The Antecedents and Innovation Consequences of Organizational Knowledge Brokering Capability

by

David H. Hsu* and Kwanghui Lim**

June 2007

ABSTRACT

We empirically examine the antecedents and innovation consequences of organizational knowledge brokering capability, the ability to effectively apply knowledge from one technical domain to innovate in another. We do so by tracking all the start-up biotechnology firms founded to commercialize the then-emergent recombinant DNA technology. Building on prior research in this area, we extend the knowledge brokering concept by examining how firms' interaction with their external environment helps bolster their heterogeneous knowledge brokering capacity, which in turn is associated with uneven ex-post innovation performance. Our results suggest that (a) knowledge brokering capability is achieved by striking equity strategic alliances and by hiring technical personnel who had previously patented in areas different than the firm's areas of expertise; (b) knowledge brokering has an inverted U-shaped relationship with innovative performance; and (c) there are important conceptual and empirical reasons to consider a variety of modes of knowledge brokering (rather than a monolithic conceptualization). Overall, the results suggest that knowledge brokering can be an important organizational capability.

Keywords: knowledge brokering, innovation, entrepreneurship, biotechnology, patents.

---

* The Wharton School, 2000 Steinberg Hall-Dietrich Hall, University of Pennsylvania, Philadelphia, PA 19104, dhsu@wharton.upenn.edu. **Melbourne Business School, k@kwanghui.com. We thank Kathy Ku of the Stanford University Office of Technology Licensing for allowing us to access the Cohen Boyer patent records. We thank Dan Levinthal, Marvin Lieberman, Hans Pennings, Scott Shane, Olav Sorenson, Scott Stern, and three anonymous reviewers for helpful suggestions. We enjoyed valuable conversations with Preeta Banerjee in the early stages of this project. We also thank conference or seminar participants at the Academy of Management, Harvard Business School, MIT, Swiss Federal Institute, UCLA, University of Maryland, USC and Wharton for useful comments. Josh Lerner generously provided access to his biotechnology index. Mike Gonsalves, Zhuang Wenyue, and Tong Zhao provided valuable research assistance. We acknowledge use of the NUS patent database. We thank the Mack Center for Technological Innovation at Wharton, National University of Singapore and IPRIA.ORG for funding this project.

1. Introduction

Organizations need to strike a balance between exploiting their capabilities and exploring new terrain (March, 1991). When firms conduct exploratory search, however, they tend to search “locally”, exploring knowledge that is familiar and within easy reach from their existing technological and geographic positions (Stuart and Podolny, 1996). This behavior has been explored at multiple levels of analysis, with most explanations based on individual-level bounded rationality (March and Simon, 1958) and firm-level routines (Nelson and Winter, 1982). Local search behavior is also perpetuated by “imprinting” by founders of new ventures (Stinchcombe, 1965) and the long-lasting impact of firms’ initial conditions (e.g., Baron et al., 1996; Cockburn et al., 2000). In environments in which innovation is important as the basis for competition, managers may be particularly concerned about the effects of local search on firm performance (March, 1991; Brown and Eisenhardt, 1997; Rosenkopf and Almeida, 2003). Hence, there has been considerable interest in mechanisms for overcoming the constraints of local search. The common theme to this research is that some type of boundary-spanning activity is necessary, so that the organization can tap into distributed knowledge domains.

Knowledge brokering, or “profitably transferring ideas from where they are known to where they represent more innovative possibilities” (Hargadon, 1998, p. 214), is one mechanism for spanning knowledge boundaries which is managerially provocative. The ability to leverage knowledge and expertise in one domain to innovate in another not only economizes on R&D expenditures (Baldwin and Clark, 2000), but also offers the tantalizing prospects of yielding breakthrough innovations (Hargadon and Sutton, 1997; Hargadon, 1998; 2003) and quickening the pace of innovation (Kodama, 1992). Yet, existing research on the topic, while usefully describing the process of how such brokers successfully organize their activities for product performance, does not allow us to conclude an empirically robust relationship between knowledge brokering and innovative performance. This is because prior studies, which have been mainly concerned with identifying common traits among knowledge brokers and the process by which brokering occurs, selected their subject organizations based on leadership in brokering in their ethnographic studies. We build on this research by empirically investigating strategy and policy questions of *why* there is a heterogeneous distribution of knowledge brokering ability across firms, even within an industry, and the performance implications of that heterogeneous ability.

We do so by addressing two related research questions: (1) What are the firm-level efforts associated with building knowledge brokering capacity?, and (2) What are the innovation consequences of knowledge brokering? We study these questions by constructing an empirical sample composed of firms not selected based on their ability as brokers (to avoid selecting on the dependent variable). Doing so allows us to theorize and test the knowledge brokering concept in further detail relative to prior studies and methodologies. In particular, we are able to explore contingencies and possible non-linear performance effects of knowledge brokering, different modes of knowledge brokering and their performance impact, and to examine the antecedents to knowledge brokering activity.

The approach we take in the paper also responds to Cockburn et al.'s (2000, p. 1124) call for empirical strategy research that "not only identifies those factors that are correlated with superior performance but also attempt to explore the origins and dynamics of their adoption." We share the philosophy that understanding the evolution of capabilities yields a deeper understanding of firms' present day competitive situation.

Our empirical strategy is to carefully choose a setting in which firms were founded to exploit a given technological innovation. This design allows us to track firms' temporal patterns of knowledge brokering from their inception, while holding initial technology constant. Since path dependencies are important in shaping trajectories of resource attainment, this method allows us to trace a sample of firms' resource trajectories from their birth in commercializing technology stemming from a common technological advance. We can then study the relative importance of various organizational mechanisms in enhancing firms' knowledge brokering capability, as well as performance consequences of such ability.

The commercialization of recombinant DNA technology via open, non-exclusive licensing of the Cohen-Boyer patent by Stanford University between 1980 and 1997 provides an excellent setting for addressing our research questions. The Cohen-Boyer innovation allowed DNA from two or more sources to be recombined into a single target, and the commercialization of this innovation helped launch the modern biotechnology industry (Kenney, 1986).[1] Due to generous access to detailed program records by the Stanford University Office of Technology Licensing, and by combining those records with firm and patent-level data from multiple other sources, we create a unique dataset of all de novo start-ups founded to commercialize this technology. Our dataset includes 19 firms (listed in Table 1) that produced 3,652 patented inventions between 1976 and 2004. In addition to the empirical setting, we adopt an empirical estimation method that factors out time invariant differences across firms (such as founder experience differences [e.g., Hsu, 2007] and conditions at the time of firm founding [e.g., Romanelli, 1989; Eisenhardt and Schoonhoven, 1990]) to mitigate the possibility that our results are driven by such unobserved differences. We are able to do this because of the longitudinal nature of our data, which allows us to report estimates based on within-firm changes over time, and move us closer to a causal interpretation of the results. We should note at the outset, however, that we are not able to observe costs or internal firm policies and activities across time and so we focus attention on what is observable, firms'

[1] The biotechnology industry is quite technologically dynamic, and thus represents an interesting empirical setting in its own right. As of 2003, biotechnology innovations accounted for 155 U.S. Federal Drug Administration (FDA) approved drugs, with over 370 biotechnology clinical trials and vaccines in development (BIO website, accessed May 24, 2004). Furthermore, biotechnology firms are a significant source of upstream innovation for pharmaceutical firms (Gans et al., 2002): of the 691 new chemical entities approved by the FDA between 1963 and 1999, 38 percent were licensed by pharmaceutical firms, primarily from biotechnology firms (DiMasi, 2000).

external efforts to build knowledge brokering capacity. While the results should therefore be interpreted in that light, we believe that our overall approach represents a step forward in this literature.

We find that after controlling for firms' initial degree of knowledge brokering behavior, brokering capability relates more strongly to some mechanisms (hiring people with different technical backgrounds and forming equity strategic alliances) than others (affiliating with venture capital networks). This analysis recognizes that brokering capability is a function of investments in multiple activities, a perspective that is not clearly brought out in the prior literature in this domain. Furthermore, understanding the relationship between various mechanisms and brokering capacity holds managerial implications (investing scarce organizational resources), though future studies should investigate differential costs of the different boundary-spanning mechanisms. A second result from the study is that there is an inverted U-shape between knowledge brokering and innovative performance. This suggests that the view that "more knowledge brokering is better" may not be warranted: beyond a threshold point, knowledge brokering is associated with diminished innovative performance. Finally, in contrast to the prior literature, which has largely conceptualized a monolithic knowledge brokering mode, we conceptually and empirically explore three distinct modes: pure recombination (taking two or more elements and producing output which is not the same as any of the inputs), pure porting (applying a given solution from one application area to another problem context), and a combination of these two. Not only are there different organizational policy levers to induce these modes of search, but their innovative impacts also differ. Taken together, these results extend the knowledge brokering concept in ways which would be difficult to accomplish without a well-designed empirical study.

The plan for the remainder of the article is as follows: in Section 2, we review the relevant literature to develop hypotheses about knowledge brokering. Section 3 discusses the data and method employed, while Section 4 presents the empirical results. A final section discusses the results and conclusions.

2. Literature and Hypothesis Development

In this section, we concentrate our discussion of the antecedents and consequences of knowledge brokering at the organization level. While the processes of knowledge brokering are multi-level, involving individuals, organizations, and networks (Hargadon, 2002), we focus our theorizing to the firm level, which best matches our data and empirical design. In the concluding section, we discuss how our findings relate to the relevant literature focusing on other levels of analysis.

A. Organizational Efforts to Promote Knowledge Brokering

The behavioral origins of localized organizational search in research and development (R&D) have been well documented in the literature (see Stuart and Podolny, 1996 and Katila and Ahuja, 2002 for excellent reviews). In brief, search tends to be localized for several reasons. Managers tend to rely on historic experiences, even in the face of new environments, and so new search efforts are often circumscribed by organizations' own experiences and evolved procedures, resulting in path dependence (Cyert and March, 1963; Nelson and Winter, 1982; Burgelman, 1994). Such organization-level standard operating procedures and routines allow for a higher likelihood for technology development with lower variation on average. Organizational routines can therefore become a source of competence for the firm – hence they are not easily abandoned (Henderson and Clark, 1990).

A second reason for local search and organizations' persistence in search direction, while often not conceptualized in this way, is due to founding team imprinting (Stinchcombe, 1965). Such imprinting can be manifested in firms' policies and procedures as they relate to organizational culture, human resource management, and R&D practices (Baron et al., 1996). The philosophies and managerial styles of founders not only shape organizational identities, but they also influence investment decisions in corporate reputation and recruiting in ways which tend to reinforce the founding philosophies, resulting in distinctive corporate styles, such as "the Hewlett-Packard way" (Packard, 1995).

