and Brewer, 1998b). The main reason is that unlike for-profit organizations, academic institutions are not constrained by the threat that the emerging field brings to 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 *et al.*, 1998a).

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 (Fleming and Sorenson, 2004; Pisano, 1994). 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).

RESEARCH DESIGN

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

DOI: 10.1002/smj

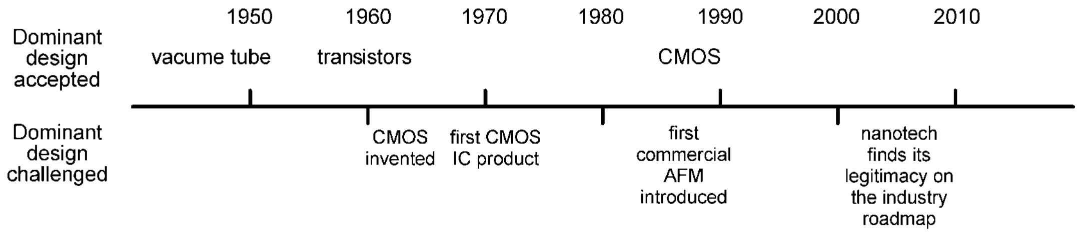

Figure 1. A timeline of dominant designs in the semiconductor industry

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 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 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 ∼ 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).

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

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

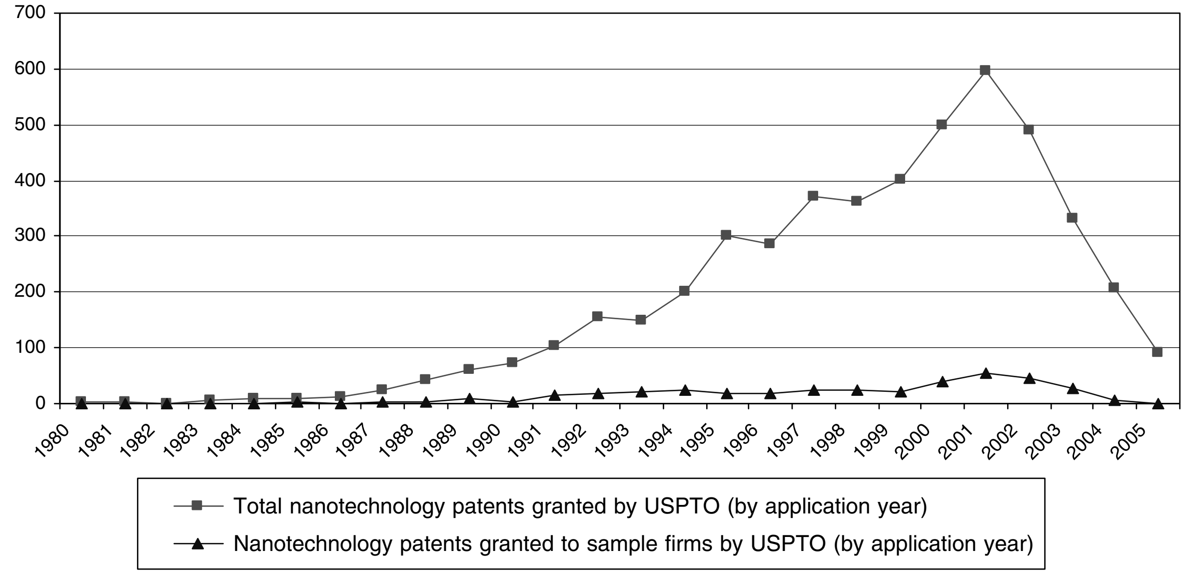

Figure 2. A contrast between all nanotechnology patents granted by USPTO and those granted to a cohort of incumbent firms (established before 1990) in the global semiconductor industry between 1980 and 2005

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

industry during this period is ideal for testing our hypotheses.

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 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: 184–185), non-U.S. semiconductor firms (Braun and MacDonald, 1982; Dorfman, 1987; Malerba,

[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.

DOI: 10.1002/smj

1985; 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 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.