Consequently, differences in founding orientations can be a powerful source of subsequent organizational heterogeneity in resources and competitive position. For example, Mintzberg and Waters (1982) found that strategic reorientation in the entrepreneurial firm they tracked over a long time horizon was rare, but was made more likely when venture growth exceeded the knowledge of the founder. Moreover, Boeker (1989) found that semiconductor start-ups typically maintained the corporate strategies they had at the time of founding. The initial positioning and resource differences across firms leads to future performance heterogeneity, a key tenet of the resource-based view of the firm (e.g., Wernerfelt, 1984; Barney, 1991; Peteraf, 1993). Helfat (1994) and Henderson and Cockburn (1994) find substantial (and varied) fixed firm effects in R&D across two different industries, petroleum and pharmaceuticals, suggesting substantial within-industry heterogeneity in R&D investment strategy and by extension, intensity of search. Cockburn et al. (2000) find that organizational "styles" (in their case, the initial extent of science-driven drug discovery by pharmaceutical firms) persist over long periods of time. Their results also suggest that while such initial orientations are important, they do not fully explain the adoption of strategies that affect organizational performance.

Another element of founding orientation, aside from those discussed above, is initial entrepreneurial opportunity recognition. This too is likely to have longed-lived organizational effects which can contribute to firms' decisions, resource access, and ultimately strategic positioning and performance. Lazear (2004) sees entrepreneurs as generalists with training in several different areas, a quality which facilitates entrepreneurial opportunity recognition. Shane (2000) shows that even for a *given* entrepreneurial opportunity (three dimensional printing technology), there are substantial differences in opinion and entrepreneurial conjectures regarding its most profitable application. Adner and Levinthal (2000) see this heterogeneity in assessing technological opportunity as more determinative of commercial success than the underlying technical development. Because Shane (2000) studies a sample of potential licensees of the technology, the distribution of entrepreneurial conjectures about the opportunity is likely to be even more diffuse in the general population, as the decision to evaluate the technology might be taken as a sign of possessing at least preliminary commercialization ideas. In turn, these different entrepreneurial conjectures about application domain will affect investment patterns and influence the style of organizational development and even R&D search. In this paper, we will be concerned with a specific type of R&D oriented search, knowledge brokering, as previously described. Given the dual forces of technological search routinization and founder imprinting, we expect:

- *Hypothesis 1: A firm with high knowledge brokering use at the time of its founding will persist in using that search strategy, and vice versa.*

The hypothesis is consistent with the notion that founding firms' heterogeneous initial opportunity recognition will determine in significant ways how effectively they will engage in future knowledge brokering. Those firms that broker technical domains less intensively during initial opportunity recognition will be less effective in developing and exploiting knowledge brokering capability, with the opposite being true for those firms with greater brokering during initial opportunity recognition.[2]

The above arguments regarding local search suggest that exploratory organizational search is unlikely to occur in the absence of conscious firm effort, serendipity aside (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). Yet, exploratory search is important for competitive success, particularly in fast-paced environments in which technical innovation continuously reconfigures the competitive landscape (March, 1991; Brown and Eisenhardt, 1997; Ahuja and Lampert, 2001). In addition, the ability to monitor and access external innovations—absorptive capacity—can be critical for firms' resource acquisition and competitive advantage (Cohen and Levinthal, 1990). The main insight from the literature is that some boundary (technical, scientific, organizational, or geographic) must be spanned in order for organizations to engage in any type of exploratory search (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003; Ahuja and Katila, 2004), including knowledge brokering oriented search.

As described by Hargadon (2002), effective knowledge brokering involves a number of individual, organizational, and network level processes which help orchestrate acquiring, retaining, recalling, recombining, and applying knowledge for commercial success. The literature on organizational learning and memory suggests that such processes can be important capabilities (e.g., Nelson and Winter,

[2] We thank an anonymous referee for suggesting this framing.

1982; Walsh and Ungson, 1991; Huber, 1991; Kogut and Zander, 1992; Hargadon and Sutton, 1997). As is the case with other organizational capabilities, firms can differ in their ability to broker knowledge.[3] Absent the ability to empirically observe and measure internal policies in this study, we concentrate our attention on mechanisms of accessing external knowledge and resources, though we note that such internal policies can be an important means of implementing knowledge brokering. For instance, firms may allow technical staff to publish portions of their research findings in professional journals (Henderson and Cockburn, 1994) and/or set aside dedicated time for exploratory research.[4]

We discuss three boundary-spanning mechanisms as avenues for the focal organization to access external ideas and resources, which may be vital for building the organization's knowledge brokering capacity. One mechanism organizations may use to facilitate knowledge cross-fertilization and boundary spanning is hiring technical staff with expertise complementary to that already possessed by the firm (e.g., Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003).[5] Engineers and scientists with distant technological knowledge may be available for hire from the scientific labor market, and so human capital mobility represents a means by which firms can access complementary technical talent, especially knowledge that is complex and/or tacit. The managerial challenge is that of productively integrating such staff into the organization to induce knowledge spillovers (for example, by organizing them into cross-functional teams). The risk of bringing together people with heterogeneous backgrounds and areas of expertise is that there may be a loss of social cohesion (as a result of different approaches, norms, assumptions and the like), not to mention possibly entrenched organizational power and politics supporting the status quo and established organizational routines.

- *Hypothesis 2(a): Hiring R&D personnel with different technical backgrounds increases a firm's knowledge brokering capability.*

A second mechanism for accessing distant knowledge is via strategic alliances. Mowery et al. (1996), Stuart and Podolny (1996), Baum et al. (2000), Gulati (1998), Banerjee (2006) and others have examined strategic alliances as a mechanism for accessing distant knowledge. Particularly for resource-constrained

---

[3] There may be intervening factors, however, preventing organizations from transforming their capabilities into performance advantages. These factors may act as indirect inputs into other capabilities or take longer to be manifested into performance differentials (Garud and Nayyagar, 1994; Peteraf and Barney, 2003). We thank an anonymous referee for pointing this out to us.

[4] Such policies may differ not only in the research latitude given to technical staff ex-ante, but also in the degree to which output monitoring/verification is required ex-post. These internal policies will also have implications for the type of individual attracted to work in such an environment, and so can have implications for accessing external knowledge.

[5] The efficacy of the latter mechanism is likely to be context-specific, however. For example, Zucker et al. (1998) find that in the early biotechnology industry, the scarce resource was specialized knowledge resident in highly accomplished university scientists. The fact that these scientists were for the most part not mobile helps explain the observed geographic concentration of the industry (large concentrations of firms located near academic centers of excellence in biology and chemistry).

start-ups, which have difficulty extending the boundaries of their organizations through vertical integration, alliances are an important organizational form allowing collaborative commercialization. Especially in more "tightly-integrated" alliances, knowledge sharing and learning can be important motivators for entering into an alliance (Khanna et al., 1998). Gomes-Casseres et al. (2006) use patent citation data to provide empirical support for the link between such alliances and knowledge flows.

- *Hypothesis 2(b): Forming strategic alliances increases a firm's knowledge brokering capability.*

A third way in which entrepreneurial organizations may be able to span boundaries is by linking into venture capital (VC) networks. Apart from being a source of funding, venture capitalists are also information intermediaries. Reputable venture capitalists connect their portfolio companies to external resources, such as the capital and labor markets, and they act as a source of valuable knowledge facilitating the entrepreneurial firm's development (see Hsu [2006] and references therein). These linkages to the VC and the VC's extended network may allow entrepreneurial ventures to broaden their range of technical and organizational exposure.

- *Hypothesis 2(c): Venture capital involvement increases a firm's knowledge brokering capability.*

It is worth noting that these mechanisms (hiring, strategic alliances and VC networks) assume that some degree of information is known about the sources of relevant external knowledge. In cases where such knowledge is not known, firm may employ broadcast search techniques (Lakhani, 2006).

B. Firm Knowledge Brokering and Innovative Performance

Schumpeter (1934, pp. 65-66) conceptualized the act of innovation itself as the process of "carrying out new combinations," while Usher (1954, p. 21), in his classic work, argued: "There are other discontinuities that may be overcome through some act of synthesis. The establishment of new organic relations among ideas, or among material agents, or in patterns of behavior is the essence of all invention and innovation." To these analysts, the act of invention itself involves the process of recombining and synthesizing existing component ideas.

To illustrate how knowledge brokering can relate to the inventive process, consider the circumstances of Kary Mullis' invention of what has become a fundamental tool in the microbiology laboratory, polymerase chain reaction (PCR) technology. Cetus Corporation hired Mullis in 1979 to synthesize oligonucleotide probes.[6] By 1983, however, oligonucleotide synthesis was becoming reliably automated, and Mullis was facing obsolescence in his job as a chemist at Cetus. With more time on his hands, Mullis began "puttering around" with oligonucleotides and became interested in ways to easily

[6] An oligonucleotide is a short chain of specifically-sequenced nucleotide bases. The oligonucleotide can bind specifically with a string of complementary nucleotide bases in single-stranded DNA, and when radioactively labeled, engineered oligonucleotides can serve as probes for detecting whether a sample of DNA contains a particular gene or nucleotide sequence.

detect single base pair changes (against a known sequence) in DNA. Since a genetic mutation may indicate the presence or the potential for a disease, Mullis was interested in finding a potential diagnostic application (Mullis, 1990). Planning this experiment led Mullis to the invention of PCR in the spring of 1983. While driving to his cabin in California, Mullis came up with the breakthrough idea that using two oligonucleotide primers working in opposite directions on each strand of denatured DNA, he could create instructions to continually "amplify," or replicate, specific DNA targets (Yoffe, 1994). Mullis had been spending a lot of time writing computer programs and recognized the power of reiterated loops; he envisioned PCR to be such a loop. When he got back to Cetus, Mullis spent three months running experiments before achieving success. Mullis won the 1993 Nobel Prize in chemistry for his invention. While Mullis relied more on his in-depth knowledge of chemistry in relation to his knowledge of computer science for the PCR invention, importing ideas and concepts from across academic fields appeared important in his discovery.[7]

More generally, we are interested in the relationship between knowledge brokering and firm level innovative performance. There are at least two reasons to believe that there is a positive relationship between brokering and innovation. First, brokering ideas from disparate domains injects greater variation into organizations' internal idea pool, leading to a broader range of ideas available for brokering. This in turn enhances the likelihood that a novel combination critical for innovative performance will be reached. Second, organizations may establish knowledge brokering "routines" such that policies related to brokerage experimentation and risk taking can result in a beneficial self-reinforcing innovative process as talented technical staff may be attracted to work for the firm.

There are also reasons to believe that beyond a certain point, brokering activity may lead to a downturn in innovative performance. First, more intensive brokering efforts may exhaust the search space, and so recombinative efforts may prove fruitless (e.g., Katila and Ahuja, 2002). A second rationale for diminished innovative performance with brokering is that internal inventive cohesion may be compromised. When organizations wish to conduct intensive knowledge brokering, they are more likely to staff the firm with personnel possessing a wider spectrum of experience and expertise. Yet more intensive brokering efforts are likely associated with more complex and tacit knowledge. The upshot is that internal inventive cohesion among disparate technical staff may backfire in this situation, yielding diminished innovative performance. As a result of both the benefits and potential costs of knowledge brokering, we predict:

---

[7] Beyond the inventive impact of knowledge brokering, researchers have found that such behavior can act as an important engine of economic growth. For example, Weitzman (1998) developed a model of macroeconomic growth that depends critically on idea recombination, and Scherer (1982) reported that inter-industry knowledge flows are a significant factor in economic growth.

- *Hypothesis 3: Knowledge brokering will have an inverted U-shaped relationship with firms' innovation performance.*

It is worth noting that knowledge brokering can lead to more variable innovative outcomes, both on the negative and positive sides (Fleming, 2001; Fleming and Sorenson, 2004) as a result of the greater number of possible combinations together with the associated experimentation (Thomke, 2003) in identifying promising brokered situations. While an experimental approach may allow discarding "failed" experiments, an inverted-U shaped relationship reflects the reality that patenting across the distribution of contemporaneous inventions may still take place as the ex-post value of inventions can be difficult to discern ex-ante.

Finally, we are interested in the possible moderating effect of complex technical environments on firms' brokering-led innovative performance. An organization faces a complex technical environment when there are many technical elements, and it is difficult to anticipate the effect of interdependencies and interactions among the elements. Simon (1962, p. 468) defined a complex system as: "one made up of a large number of parts that interact in a non-simple way." When the technical environment is complex, organizational innovation via technology brokering may be made more difficult since brokering requires knowledge flows, and such flows may be made more viscous as a result of environmental complexity (Sorenson et al., 2006). More generally, in complex technical environments, firms may conduct R&D search based more on learning and heuristics (which will tend to dampen innovative performance) rather than on established solution algorithms or recipes, which may be more effective in simple environments (Rivkin, 2000). We therefore anticipate:

- *Hypothesis 4: Firms' innovative performance associated with knowledge brokering is negatively moderated by the complexity of its technical environment.*

C. Modes of Knowledge Brokering and Innovative Performance

While we have thus far referred to knowledge brokering as a monolithic concept involving the generic application of technical ideas from one area to innovate in another, we propose that there are three modes in which such brokering can take place. These different modes are depicted schematically in Figure 1, along with a baseline mode with no brokering. In this section, we discuss why making distinctions among the various brokering modes might be important conceptually and empirically by discussing how each mode might require different organizational investments and result in differing innovative outcomes.

The first mode, "pure porting," takes solution concepts from one application area and applies it to another domain. Baldwin and Clark (2000) state that porting occurs when a module "is able to function in more than one system, under different sets of design rules," (p. 140), and they identify porting as a basic operator of modular systems. Similarly, Adner and Levinthal (2000) describe a “speciation event” as “transplanting the existing technological know-how to a new domain of application where it evolves in new directions.” The second mode of technology brokering, pure recombination, refers to the case in which elements from different domains are “recombined,” “melded,” or “fused” to create a new entity distinct from its original elements (Schumpeter, 1934; Basalla, 1988; Kodama, 1992; Hargadon and Sutton, 1997; Levinthal, 1998; Fleming, 2001). Kogut and Zander (1992) conceptualized organizational renewal as the result of recombining organizational capabilities. The third mode is a mix between porting and recombination.

To give an example of the pure “porting” mode of knowledge brokering, consider the birth and development of the academic field of evolutionary economics. Borrowing key ideas from evolutionary biology—such as principles of genetic variation and selection—evolutionary economists have advanced our knowledge of how organizations evolve in a way analogous to that of living organisms (Nelson and Winter, 1982). A practical example of porting is the application by Bose Corporation of acoustics technology to improving the suspension systems of automobiles: both technical domains are quite distinct, but Bose was able to port mathematical techniques used for designing high-fidelity sound systems into the domain of car manufacturing. Porting helps to lower the cost of design and innovation, but for this benefit to be realized there should be a partitioning of state space into the part affected by the surrounding system and that which is stand-alone (Baldwin and Clark, 2000). This increases the chance that the stand-alone portion is successfully transplanted to a different domain. However, if the transplanted module is difficult to partition from the rest of the system, the likely result is more uncertainty. This may result in a lower probability of success, although it may sometimes be beneficial by injecting unexpected new variations into the target domain. Hence, porting can be the basis of breakthrough innovations, as Adner and Levinthal (2000) observe: “the revolution of emerging technologies is often not a result of a major scientific breakthrough as much as a shift in the domain of application of the technology” (p. 57). These authors cite the use of protocols for distributed computing, which were applied by government scientists to the public internet and leading to its phenomenal popularity (while leaving the underlying communication protocols largely unchanged).

One concern related to porting is identified by Gavetti et al. (2005) in their paper on managerial analogies for problem solving. Through an agent-based simulation model, they find that false analogy can be destructive. In other words, decision makers may experience performance shortfalls if they are overly reliant on analogy-based heuristics without understanding possible mitigating circumstances (“the problem looks like situation Z, in which case we have always successfully applied solution X”). If the expected net benefits to porting are positive, and an organization wishes to induce this method of brokerage, a first step would be to assemble the personnel who might recognize opportunities to apply knowledge across domains. Managers may wish to institutionalize a means of broadcasting the problem widely to different technical staff with expertise in different domains than the focal technology and perhaps to rotate scientists across different domain areas.

The other two modes of brokering involve recombining prior elements to yield a novel output different than any of the inputs. We make a distinction between "pure recombination", which involves only elements from the focal domain of knowledge, and "mixed recombination and porting", which also includes elements from other domains of knowledge. Henderson and Clark's (1990) description of how entrants in the semiconductor lithography industry used new architectures to recombine elements from within that technical domain to create novel and competitive products (to the detriment of incumbent firms) is an example of pure recombination.[8] As an example of "mixed recombination and porting," consider the academic field of strategic management. In contrast to the case of "pure" recombination, it borrows knowledge from a number of disparate fields such as economics, sociology, history, and political science—and recombines insights and methods from those fields to create new knowledge about corporate strategy.

While most of the literature has discussed the possibility that innovation and new capabilities can be formed as a result of recombination (e.g., Hargadon and Sutton, 1997; Fleming, 2001), there is also the possible risk of recombining inappropriate elements, resulting in poor innovative outcomes. As described by Fleming and Sorenson (2001), "variance implies outcomes at both extremes — some much better and some much worse." Many possible combinations of elements are not likely to have technical or commercial value, and there are likely significant organizational costs associated with trying to induce recombination-based brokering or conducting the necessary experiments to identify those rare combinations that lead to good outcomes. To yield innovative performance beyond serendipity, this mode of knowledge brokering requires tolerance for experimentation (Thomke, 2003) and measured failure (Manso, 2006). In addition, it may require significant organizational learning about the innovation profile of a given recombination obtained at the least possible cost (McGrath and MacMillan, 2000).

Mixing recombination and porting should yield superior innovative performance relative to either of the individual brokering modes used individually. This is because one mode is beneficial for innovation where the other mode experiences a shortfall, and vice-versa. On the one hand, the strength of recombination is that it can generate a wide variety of ways in which knowledge is reassembled, which is necessary for experimentation. This is an area where porting is weak, due to the relative scarcity of modules that can be cleanly partitioned and transplanted across technical domains. On the other hand, the

[8] Pure recombination does not have to be accompanied by architectural change. For example, Lim (2006) describes how IBM recombined skills from within the semiconductor industry in unexpected ways to introduce copper interconnect technology, an economically valuable invention that is now becoming widely diffused.

strength of porting (the predictability of performance if the module is stand-alone and the variance of performance if the module ported has an interaction with the existing system) offsets the weakness of recombination (most attempts at recombination generate outcomes that are not useful). We therefore predict:

- *Hypothesis 5*: Mixing porting and recombination as modes of knowledge brokering leads to better innovation performance than pure porting or pure recombination.

This hypothesis is consistent with Hargadon (2002, p. 79), who suggests that in order to promote recombination-based brokering, "hiring creative people and building creative cultures may not be sufficient. Providing organizational members with broad exposure to a variety of domains, and with flexibility in choosing the problem definitions they work on, may also be necessary to increase their ability to generate novel insights and recombinations."

3. Data and Method

To test these hypotheses, we need an empirical setting in which there is variation in the degree to which a sample of firms have accumulated knowledge brokering capacity (though the firms should not be selected on this basis). As well, we need variation in the firms' innovative output, together with controls for non-knowledge brokering factors that might be associated with innovative performance. It will also be useful to examine an empirical context in which the sample is comprised entirely of new ventures, as the evolutionary literature has argued that established firms have developed sets of organizational routines and may already be on differing resource attainment trajectories (even if we could adequately control for beginning period resource inequality across established firms), which may cloud our ability to attribute ex-post differences to knowledge brokering capability. Tracing ventures from their birth therefore allows for a "clean slate" approach to the study. Finally, it would be ideal if the initial technology which the new ventures are seeking to exploit were relatively uniform, as it may be the case that new enterprises may have different inherent abilities to broker knowledge or realize performance outcomes across different starting technologies. In short, we would like to follow a group of new ventures that were founded to exploit a given technological opportunity and to assemble a longitudinal dataset tracking their activities over time. Fulfilling all of these requirements is a considerable challenge.

The commercialization of recombinant DNA by new ventures following its technological discovery in 1973 by University of California-San Francisco scientist Herb Boyer and Stanford scientist Stan Cohen provides a fortuitous empirical context in light of our study requirements. Because the history of the discovery and patenting of the landmark technology is recounted in detail elsewhere (e.g., Reimers, 1987 and Hughes, 2001), we will not duplicate those efforts here. Instead, we merely note that Stanford University conducted an open non-exclusive licensing program of the patent (which they advertised in the scientific journals *Science* and *Nature*), and so we are able to observe with great precision de novo firms founded to commercialize recombinant DNA technology (users of the technology that did not participate in the licensing program would be infringing the patent and subject to litigation).[9] Aside from the scientific importance of the Cohen-Boyer invention (opening up the basic technique of recombining DNA), the patent was also clearly important commercially: over its lifetime, the patent yielded approximately $200M in licensing revenues, which implies product sales based on the innovation of some $40B.[10]

A quick comparison of the data used in this study in relation to Hargadon and Sutton (1997) and Hargadon's subsequent knowledge brokering studies (1998, 2002, and 2003) will be useful. These studies employ a handful of organizations, each of which interfaces with a diversity of clients. For example, several of the organizations are leading design and engineering firms (IDEO and Design Continuum) or consulting firms (McKinsey and Company). These firms are therefore likely to be in privileged positions from the standpoint of coming into contact with disparate communities necessary for knowledge brokering to take place and by virtue of being leaders in their respective fields. This study, by contrast, suffers from a different type of selection bias. Specifically, it is likely that founding teams were put together purposefully to capitalize on the Cohen-Boyer patent, and because founders likely face a high opportunity costs (due to their specialized human capital), these individuals may have already started from a privileged position in that they recognized the potential opportunity (in other words, they may have engaged in individual-level knowledge brokering). We address this selection in two ways. First, we assemble a longitudinal data set of the new ventures established to commercialize the Cohen-Boyer patent so that we can control for unobserved (time invariant) firm characteristics such as initial founding team quality, and base our estimates on the within-firm, across time dimension of variation in the data. Second, we only compare the start-ups observed to have been founded to commercialize the technology among themselves (rather than to an outside set of new ventures), and so the results are estimated based on heterogeneity *within* this sample of firms which may on average have a higher baseline potential for knowledge brokering than the outside firms. Nevertheless, our results should be interpreted as conditional on this dimension of selection. The remainder of this section describes our method and the variables used in the analysis.