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.

Dependent and independent variables

Inventive performance. Our interest is in incumbent firms' inventive output during the early 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] To do this, we first identify this firm's learning

[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

DOI: 10.1002/smj

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.

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., Galasso, 2007; Oxley and Sampson, 2004). We calculated it longitudinally, since a firm's expertise may change over time.

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

T_{it} 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: 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

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 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.

[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.

DOI: 10.1002/smj

of 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 (Rothaermel and Thursby, 2007; Zucker *et al.*, 1998a; Zucker *et al.*, 2002). The square of each variable allows us to test the diminishing marginal returns stated in the hypothesis.

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.

STATISTICAL ANALYSES AND RESULTS

Analytical approach

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

DOI: 10.1002/smj

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	0.30		
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.

would not be appropriate (Cameron and Trivedi, 1986).

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).[9] 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. 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, 1999; Blundell, Griffith, and Van Reenen, 1995). Following this method and recent practices (Dushnitsky and Lenox, 2005; O'Shea *et al.*, 2005; Schilling and Phelps, 2007), we include the *pre-sample dependent variable* into an RE estimation.

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.

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 areas*^{2} 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 ($= e^{0.07\times4.3}$), 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

[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.

DOI: 10.1002/smj

Table 2. Negative binomial regression results

Independent variables	Model 1		Model 2		Model 3		Model 4a		Model 4b	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	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	

DOI: 10.1002/smj

Table 2. (*Continued*)

Independent variables	Model 5a		Model 5b		Model 6a (include n*ano partner*)		Model 6b (include n*ano partner*)	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	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)
Citing 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)
Citing 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	

The significance levels of one tailed tests: *** significant at 0.001; ** significant at 0.01; * significant at 0.05; † significant at 0.1

scientific knowledge. This is indeed correct in 98 percent of the cases (firm-year observations).

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.

Robustness check

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.

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.

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

DOI: 10.1002/smj

finding in the search literature that firms engaging in more exploration are better able to create knowledge outside their core focus (March, 1991; Rosenkopf and Nerkar, 2001; Stuart and Podolny, 1996). 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 (Fleming and Sorenson, 2004; Zucker *et al*., 2002). 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., Hill and Rothaermel, 2003; Mitchell, 1989; Rothaermel, 2001; Sinha and Noble, 2005; Teece, 1986; Tripsas, 1997; Tushman and Anderson, 1986). 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 (Hill and Rothaermel, 2003; Rothaermel and Hill, 2005; Tripsas, 1997; Tushman and Anderson, 1986). 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.

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 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.

ACKNOWLEDGEMENTS

We thank Jerry Thursby, Frank Rothaermel, and anonymous referees for helpful comments and suggestions, and Greg Book, Russell Dupuis, Chuan Lin, and James Meindl for information on nanotechnology and the semiconductor industry. Jiang and Thursby gratefully acknowledge funding from the National Nanotechnology Infrastructure Network (Sub-award 44771–7471 and NSF Award 0335765) and the Mildred and Alan Peterson Foundation. Tan acknowledges support from SSHRC and Cisco Global Leadership Institute. We are particularly thankful to Associate Editor Constance Helfat and the anonymous SMJ reviewers for valuable suggestions. The usual disclaimer applies.

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

REFERENCES

Ahuja G. 2000. Collaboration networks, structural holes, and innovation: a longitudinal study. *Administrative Science Quarterly* **45**(3): 425–455.

Ahuja G, Lampert CM. 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, June–July Special Issue **22**: 521–543.

Anderson P, Tushman ML. 1990. Technological discontinuities and dominant designs: a cyclical model of technological change. *Administrative Science Quarterly* **35**(4): 604–633.

Arora A, Fosfuri A. 2003. Licensing the market for technology. *Journal of Economic Behavior & Organization* **52**(2): 277–295.

Arora A, Fosfuri A, Gambardella A (eds). 2001. *Markets for Technology*. MIT Press: Cambridge, MA.