---

[9] The Cohen Boyer invention was covered by three patents, with the most important being a process patent, U.S. patent number 4,237,224, entitled "Process for Producing Biologically Functional Molecular Chimeras." This patent, which became the backbone of the Stanford Technology Licensing Office's licensing efforts of recombinant DNA, was issued on December 2, 1980, and expired 17 years later, in 1997. Stanford offered licenses to the patent for a modest fee ($10,000 annual payments, with 0.5% royalty rates on end products).

[10] Between 1980 and 2000, the patent was cited 235 times by other patents, while the average patent of this vintage in this technology class was cited 9.64 times (Jaffe and Trajtenberg, 2002). Despite the economic value of this patent, which yielded such products as recombinant growth hormone and recombinant insulin, its legal validity was not subsequently challenged.

A. Method

We first identify start-up firms that entered as a result of opportunities to commercialize recombinant DNA technology. We rely on records of licensees to the Cohen Boyer technology from the Stanford University Office of Technology Licensing. We include firms in this sample if: (1) they are de novo firms (as opposed to established pharmaceutical firms), and (2) licensed the Cohen Boyer patents at the time of founding, or within a time window of two years after their founding. This process yielded a total of 19 firms listed in Table 1. We assemble a longitudinal data set by tracing these firms forward in time and recording information on a yearly basis. We conduct three sets of analyses. First we examine firms' efforts in building knowledge brokering capacity. Second, we explore innovation consequences of knowledge brokering. Third, we examine the effects of different types of knowledge brokering. Several of the variables used are constructed from patent data, and so it is worth briefly describing the procedure we use in gathering such data.

We identified all U.S. patents granted to the set of firms between January 1976 and December 2004. This resulted in a dataset of 3,652 firm-patent pairs. For each focal patent, we gathered primary patent class information. We then traced backward citations (references made by these patents) to all other U.S. patents to construct measures of knowledge brokering.[11] We also traced all forward citations (and their primary patent classes) to the focal set of patents through 2004 to construct measures of economic value, in line with standard measures in this literature (e.g., Jaffe and Trajtenberg, 2002). In total, our dataset contains 26,770 backward citations and 22,676 forward citations. As well, for each focal patent, we record the names and addresses of each inventor (2,901 persons). Finally, we identified all other patents awarded to the same inventors including those obtained while they were at other organizations, thereby building an innovation profile of each inventor over time.[12] The inventor data allows us to construct measures of inventor-level mobility and knowledge flows between organizations.

The following section describes the variables and empirical tests used in the analyses. The summary statistics and descriptions of all variables are presented in Table 2, and a pair-wise correlation matrix is shown in Table 3.

---

[11] Approximately 3.5% of backward citations are to patents issued prior to 1976. These are not available electronically from the U.S. Patent Office; we therefore used the Delphion database for these data. Therefore, our dataset contains *all* backward citations regardless of dates, and so left-censoring of the data is not an issue.

[12] We found 22,491 patents awarded to inventors with these or similar names. A research assistant was assigned the arduous task of filtering this dataset row by row, identifying each unique inventor based on their names as well as the address of the company the patent was assigned to. The main difficulty encountered was with common names (did an inventor work in multiple firms or did different people with the same name work across those firms?). There are only 41 such inventor names in our database, accounting for 1,142 patents. For these cases, we set a dummy variable to 1, and this variable is included in the regressions when appropriate as a robustness check.

B. Measuring Knowledge Brokering

We follow an established approach of using patent class data to identify the technological position of each invention (e.g. Jaffe, 1986). Knowledge brokering emphasizes the overlap between the technical domain a firm relies upon and the technical area in which it produces new knowledge. For example, Mowery et al. (1996) measure the degree to which two firms overlap in their technical knowledge by measuring the extent to which their patents make cross-citations to one another. Rosenkopf and Nerkar (2001), in the context of optical disk drive firms, use backward citations to non-disk patents as a measure of technological exploration (and non-self citations as a measure of organizational exploration). Because we wish to develop a more flexible measure concerning the knowledge base of the focal invention relative to knowledge relied upon to derive the invention, we develop a more general version of the Rosenkopf-Nerkar measure. This variable, *knowledge brokering*, is defined as [1 – (share of backward-cited patents that are in the same primary class as the focal patent)]. The extent to which a focal patent cites patents in different technical areas relative to the focal invention indicates the degree of knowledge brokering. The measure is based on the patent class of a focal patent (a measure of knowledge outputs) *in relation* to the patent classes of the patents cited by the focal patent (a measure of technological knowledge inputs).[13,14] High measures of *knowledge brokering* imply substantial use of technical knowledge originating from outside the focal patent area.

An alternate definition of knowledge brokering in the firm-patent analysis is the variable *patent originality*. This variable is defined as: $O_i = \left[1 - \sum_{j=1}^{J}\left(\frac{N_{ij}}{N_i}\right)^2\right]\left(\frac{N_i}{N_i - 1}\right)$, where *i* indexes the patent, *j* indexes patent classes, and *N* represents counts of backward citations (Henderson et al. 1998). The expression outside of the square brackets adjusts for bias associated with small numbers of backward patent counts (Hall and Trajtenberg, 2005). Patents that draw upon a broader diversity of patent classes receive a higher "originality" score. While *patent originality* is related to patent level *knowledge brokering*, the conceptual difference is important: *patent originality* measures the breadth of patent classes cited, while patent level *knowledge brokering* measures the overlap between a patent's own class and those it cites. For example, two patents may both have originality measures at the maximal value of 1, with the first patent having all its backward citations concentrated in the same class as the focal patent, while the second patent has all its backward citations concentrated in a different class relative to the focal patent. The first patent would thus

[13] There is also the issue of how to treat patents without prior patent references as prior art. Such cases are very rare in our dataset. The empirical results are robust to including an indicator variable for such instances.

[14] We do not use subclass information in the measure. Because of the large number of subclasses in both the focal and the backward cited patents, calculating a relative measure using all the subclass information becomes computationally difficult. As well, we wish to capture knowledge flowing from other technical areas into that of the focal patent, not from within one sub-specialty to another of the focal patent's technological area. We therefore confine ourselves to primary three digit patent classes rather than sub-classes.

exhibit no brokering while the second one would. This difference would be reflected in *knowledge brokering* but not in *patent originality*.

An added benefit to our measurement of *knowledge brokering* is that we easily construct derivative indicator variables to measure the different modes of knowledge brokering shown in Figure 1. The base case is the situation where there is neither porting nor recombination (*knowledge brokering* = 0). At the other extreme, a variable *pure porting* is used to identify patents that rely upon ideas from a single technical area to produce inventions in a different technical area. This variable is set to 1 if all of the backward citations for a patent are to a single technological class, and if that class is different from that of the focal patent. A second variable, *pure recombination*, is used to identify patents for which all the backward citations are to technical areas different from that of the focal patent and which cover a range of different classes rather than a single class. Such patents have a *knowledge brokering* value of 1 and a Herfindahl of cited patent classes not equal to 1. A third variable, *mixed recombination and porting*, is used to identify patents which exhibit both recombination and porting. It is set to 1 if the patent's *knowledge brokering* measure has a value greater than zero and less than one. The patents in our sample are quite varied, with 336 cases of pure porting, 364 of pure recombination, 1,767 mixed cases, and the remaining 1,185 patents exhibiting no recombination or porting.

In addition to the patent-level variables, we also measure knowledge brokering at the firm-year level. We measure firm level brokering as the percentage of citations made in a given firm-year to patent classes in which the firm *did not* also receive patents.[15] For firm *i* in year *t*,

$firmbroker_{it}$ = 1 – (#backward citations in to patents in primary classes firm *i* did not patent in during year *t*)/ (#backward citations made by firm *i* in year *t*)

For the regression analysis, we create a stock measure of this firm level measure, called *firm knowledge brokering stock*. Since *firmbroker* is a fraction it must be multiplied by the number of patents awarded to firm *i* in year *t* to create a stock. Starting from its founding year, each firm's *knowledge brokering stock* is calculated as the cumulative sum over previous years of ($firmbroker_{it}$ * $number\ of\ patents_{it}$).[16] Following Argote et al. (1990) and Macher and Boerner (2006), we include an exponential depreciation parameter in computing these stocks. We vary the depreciation parameter from 0 to 20% to test robustness, in line with the 20% rate used by Macher and Boerner for the pharmaceutical industry and the 15% depreciation rate for patent stocks used by Hall et al. (2005) to accommodate the possibility that there could be a degree of organizational "forgetting" over time (e.g., Nelson and Winter, 1982) and to test result robustness.

---

[15] We thank an anonymous reviewer for proposing this measure.

[16] Left-censoring is not a problem because all the firms were founded after 1976, the earliest date for which patent data is available in electronic format.

To measure recombination complexity, we adopt the approach used by Fleming (2001) and Fleming and Sorenson (2001, 2004). Using the insight that truly novel inventions recombine technical components that have historically not been recombined, Fleming and Sorenson develop a measure of recombination complexity. Each patent may be conceptualized as being composed of components, as reflected by the number of technological subclasses it is assigned (*N*). The observed ease of recombination of subclass *i* is defined as E_i :

E_i = (# subclasses previously combined with subclass *i*) / (# previous patents in subclass *i*)

Next, the coupling of patent *j* is defined as K_j :

K_j = (# subclasses on patent *j*) / $\sum_{j \in i} E_i$

The *coupling* measure is therefore a proxy for how difficult it is to recombine the components in a patent, benchmarked against the historic population of combinations of patent subclasses. A high level of *coupling* suggests that the focal patent uses subclass combinations that have historically been rarely observed. Finally, the recombinant complexity of each patent is calculated as C_i:

$C_i = K_j / N_j$ = *coupling of patent j / # subclasses on patent j*

Thus, *complexity* depends on the number of components in a patent (N) and the extent to which these components are tightly coupled (K), in line with the Kauffman (1993) N-K model it is based upon. This variable serves two purposes in our analyses: it controls for the degree of recombinative difficulty (based on historic distributions), and allows an assessment of how the performance impact of brokering might depend on the complexity of the technical environment.

C. Analyzing Organizational Antecedents of Knowledge Brokering

We first investigate organizational efforts that shape knowledge brokering capacity at the firm-year level of analysis. We regress the knowledge brokering stock measure on three sets of independent variables (beyond a set of firm fixed effects): a measure of initial firm conditions, organization boundary-spanning measures, and control variables. Each is discussed in turn.

The prior literature suggests that taking account of initial search conditions is important, as a range of theories, reviewed in the prior section, predict long-lasting organizational effects based on initial conditions. In the empirics, we adopt Cockburn et al.'s (2000) philosophy of examining organizational strategy while taking into account the impact of imprinting of initial conditions. We do this by constructing a variable, *overlap with initial technology focus*, which is defined as the share of firms' patents with the same technology classes with those applied for in its first three years since founding. A three year window allows sufficient time for firms to have several patents in the application process after being founded, while being reasonably short relative to the 28-year period that our panel of data covers. Moreover, the initial discovery process for new biotechnology-based drugs takes two to ten years (Hugesman, 2004), with most biotechnology firms having a three to five year research timeframe (Office of Technology Assessment, 1984), so a three year window seems reasonable in mapping firms' initial technological positions. Allowing for one or two year time periods yield qualitatively similar results.

A second group of right hand side variables contain three measures of various types of organizational boundary-spanning. The first, *equity alliances stock* as of *t*-2, is a proxy for the extent to which firms engage in boundary-spanning via tightly-coupled alliances (those involving equity use). The measure is based on count data, which is sourced from Recombinant Capital (a specialist in biotechnology industry data) and triangulated with the SDC database. A second measure, *venture capital funding stock* as of *t*-2, is a measure of the degree to which VCs, who may offer ventures access to an extended resource network, have funded the entrepreneurial firm (in millions of dollars). The VC data come from the Venture Economics database. Finally, *hired inventors with different technical knowledge stock* as of *t*-2, is a measure of the extent to which organizations hired technical staff with a different knowledge base relative to the firm's technical capability at that point in time. We construct this variable using US patent data. For each firm, we first identify all inventors new to the firm in each year, along with all patents awarded to the inventor throughout her career. Among these inventors, we identify those who had previously patented in technological classes different than the ones the firm received patents in within the past five years.[17] We then transformed this flow variable into a cumulative stock of new hires with different technical knowledge for each firm-year.

The *number of therapeutic areas* indicates the number of distinct therapeutic areas in which a firm operates in a given year (as reported by Recombinant Capital). We interpret this variable as a proxy for the firm's scope of operations. Finally, the variable *funding ease dummy* is based on Lerner's (1994) index of biotechnology funding environment (including funds from VC, initial public offerings and other forms of external funding for biotechnology firms). The *funding ease dummy* is a proxy for funding environment munificence, and is an indicator of being in an environment in which the index reaches the top 10% of its distribution. The variable therefore takes a value of one when the funding environment is favorable for biotechnology firms. For start-up firms, resource constraints, such as access to financial and human capital, often limit business development. During periods when the venture capital environment is "hot" and funding is relatively easy to obtain, firms may enjoy more organizational slack and surplus resources, and may therefore experiment and engage in more exploratory search.

[17] We used the five year window to capture the idea that firms would hire people with fairly recent knowledge in different areas in order to effectively broker knowledge. Given the rapid rate of knowledge obsolescence, hiring an active inventor with recent experience in a given technical area may be more beneficial relative to someone who may have worked in that area sometime in the distant past.

D. Analyzing the Consequences of Knowledge Brokering

A second analysis examines the innovation consequences of knowledge brokering as measured by forward patent citations. The variable *external forward citations* counts the number of external citations to the focal patent within five years of its issue, a well-established measure of innovative impact (Hall et al., 2005; Jaffe and Trajtenberg, 2002). We restrict the forward citation count to those made by external entities (by excluding self-citations) to emphasize the importance of knowledge bridging across organizational boundaries. The main right hand side variable of interest is the *knowledge brokering* measure. In the regressions, we control for the *number of references to the scientific literature*, which indicates the degree of reliance on fundamental scientific knowledge. We also control for *inventor patent experience at other firms*, which is defined as the number of patents issued to a focal patent's inventors while employed by *other* organizations prior to the application date of the focal patent. The measure aims to capture the degree to which inventors at a focal organization have patenting experience at other firms.[18]

4. Empirical Results

A. Factors Affecting Knowledge Brokering Stock

The analysis of firms' efforts to promote knowledge brokering is presented in Table 4. The dependent variable is *firm knowledge brokering stock*, and the estimation method is firm fixed effects OLS regression, which allows us to mitigate the risk of unobserved time invariant firm effects overturning the results. It is worth noting at the outset that the independent variables are each lagged by two years, and that we use stock variables for both the dependent and key independent variables. We lag the independent variables because current period knowledge brokering capabilities likely reflect actions taken in the recent past (our results are similar for other small time period lags). Using stock rather than flow variables recognizes the cumulative nature of search processes and R&D efforts. While the coefficients we report have not been depreciated (to reflect organizational decay of knowledge and capability), the results are similar for depreciation rates up to 20 percent.

The first three columns of Table 4 show each of the hypothesized boundary spanning mechanisms, *equity alliances stock*, *VC inflows stock*, and *hired inventors with different technical knowledge stock*, in a parsimonious specification with the variable *overlap with initial technology focus*. Across specifications 4-1, 4-2 and 4-3, *overlap with initial technology focus* is negative and statistically significant at either the 1 or 10 percent level, which is consistent with an established stream of local

[18] The analysis is also robust to the inclusion of the number of primary patent classes and number of patent subclasses as control variables, which may be proxies for patent scope breadth (Lerner, 1994). We do not include these variables in the analysis, however, as they are likely to be an intermediate outcome of the knowledge brokering process. We thank an anonymous reviewer for pointing this out.

search and founder imprinting literature suggesting that firms' initial orientation importantly shapes its subsequent R&D behavior, in this case knowledge brokering. The effect is not all-encompassing, however, and in the fully specified model (4-5) is no longer statistically significant, thus providing mixed support for H1. The three boundary-spanning mechanisms (alliances, venture capital and hiring) are each individually positive and statistically significant at the 1 percent level. Specifications 4-4 include all three mechanisms together, and specification 4-5 adds several control variables. The control variables are *number of therapeutic areas* and *funding ease dummy*. The *number of therapeutic areas* variable is weakly positive and statistically significant at the 10% level, while the funding ease variable is positive and significant at the 1% level. Across these two final specifications, the *equity alliances stock* and *hired inventors with different technical knowledge* effects persist at conventional levels (supporting H2a and H2b), while the *VC inflows stock* effect is not statistically significant (H2c is therefore not supported). This might result from a VC selection effect in which on average, VCs are selecting start-ups that do not use knowledge brokering extensively. This in turn may result from the time pressure associated with the VC fundraising and investing cycles (e.g., Gompers and Lerner, 1999) and the possible effect on entrepreneurial decision making choices. A second possibility is that VC involvement in the venture helps focus the entrepreneurial team on product development and execution for commercialization success, with less tolerance for exploratory search. These explanations are conjectures, however, and so future research efforts may wish to explore these effects more systematically.

B. Innovation Impact of Knowledge Brokering

In the remaining two empirical tables, we examine the innovative impact of knowledge brokering at the firm-patent level, and so the unit of observation in these tables is a firm-patent. We begin the analysis in Table 5 by studying the correlates of the number of external forward citations within 5 years of patent issue, a well-established measure of innovative impact (Jaffe and Trajtenberg, 2002). We restrict the forward citation count to those made by external entities (excluding self-citations) to emphasize the importance of knowledge brokering across organizational boundaries (the results are generally robust to inclusion of self-forward citations). Specifying a citation window of five years post patent issue allows for a meaningful citation comparison across observations. Since the dependent variable in the analysis is a non-negative count, we estimate negative binomial models.

A first specification, (5-1), does not cluster the patents by firm, and reports a parsimonious regression specification: knowledge brokering is the sole right hand side variable. The next column adjusts for added information we have about each observation by including fixed effects for each of the following: firms, patent application cohort, and primary patent classes. Controlling for each of these groups of potential effects is important because each different group could have different baseline forward citation rates. For example, due to the censoring of forward citations, it is important to include the patent application year fixed effects to take into account patent cohorts.[19] While the knowledge brokering effect is slightly diminished when the fixed effects are included, the statistical significance of knowledge brokering remains significant at the 5% level.

The next specification, (5-3), adds patent control variables. A first group controls for the extent to which patents span boundaries, and so would be otherwise potentially subject to different rates of forward patent citations. We include a variable for the *number of references to the scientific literature* (as opposed to references to prior patents), which Fleming and Sorenson (2004) have argued can aid in the technological search process. We also control for *inventor patent experience at other firms*, which is a proxy for the degree to which inventors at the focal firm had prior experience patenting in other organizations, as technical staff job mobility may be an important mechanism by which knowledge is transferred across boundaries (e.g., Agrawal and Henderson, 2002). This variable helps to partial out such differences in the technical staff of each firm. Neither of these variables is significant in the regression. A second set of variables in specification (5-3) controls for the degree of technical complexity and "innovativeness" of a particular patent. We use Fleming and Sorenson's (2004) *complexity* measure, which incorporates as one dimension the degree to which a focal patent uses subclass combinations that have historically been rarely observed (the "coupling" component). *Complexity* therefore implicitly adjusts for the technological "distance" of the focal invention, at least at the level of the focal patent classes (the estimated coefficient is negative and statistically significant). An included squared term of *complexity* tests the linearity of the effect (which is estimated with a positive and statistically significant coefficient). Our estimates therefore suggest a U-shaped relationship between *complexity* and *external forward cites*: at low levels of forward citations diminish with complexity until a certain critical point (possibly because less complex patents are easier to grasp and therefore cite), after which the relationship is positively-sloped (possibly associated with a high degree of patent novelty).

The main variables of interest, however, are *knowledge brokering* and its square term. The former is positive and significant at the 1 percent level while the latter is negative and significant at the same level. This confirms the inverse-U shaped hypothesis between *knowledge brokering* and *external forward cites* (H3), which suggests that relatively low levels of brokering injects useful variety into an invention, but that beyond a certain point, brokering can be detrimental to innovative performance due to exhaustion of the search space and/or internal cohesion shortfalls associated with more intensive brokering. The next specification, (5-4), retains the same structure as the prior specification, only adding an interaction term,

[19] An alternate approach is to deflate the forward citations by the average value for its scientific field-year cohort as a fixed effect, as discussed in Jaffe and Trajtenberg (2002). Because we do not use the National Bureau of Economic Research dataset for our patent data (this allows us to include more recent patents), we do not use these deflators in our analysis.

*knowledge brokering * complexity*. While the results from (5-3) are largely preserved, the interaction term itself is not significantly different than zero. This suggests that knowledge brokering does not appear to be more or less difficult in more technically complex environments (failing to confirm H4, though we will revisit this in the next section).

Using the specification in Model (5-4), we plot the expected number of *forward citations* within 5 years of patent issue against *knowledge brokering*, using in the prediction the mean values of all the other variables. Figure 2 shows that as *knowledge brokering* increases from 0 to around 0.6 (slightly above its mean value), the number of external citations is predicted to rise. As *knowledge brokering* continues to increase towards its maximal value of 1, the number of external citations begins to decline, but not down to the initial level along the y-axis.