Benner MJ, Tushman M. 2002. Process management and technological innovation: a longitudinal study of the photography and paint industries. *Administrative Science Quarterly* **47**(4): 676–706.

Benner MJ, Tushman M. 2003. Exploitation, exploration, and process management: the productivity dilemma revisited. *Academy of Management Review* **28**(2): 238–256.

Blundell R, Griffith R, Van Reenen J. 1995. Dynamic count data models of technological innovation. *Economic Journal* **105**(429): 333–344.

Blundell R, Griffith R, Van Reenen J. 1999. Market share, market value and innovation in a panel of British manufacturing firms. *Review of Economic Studies* **66**(3): 529–554.

Braun E, MacDonald S. 1982. *Revolution in Miniature: The History and Impact of Semiconductor Electronics* (2nd edn). Cambridge University Press: New York.

Burgelman RA, Grove AS. 2007. Let chaos reign, then rein in chaos—repeatedly: managing strategic dynamics for corporate longevity. *Strategic Management Journal* **28**(10): 965–979.

Cameron AC, Trivedi PK. 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. *Journal of Applied Econometrics* **1**(1): 29–53.

Cameron AC, Trivedi PK. 1998. *Regression Analysis of Count Data.* Cambridge University Press: Cambridge, UK.

Chan T, Nickerson JA, Owan H. 2007. Strategic management of R&D pipelines with cospecialized investments and technology markets. *Management Science* **53**(4): 667–682.

Christensen CM, Bower JL. 1996. Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal* **17**(3): 197–218.

Christensen CM, Rosenbloom RS. 1995. Explaining the attacker's advantage: technological paradigms, organizational dynamics, and the value network. *Research Policy* **24**(2): 233–257.

Cohen WM, Levinthal DA. 1989. Innovation and learning: the two faces of R&D. *Economic Journal* **99**(397): 569–596.

Darby MR, Zucker LG. 2003. Grilichesian breakthroughs: Inventions of methods of inventing and firm entry in nanotechnology. *NBER Working paper No. 9825*. National Bureau of Economic Research, Cambridge, MA.

Day GS, Schoemaker PJH. 2000. Avoiding the pitfalls of emerging technologies. *California Management Review* **42**(2): 8–33.

Dorfman NS. 1987. *Innovation and Market Structure: Lessons from the Computer and Semiconductor Industries*. Ballinger: Cambridge, MA.

Dushnitsky G, Lenox MJ. 2005. When do firms undertake R&D by investing in new ventures? *Strategic Management Journal* **26**(10): 947–965.

Fleming L. 2001. Recombinant uncertainty in technological search. *Management Science* **47**(1): 117–132.

Fleming L. 2002. Finding the organizational sources of technological breakthroughs: the story of Hewlett–Packard's thermal ink–jet. *Industrial and Corporate Change* **11**(5): 1059–1084.

Fleming L, Sorenson O. 2001. Technology as a complex adaptive system: evidence from patent data. *Research Policy* **30**(7): 1019–1039.

Fleming L, Sorenson O. 2004. Science as a map in technological search. *Strategic Management Journal*, August–September Special Issue **25**: 909–928.

Galasso A. 2007. Broad cross–license agreements in the semiconductor industry: Waiting to persuade? Job Market Paper, London School of Economics, London, UK.

Gans JS, Hsu DH, Stern S. 2002. When does start-up innovation spur the gale of creative destruction? *RAND Journal of Economics* **33**(4): 571–586.

Gans JS, Murray FE, Stern S. 2008. Patents, papers, pairs & secrets: contracting over the disclosure of scientific knowledge. Working paper, MIT Sloan School of Management, Cambridge, MA.

Garud R, Nayyar PR. 1994. Transformative capacity: Continual structuring by intertemporal technology transfer. *Strategic Management Journal* **15**(5): 365–385.

Gasman L. 2004. Why nanotechnology is so important for the semiconductor industry. White paper, NanoMarkets, Sterling, VA (http://www.infoedge.com/samples/na-0005free.pdf).

Griliches Z (ed.). 1984. *R&D, Patents, and Productivity* University of Chicago Press: Chicago, IL.