Finally, it is well-established that the economic value of patents is highly skewed, with only a small number of patents holding most of the collective value (e.g., Harhoff et al., 1999). Hence, it would be worthwhile to examine how well knowledge brokering predicts the likelihood that a given patent is in the right tail of the patent value distribution. We therefore examine a fixed effects logit model of the probability of being in the top 5% of the forward citation distribution in specification (5-5). We employ the same right hand side variables as in specification (5-4), and find that knowledge brokering has an inverted U-shaped relationship with the probability of being in the top 5% of the sample external forward citation distribution. In this specification, we include fixed effects for only the six most frequently occurring primary patent classes because a specification that includes the full set of primary patent classes does not converge (nor does a dependent variable that takes a value of one only when a patent is in the top 1 percent of the external forward citation distribution).

The results described in Table 5 also largely hold (though are slightly weaker) for an alternative measure of innovative performance, *patent generality*. A patent with high generality is one that has other patents from a broader range of technological classes citing the focal patent. This measure has been used by Henderson et al. (1998) and others as a proxy for innovative performance, especially as related to the production of more "fundamental" or "general" inventions. In addition, we examined an organization-level hazard model in which the dependent variable is an initial public offering (IPO). While we find broadly consistent results to the firm-patent level analysis, due to the relatively small number of observations, we do not report the results formally, and so we leave a more definitive study using firm-year level outcome data to future work.

C. Effects of Different Types of Brokering

Finally, in Table 6, we report results of fixed effects negative binomial regressions of *external forward cites*, but with knowledge brokering divided into three different modes: *pure porting*, *pure* *recombination*, and *mixed recombination and porting*. In the first specification, we include these three modes of brokering (the excluded mode involves no knowledge brokering). Using the same fixed effects as reported in the previous table (for firm, patent application year, and patent class), we find that neither *pure porting* nor *pure recombination* is significant, while *mixed recombination and porting* is positive and significant at the 1 percent level (lending support for H5). The next specification, (6-2), adds several patent level control variables and interacts each of the brokering modes with *complexity*. The direct brokering effects are largely the same as before (although *pure porting* is now positive and marginally significant). The main result of interest is the interaction term *mixed porting and recombination * complexity*. While the *mixed porting and recombination* variable is once again positive and significant, the interaction effect with *complexity* is negative and significant at the 5 percent level, suggesting that this method of brokering is less effective under technically complex environments, which lends support for H4. Recall that when the various modes of brokering were not distinguished (specification 5-4), the composite measure of brokering did not yield a statistically significant interaction effect with *complexity*, in contrast to what we find here. This suggests that disaggregating the various brokering modes is important.

5. Discussion and Conclusions

We empirically examined the antecedents and innovation consequences of organizational knowledge brokering capability, the ability to effectively apply knowledge from one technical domain to innovate in another. The commercialization of recombinant DNA technology via non-exclusive licensing offered a fortuitous empirical setting in which initial technology is uniform, and in which multiple new ventures were started in an attempt to exploit that technology. This clean empirical setting allows us to study the efforts of firms in building knowledge brokering capability and its performance implications without the potential confounding effects of diverse initial technologies, firms at different stages of their life cycle, and established organizational routines which might confound the estimated antecedents and consequences of knowledge brokering.

This study design allows us to complement prior research in this area by examining how firms' interaction with their external environment helps build their heterogeneous knowledge brokering capacity, which in turn is associated with the ex-post uneven innovative performance landscape. Our results suggest that (a) knowledge brokering capability is achieved by striking equity strategic alliances and hiring technical personnel with prior patenting experience in areas other than the firm's own, more so than other boundary-spanning mechanisms; (b) knowledge brokering has an inverted U-shaped relationship with innovative performance; and (c) there are important conceptual and empirical reasons to consider different modes of knowledge brokering, rather than as a monolithic concept. Overall, the results suggest that knowledge brokering can be an important organizational capability.

While these results help deepen our understanding of knowledge brokering, several interpretational issues merit discussion. These involve: (1) firms' efforts to promote knowledge brokering, (2) level of analysis issues, and (3) inference based on patent data. Each is discussed in turn.

There are a number of issues related to interpreting firms' efforts at promoting knowledge brokering. First, a more comprehensive analysis addressing possible omitted variable bias would be worthwhile. Our empirical strategy in this paper was to include firm fixed effects in the regression analyses. While using this estimation methodology can result in bias in either direction (e.g., Azoulay et al., 2006), the primary advantage is controlling for unobserved factors that are time invariant across the panel data. However, if there are firm-specific, temporally changing variables which significantly affect knowledge brokering capacity that are uncontrolled in the analysis, our results may suffer from omitted variable bias. For example, organizational search importantly depends on managerial aspiration levels (e.g., Greve, 1998 and references therein), which may change over time and are difficult for analysts to observe and measure. As well, organizational failure or resource exhaustion may trigger organizational search (Cyert and March, 1963; Bromiley, 1991; Ahuja and Katila, 2004).

A second area related to promoting knowledge brokering is that we are not able to observe failed efforts to innovate. We therefore hesitate to give prescriptive advice without a better understanding of the costs associated with trying to induce brokering. Firms may face different costs when accessing, storing, retrieving, and brokering knowledge. Brokering highly disparate knowledge domains can lead to valuable innovations, but making the investment may not be worthwhile for the average individual or organization.[20] A final interpretational issue relating to firms' efforts to promote knowledge brokering is the process by which knowledge brokering-oriented invention takes place. The debate on the extent to which social interaction is necessary for invention (including knowledge brokering invention) is a long-standing one (e.g., Gilfillan [1935] versus Usher [1954]), and relates to the individual versus team nature of invention and innovation. While anecdotes supporting either view can be offered, it is difficult empirically to adjudicate between these views using patent data, as we only observe successful inventions which are granted patents. In any case, we know of no systematic effect in this realm that would bias our results.

This last point raises a broader issue, that of the appropriate level of analysis to study knowledge brokering. While we largely abstract away from individual and network level factors from the analysis in

[20] Efforts at brokering, as in any exploratory search process, may be expected to have higher failure rates relative to local search efforts, but individuals and firms may wish to allocate a certain percentage of their efforts into such endeavors (which have associated policy implications, such as designing effective incentives for such behavior), in order to leave open the possibility of higher variance returns (higher potential upside) relative to local search.

the interest of focusing our attention on conceptual and empirical development of knowledge brokering at the organizational level, we know from Hargadon (2002) that knowledge brokering is a multi-level phenomenon. Moreover, brokering at one level of analysis can influence such action at another level. These complex effects make it difficult to address empirically. Nevertheless, we do have measures of organizational and individual level brokering, and so we conducted a preliminary analysis with the aim of motivating future work on the topic (ideally a paper or project designed to study this issue). We regressed organizational knowledge brokering on individual knowledge brokering and a set of start-up firm fixed-effects. When we run this simple regression, we find that individual brokering is significantly correlated with organization-level brokering (as expected); however, there is still quite a bit of unexplained variation, with a 0.45 adjusted R-squared value for the regression. This suggests that there are organizational processes above and beyond individual brokering explain the variation in organization-level knowledge brokering. Therefore more systematic work in this domain in the future would be interesting (we propose one direction below).

A third group of interpretational issues surrounds the use of patent data. The costs and benefits to patent-based measures have been extensively discussed elsewhere (see for example, Jaffe and Trajtenberg, 2002). A first issue involving patent citation data is that inventors might strategically cite prior art across technical domains to appear more novel, thus improving the likelihood of receiving a patent in the first place. Inventors have an incentive not to over-cite in this manner, however, since doing so will enlarge the relevant prior art, thus narrowing the scope of the patent. Reinforcing this, patent examiners are charged with ensuring relevant citations, since citations are used as a legal device to circumscribe patent scope through the identification of prior art. The ideal way to test for this effect would be to assemble a sample of patent applications, some of which are granted, others of which are not—and look for differences based on prior art. Without conducting a well-designed study on the topic, however, we are not prepared to speculate on potential bias from this issue.

A second issue relates to the reliability of patent citations as a measure. Alcacer and Gittelman (2006) argue that patent examiner-imposed citations may be an important phenomenon. If true, then our calculation of the knowledge brokering measures may not accurately represent search behavior by scientists and organizations. Because the data on patent examiner-imposed citations are only available since 2001, we are not able to empirically examine the extent to which this phenomenon holds in our sample. We are ultimately concerned, however, with knowledge *use*, and as long as each patent does depend on other patents it cites for prior technical knowledge, we are less concerned about whether a patent examiner or the inventor herself was responsible for adding those citations to the patent.[21]

[21] Thompson and Fox-Kean (2005) raise concerns over the patent matching procedure used by Jaffe et al. (1993). In their study of the geographic localization of knowledge spillovers, Jaffe et al. use patent citations to create a

With these caveats and interpretational issues in mind, we wish to reflect on the contributions of this paper to the literature beyond the empirical setting and study design, which we believe complement prior qualitative efforts in studying knowledge brokering. First, we believe that we make a contribution to the resource-based view theory in two ways. While we are not the first to study the origins and antecedents to heterogeneous resources, we join the few studies (e.g., Cockburn et al., 2000; Ahuja and Katila, 2004; Cattani, 2005) which have taken this approach, which improves our understanding of "why firms differ, and how does it matter?" to borrow Nelson's (1991) title to his influential essay. We are differentiated from prior studies, however, in that we begin our analysis at firms' births, which has the advantage of removing the potentially confounding factor of existing path dependent resource trajectories associated with established organizations. A second contribution to the RBV literature is relating initial recognition of entrepreneurial opportunity to firms' resource and performance heterogeneity. This is based on our finding that those founding teams that broker technical domains less intensively during their initial entrepreneurial opportunity recognition will be less effective in developing and exploiting knowledge brokering capability, with the opposite being true for those firms with greater brokering during initial opportunity recognition. While our empirical results on this point are mixed, size of sample issues may be at issue, which presents future research opportunities.

A second contribution is to the evolutionary perspective on organizational innovation and exploratory R&D search. Relative to prior studies, we develop the view that knowledge brokering is more nuanced than previously conceptualized. First, more knowledge brokering is not necessarily better from an innovation performance standpoint. While knowledge brokering yields beneficial effects including breakthrough innovation (as measured by being in the top five percent of the patent forward citation distribution), we argue and empirically affirm an eventual downturn in innovative performance with increasing levels of knowledge brokering. As well, the innovative impact of brokering may be contingent on the complexity of firms' technical environment. Finally, knowledge brokering is not a monolithic concept; instead, there may be different modes with differing means of inducing each mode, with differing innovative impacts. In particular, a mixture of porting and recombination yields higher innovative performance relative to either mode alone.

We end with some thoughts on ways to extend this research given the discussion in this section. First, while we have taken a first step at empirically accounting for prior access to exploratory search mechanisms, we believe that this issue needs more systematic attention in this literature. This relates to differential organizational costs of building knowledge brokering capabilities discussed above, as well as to differential firm-level productivity for a given level of investment in organizational knowledge

matched sample, which they use to control for the pre-existing distribution of inventive activity. The empirical design in our paper does not rely on constructing such patent citation-based matched samples.

brokering capability. Second, while we have concentrated our attention on external correlates of knowledge brokering, future efforts to understand the efficacy of internal policies and procedures would be welcome. For example, to what extent do firm policies such as allowing scientists to engage in the broader scientific community (e.g., Henderson and Cockburn, 1994), setting aside time for engaging in scientific endeavors (such as at 3M, Google, and IBM), and/or establishing corporate "wikis" (e.g., Vara, 2007) result in more knowledge brokering? Third, while we purposefully investigated knowledge brokering in a well-designed empirical setting, it would be useful to examine the phenomenon in other arenas to better understand the generality of our results, particularly given the relatively modest sample size in this study (Banerjee [2006], for example, finds that marketing alliances facilitate cross-application of knowledge). Finally, we end with a call for better understanding the interaction between individual and organization level knowledge brokering. Firms (through their managers) can take a number of steps to promote brokering at the organizational level. These range from the external mechanisms studied here, together with internal efforts such as building a corporate culture (through formal and informal means) and instituting policies and organizational design choices. Individuals, however, are the ones carrying out inventive activities. Establishing a "baseline" amount of knowledge brokering will be important, as serendipity and other factors may give rise to organic brokering. The question then becomes how business policy interventions, when applied as a "treatment", will affect brokering at both the individual and organizational levels. Exploring these and other multi-level knowledge brokering mechanisms would deepen our understanding of this form of R&D search.

References

Adner, R. and D. Levinthal (2000). "Technological Speciation and the Emergence of Emerging Technologies," in G. Day and R. Shoemaker, eds. Wharton on Emerging Technologies. John Wiley & Sons.

Agrawal, A. and R.M. Henderson (2002). "Putting Patents in Context: Exploring Knowledge Transfer from MIT," *Management Science*, 48: 44-60.

Ahuja, G. and R. Katila (2004). "Where Do Resources Come From? The Role of Idiosyncratic Situations," *Strategic Management Journal*, 25: 887-907.

Ahuja, G. and C. Lampert (2001). "Entrepreneurship in the Large Corporation: A Longitudinal Study of How Established Firms Create Technological Breakthroughs," *Strategic Management Journal*, 22: 521-543.

Alcacer, J. and M. Gittelman (2006). "Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations," *Review of Economics and Statistics*, 88: 774-779.

Almeida, P. and B. Kogut (1999). "Localization of Knowledge and the Mobility of Engineers in Regional Networks," *Management Science*, 45: 905-917.

Argote, L., S. Beckman, and D. Epple. (1990). "The Persistence and Transfer of Learning in Industrial Settings," *Management Science*, 36(2): 140–154.

Azoulay, P., W. Ding and T. Stuart (2006). "The Impact of Academic Patenting on the Rate, Direction, and Quality of (Public) Research Output" *NBER Working Paper* 11917.

Baldwin, C. and K. Clark (2000). Design Rules: The Power of Modularity. MIT Press, Cambridge, MA.

Banerjee, P. (2006). "Learning from the Banyan Tree: Branching Through Cross-Application as a Strategy for High-Tech Entrepreneurial Innovation," PhD dissertation, Wharton School, University of Pennsylvania.

Barney, J. (1991). "Firm Resources and Sustained Competitive Advantage," *Journal of Management*, 17: 99-120.

Baron, J.N., M.D. Burton, and M.T. Hannan (1996). "The Road Taken: Origins and Evolution of Employment Systems in Emerging Companies," *Industrial and Corporate Change*, 5: 239-275.

Basalla, G. (1988). The Evolution of Technology. Cambridge University Press, Cambridge, UK.

Baum, J., T. Calabrese and B.S. Silverman (2000). "Don't go it Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology," *Strategic Management Journal*, 21: 267-294.

Boeker, W. (1989). "Strategic Change: The Effects of Founding and History, *Academy of Management Journal*, 32: 489-515.

Bromiley, P. (1991). "Testing a Causal Model of Corporate Risk Taking and Performance," *Academy of Management Journal*, 34: 37-59.

Brown, S.L. and K.M. Eisenhardt (1997). "The Art of Continuous Change: Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations," *Administrative Science Quarterly*, 42: 1-34.

Burgelman, R. (1994). "Fading Memories: A Process Theory of Strategic Business Exit in Dynamic Environments," *Administrative Science Quarterly*, 39: 24-56.

Cattani, G. (2005). "Preadaptation, Firm Heterogeneity, and Technological Performance: A Study on the Evolution of Fiber Optics, 1970-1995," *Organization Science*, 16: 563-580.

Cockburn, I., R. Henderson, and S. Stern (2000). "Untangling the Origins of Competitive Advantage," *Strategic Management Journal*, 21: 1123-1145.

Cohen, W.C. and D.A. Levinthal (1990). "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35: 128-152.

Cyert, R.M. and J.G. March (1963). A Behavioral Theory of the Firm. Blackwell Publishers: Malden, MA.

DiMasi, J.A. (2000). "New Drug Innovation and Pharmaceutical Industry Structure: Trends in the Output of Pharmaceutical Firms," *Drug Information Journal* 34: 1169-1194.

Eisenhardt, K.M. and C.B. Schoonhoven (1990). "Organizational Growth: Linking Founding Team Strategy, Environment, and Growth among U.S. Semiconductor Ventures, 1978-1988", *Administrative Science Quarterly*, 35: 504-529.

Fleming, L. (2001). "Recombinant Uncertainty in Technological Search," *Management Science*, 47: 117-132.

Fleming, L. and O. Sorenson (2001). "Technology as a Complex Adaptive System: Evidence from Patent Data," *Research Policy*, 30: 1019-1039.

Fleming, L. and O. Sorenson (2004). "Science as a Map in Technological Search," *Strategic Management Journal*, 25: 909-928.

Gans, J.S., D.H. Hsu and S. Stern (2002). "When Does Start-up Innovation Spur the Gale of Creative Destruction?" *RAND Journal of Economics*, 33: 571-586.

Garud, R. and P.R. Nayyar, "Transformative Capacity: Continual Structuring by Intertemporal Technology Transfer," *Strategic Management Journal*, 15: 365-385.

Gavetti, G. D. Levinthal and J. Rivkin (2005). "Strategy Making in Novel and Complex Worlds: The Power of Analogy," *Strategic Management Journal*, 26: 291-712.

Gilfillan, S.C. (1935). The Sociology of Invention. MIT Press: Cambridge, MA.

Gomes-Casseres, B., J. Hagedoorn, and A.B. Jaffe (2006). "Do Alliances Promote Knowledge Flows?" *Journal of Financial Economics*, 80: 5-33.

Gompers, P. and J. Lerner (1999). The Venture Capital Cycle. MIT Press: Cambridge, MA.

Greve, H.R. (1998). “Performance, Aspirations, and Risky Organizational Change,” *Administrative Science Quarterly*, 43: 58-86.

Gulati, R. (1998). “Alliances and Networks,” *Strategic Management Journal*, 19: 293-317.

Hall, B, A.B. Jaffe, and M. Trajtenberg (2005). “Market Value and Patent Citations,” *RAND Journal of Economics*, 36:16-38.

Hall, B. and M. Trajtenberg (2005). “Uncovering GPTs Using Patent Data,” in Antonelli, Foray, Hall, and Steinmueller (eds.), *Festschrift in Honor of Paul A. David*, Edward Elgar.

Hargadon, A. and R. Sutton (1997). “Technology Brokering and Innovation in a Product Development Firm,” *Administrative Science Quarterly*, 42: 716-749.

Hargadon, A. (1998). “Firms as Knowledge Brokers: Lessons in Pursuing Continuous Innovation,” *California Management Review*, 40: 209-227.

Hargadon, A. (2002). “Brokering Knowledge: Linking Learning and Innovation,” *Research in Organizational Behavior*, 24:41-85.

Hargadon, A. (2003). How Breakthroughs Happen: The Surprising Truth About How Companies Innovate. Harvard Business School Press, Boston.

Harhoff, D., F. Narin, F.M. Scherer, and K. Vopel (1999). “Citation Frequency and the Value of Patented Inventions,” *Review of Economics and Statistics*, 81: 511-515.

Helfat, C.E. (1994). “Evolutionary Trajectories in Petroleum Firm R&D,” *Management Science*, 40: 1720-1747.

Henderson, R.M. and K.B. Clark (1990). “Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms,” *Administrative Science Quarterly*, 35: 9-30.

Henderson, R. and I. Cockburn (1994). “Measuring Competence? Exploring Firm Effects in Pharmaceutical Research,” *Strategic Management Journal*, 15: 63-84.

Henderson, R., A. Jaffe, M. Trajtenberg, (1998). “Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965-1988,” *The Review of Economics and Statistics*, 80: 119-127.

Hsu, D.H. (2006). “Venture Capitalists and Cooperative Start-up Commercialization Strategy,” *Management Science*, 52: 204-219.

Hsu, D.H. (2007). “Experienced Entrepreneurial Founders, Organizational Capital, and Venture Capital Funding,” *Research Policy*, 36: 722-741.

Huber, G.P. (1991). “Organization Learning: The Contributing Processes and the Literatures,” *Organization Science*, 2: 88-115.

Hughes, S.S. (2001). “Making Dollars out of DNA: The First Major Patent in Biotechnology and the Commercialization of Biotechnology,” *Isis*, 92: 541-575.

Hugesman (2004). "The Business of Biotechnology," http://www.scq.ubc.ca/the-business-of-biotechnology.

Jaffe, A. (1986). "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," *American Economic Review*, 76: 984-1001.

Jaffe, A., M. Trajtenberg, and R. Henderson (1993). "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics*, 108: 577-598.

Jaffe, A. and M. Trajtenberg (2002). Patents, Citations, and Innovations: A Window on the Knowledge Economy. MIT Press: Cambridge, MA.

Katila, R. and G. Ahuja (2002). "Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction," *Academy of Management Journal*, 45: 1183-1194.

Kauffman, S.A. (1993). The Origins of Order: Self-organization and Selection in Evolution. Oxford University Press: New York, NY.

Kenney, M. (1986). Biotechnology: The University-Industry Complex. Yale University Press: New Haven, CT.

Khanna, T., R. Gulati, and N. Nohria (1998). "The Dynamics of Learning Alliances: Competition, Cooperation, and Relative Scope," *Strategic Management Journal*, 19: 193-210.

Kodama, F. (1992). "Technology Fusion and the New R&D," *Harvard Business Review*, 70: 70-78.

Kogut, B. and U. Zander (1992). "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science*, 3: 383-397.

Lakahani, K. (2006). "Solving Scientific Problems by Broadcasting them to Diverse Solvers," working paper, MIT Sloan.

Lazear, E. (2004). "Balanced Skills and Entrepreneurship," *American Economic Review*, May, 94: 208-211.

Lerner, J. (1994). "The Importance of Patent Scope: An Empirical Analysis," *RAND Journal of Economics*, 25: 319-333.

Levinthal, D.A. (1998). "The Slow Pace of Rapid Technological Change: Gradualism and Punctuation in Technological Change," *Industrial and Corporate Change*, 7(2): 217-247.