Hagedoorn J, Duysters G. 2002. Learning in dynamic inter-firm networks: the efficacy of multiple contacts. *Organization Studies* **23**(4): 525–548.

Henderson RM. 1993. Underinvestment and incompetence as responses to radical innovation: evidence from the photolithographic industry. *RAND Journal of Economics* **24**(2): 248–270.

Henderson RM, Clark KB. 1990. Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly* **35**(1): 9–30.

Henderson R, Cockburn I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal*, Winter Special Issue **15**: 63–84.

DOI: 10.1002/smj

Higgins MJ. 2008. Introduction to finance and valuing early stage technology. In *Technological Innovation: Generating Economic Results* (Vol. 18) *(Advances in the Study of Entrepreneurship, Innovation and Economic Growth)* Libecap GD, Thursby MC (eds). JAI Press: Oxford, UK; 253–285.

Hill CWL, Rothaermel FT. 2003. The performance of incumbent firms in the face of radical technological innovation. *Academy of Management Review* **28**(2): 257–274.

Jaffe AB. 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. *American Economic Review* **76**(5): 984–1001.

Jaffe AB. 1989. Characterizing the 'technological position' of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy* **18**(2): 87–97.

Jaffe AB, Trajtenberg M, Henderson RM. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* **108**(3): 577–598.

Jansen JJP, Van den Bosch FAJ, Volberda HW. 2006. Exploratory innovation, exploitative innovation, and performance: effects of organizational antecedents and environmental moderators. *Management Science* **52**(11): 1661–1674.

Katila RA, Ahuja G. 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. *Academy of Management Journal* **45**(6): 1183–1194.

Kline S, Rosenberg N. 1986. An overview of innovation. In *The Positive Sum Strategy*, Landau R, Rosenberg N (eds). National Academy Press: Washingon DC; 275–305.

Lane PJ, Lubatkin M. 1998. Relative absorptive capacity and interorganizational learning. *Strategic Management Journal* **19**(5): 461–477.

Levitt B, March JG. 1988. Organizational learning. *Annual Review of Sociology* **14**: 319–340.

Libaers D, Meyer M, Geuna A. 2006. The role of university spinout companies in an emerging technology: the case of nanotechnology. *Journal of Technology Transfer* **31**(4): 443–540.

Lin Z, Yang H, Demirkan I. 2007. The performance consequences of ambidexterity in strategic alliance formations: Empirical investigation and computational theorizing. *Management Science* **53**(10): 1645–1658.

Malerba F. 1985. *The Semiconductor Business: The Economics of Rapid Growth and Decline*. University of Wisconsin Press: Madison, WI.

March JG. 1991. Exploration and exploitation in organizational learning. *Organization Science* **2**(1): 71–87.

Martin X, Mitchell W. 1998. The influence of local search and performance heuristics on new design introduction in a new product market. *Research Policy* **26**(7–8): 753–771.

McCray WP. 2007. Beyond the red brick wall: spintronics, novelty, and over–the–horizon technologies. Symposium on the Social Studies of Nanotechnology: Wharton School at University of Pennsylvania, Philadelphia, PA.

Mitchell W. 1989. Whether and when? Probability and timing of incumbents entry into emerging industrial subfields. *Administrative Science Quarterly* **34**(2): 208–230.

Moore GE. 1965. Cramming more components onto integrated circuits. *Electronics* **38**(8): 114–117.

Morris PR. 1990. *A History of the World Semiconductor Industry*. Peregrinus: London, UK.

Mowery DC, Oxley JE, Silverman BS. 1996. Strategic alliances and interfirm knowledge transfer. *Strategic Management Journal*, Winter Special Issue **17**: 77–91.

Narin F, Hamilton KS, Olivastro D. 1997. The increasing linkage between U.S. technology and public science. *Research Policy* **26**(3): 317–330.

Nicholls-Nixon CL, Woo CY. 2003. Technology sourcing and output of established firms in a regime of encompassing technological change. *Strategic Management Journal* **24**(7): 651–666.

Nichols NA. 1994. Scientific management at Merck: an interview with CFO Judy Lewent. *Harvard Business Review* **72**(1): 88–99.

O'Reilly CA, III, Tushman ML. 2004. The ambidextrous organization. *Harvard Business Review* **82**(4): 74–81.

O'Shea RP, Allen TJ, Chevalier A, Roche F. 2005. Entrepreneurial orientation, technology transfer and spinoff performance of U.S. universities. *Research Policy* **34**: 994–1009.

Oxley JE, Sampson RC. 2004. The scope and governance of international R&D alliances. *Strategic Management Journal*, August–September Special Issue **25**: 723–749.

Phene A, Fladmoe–Lindquist K, Marsh L. 2006. Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space and geographic origin. *Strategic Management Journal* **27**(4): 369–388.

Pisano GP. 1994. Knowledge, integration, and the locus of learning: an empirical analysis of process development. *Strategic Management Journal*, Winter Special Issue **15**: 85–100.

Riezenman MJ. 1991. Wanlass's CMOS circuit. *IEEE Spectrum* **28**(5): 44.

Roberts K, Weitzman ML. 1981. Funding criteria for research, development, and exploration projects *Econometrica* **49**(5): 1261–1288.

Rosenkopf L, Almeida P. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6): 751–766.

Rosenkopf L, Nerkar A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal* **22**(4): 287–306.

Rothaermel FT. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal*, June–July Special Issue **22**: 687–699.

Rothaermel FT, Hill CWL. 2005. Technological discontinuities and complementary assets: a longitudinal study of industry and firm performance. *Organization Science* **16**(1): 52–70.

Rothaermel FT, Thursby M. 2007. The nanotech vs. the biotech revolution: sources of productivity in incumbent firm research. *Research Policy* **36**(6): 832–849.

Sampson RC. 2007. R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation. *Academy of Management Journal* **50**(2): 364–386.

Schilling MA, Phelps CC. 2007. Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. *Management Science* **53**(7): 1113–1126.

Sinha RK, Noble CH. 2005. A model of market entry in an emerging technology market. *IEEE Transactions on Engineering Management* **52**(2): 186–198.

Stuart TE. 2000. Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. *Strategic Management Journal* **21**(8): 791–811.

Stuart TE, Podolny JM. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal*, Summer Special Issue **17**: 21–38.

Tan J, Peng MW. 2003. Organizational slack and firm performance during economic transitions: two studies from an emerging economy. *Strategic Management Journal* **24**(13): 1249–1263.

Taylor A, Helfat CE. 2009. Organizational linkages for surviving technological change: complementary assets, middle management, and ambidexterity. *Organization Science* **20**(4): 718–739.

Teece DJ. 1986. Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. *Research Policy* **15**(6): 285–305.

Thompson JD. 1967. *Organizations in Action*. McGraw–Hill: New York.

Thursby J, Thursby M. 2006. Where is the new science in corporate R&D? *Science* **314**(5805): 1547–1548.

Tripsas M. 1997. Unraveling the process of creative destruction: complementary assets and incumbent survival in the typesetter industry. *Strategic Management Journal*, Summer Special Issue **18**: 119–142.

Tushman ML, Anderson P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly* **31**(3): 439–465.

Tushman ML, O'Reilly CA, III. 1996. Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review* **38**(4): 8–30.

Walsh J, Kosnik R. 1993. Corporate raiders and their disciplinary role in the market for corporate control. *Academy of Management Journal* **36**(4): 671–700.

Zucker LG, Darby MR, Armstrong J. 1998a. Geographically localized knowledge: spillovers or markets? *Economic Inquiry* **36**(1): 65–86.

Zucker LG, Darby MR, Armstrong JS. 2002. Commercializing knowledge: university science, knowledge capture, and firm performance in biotechnology. *Management Science* **48**(1): 138–153.

Zucker LG, Darby MR, Brewer MB. 1998b. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* **88**(1): 290–306.

DOI: 10.1002/smj