Lim, Kwanghui (2006). "The Many Faces of Absorptive Capacity: Spillovers of Copper Interconnect Technology for Semiconductor Chips." SSRN: http://ssrn.com/abstract=562862

Macher, J. and C.S. Boerner (2006). "Experience and Scale and Scope Economies: Trade-offs and Performance in Development," *Strategic Management Journal*, 27: 845-865.

Manso, G. (2006). "Motivating Innovation," working paper, MIT Sloan School of Management.

March, J.G. (1991). "Exploration and Exploitation in Organizational Learning," *Organization Science*, 2: 71-87.

March, J.G. and H.A. Simon (1958). Organizations. John Wiley, New York.

McGrath, R.G. and I. MacMillan (2000). The Entrepreneurial Mindset. Harvard Business School Press: Boston.

Mintzberg, H. and J.A. Water (1982). "Tracking Strategy in an Entrepreneurial Firm," Academy of Management Journal, 25: 465-499.

Mowery, D.C., J.E. Oxley and B.S. Silverman (1996). "Strategic Alliances and Interfirm Knowledge Transfer," *Strategic Management Journal*, 17: 77-91.

Mullis, Kary B. (1990). "The Unusual Origin of the Polymerase Chain Reaction," *Scientific American*, April, pp. 56-65.

Nelson, R.R. and S.G. Winter (1982). An Evolutionary Theory of Economic Growth. Harvard University Press, Cambridge, MA.

Nelson, R.R. (1991). "Why Do Firms Differ, and How Does It Matter?" *Strategic Management Journal*, 12: 61-74.

Office of Technology Assessment (1984). Commercial Biotechnology: An International Analysis. Washington, D. C.: U.S. Congress, Office of Technology Assessment, OTA-BA-218, January, p. 96.

Packard, D. (1995). The HP Way: How Bill Hewlett and I Built Our Company. HarperBusiness: New York.

Peteraf, M.A. (1993). "The Cornerstones of Competitive Advantage: A Resource-Based View," *Strategic Management Journal*, 14: 179-191.

Peteraf, M.A. and J.B. Barney (2003). "Unraveling the Resource-Based Tangle," *Managerial and Decision Economics*, 24: 309-323.

Reimers, N. (1987). "Tiger by the Tail," *Chemtech*, 17: 464-471.

Rivkin, J.W. (2000). "Imitation of Complex Strategies," *Management Science*, 46: 824-844.

Romanelli (1989). "Environments and Strategies of Organization Start-Up: Effects on Early Survival," *Administrative Science Quarterly*, 34: 369 387.

Rosenkopf, L. and A. Nerkar (2001). "Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Industry," *Strategic Management Journal*, 22: 287-306.

Rosenkopf, L. and P. Almeida (2003). "Overcoming Local Search Through Alliances and Mobility," *Maangement Science*, 49: 751-766.

Scherer, F.M. (1982). "Inter-industry Technology Flows and Productivity Growth," *The Review of Economics and Statistics*, 64: 627-634.

Schumpeter, J. (1934). The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest and the Business Cycle. Harvard University Press: Cambridge, MA.

Shane, S. (2000). "Prior Knowledge and the Discovery of Entrepreneurial Opportunities," *Organization Science*, April, 448-469.

Simon, H.A. (1962). "The architecture of complexity," *Proceedings of the American Philosophical Society*, 106: 467-482.

Sorenson, O., J.W. Rivkin, and L. Fleming (2006). "Complexity, Networks and Knowledge Flow," *Research Policy*, 35: 994-1017.

Stinchcombe, A.L. (1965). "Social Structure and Organizations," in Handbook of Organizations, J. March (ed.), Rand-McNally: Chicago, IL, 142-193.

Stuart, T.E. and J.M. Podolny (1996). "Local Search and the Evolution of Technological Capabilities," *Strategic Management Journal*, 17: 21-38.

Thomke, S.H. (2003). Experimentation Matters: Unlocking the Potential of New Technologies for Innovation. Harvard Business School Press: Boston, MA.

Thompson, P. and M.E. Fox-Kean (2005). "Patent Citations and the Geography of Knowledge Spillovers: A Reassessment," *American Economic Review*, 95: 450-460.

Usher, A.P. (1954). A History of Mechanical Inventions, 2nd edition, Harvard University Press.

Vara, V. (2007). "Wikis at Work: Companies Turn the Wikipedia Concept into a Powerful Corporate-Information Tool for Employees," Wall Street Journal, June 18, p. R11.

Walsh, J.P. and G.R. Ungson (1991). "Organizational Memory," *Academy of Management Review*, 16: 57-91.

Weitzman, M. (1998). "Recombinant Growth," *Quarterly Journal of Economics*, 63: 331-360.

Wernerfelt, B. (1984). "A Resource-Based View of the Firm," *Strategic Management Journal*, 5: 171-180.

Yoffe, E. (1994). "Is Kary Mullis God? Nobel Prize Winner's New Life," *Esquire*, July.

Zucker, L., M. Darby and M. Brewer (1998). "Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises," *American Economic Review*, 88: 290-306.

Figure 1: Modes of Knowledge Brokering

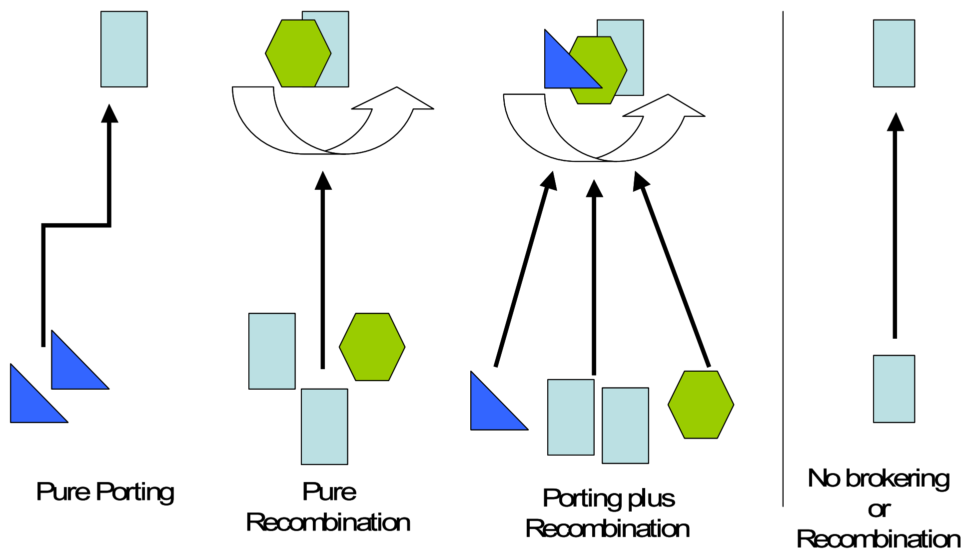

Figure 2: Predicted External Forward Cites within 5 years of Patent Issue (at the Mean Value of Other Variables)

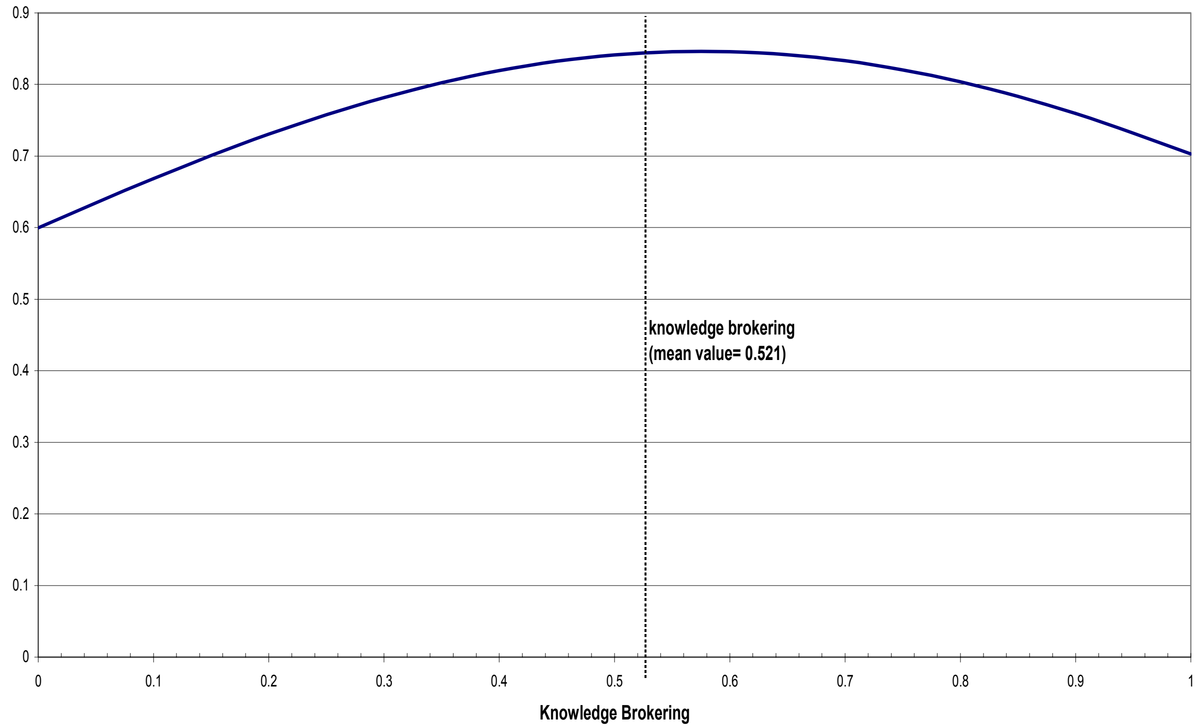

Table 1: List of Firms Included in the Study

Firm#	Firm	Founded	Headquarters Location
1	Amgen	1980	Thousand Oaks, CA
2	Biogen	1978	Cambridge, MA
3	Celltech	1980	Cambridge, UK
4	Chiron	1981	Emeryville, CA
5	Genelabs	1983	Redwood City, CA
6	Genzyme	1981	Cambridge, MA
7	Mycogen	1982	San Diego, CA
8	DNA Plant Technology	1980	Oakland, CA
9	Genentech	1976	San Francisco, CA
10	Genetics Institute	1980	Boston, MA
11	New England Biolabs	1978	Ipswich, MA
12	Repligen Corp	1981	Waltham, MA
13	Creative Biomolecules	1981	Hopkinton, MA
14	GenPharm International	1988	Mountain View, CA
15	Therion Biologics	1991	Cambridge, MA
16	VYSIS, Inc	1991	Downers Grove, IL
17	Neurex	1986	Menlo Park, CA
18	Enzon	1981	Bridgewater, NJ
19	ICOS Corporation	1989	Bothwell, WA

Table 2
Summary Statistics and Variable Definitions

VARIABLE	DEFINITION	MEAN	SD
Firm-year measures			
Firm knowledge brokering stock	Stock of firm-year aggregation of *knowledge brokering* (see text)	41.52	73.02
Overlap with initial technology focus	Share of firm's patents with the same technology classes with those applied for in the firm's first three years since founding	0.59	0.37
Equity alliances stock	Stock of number of equity-based strategic alliances	1.05	1.52
Hired inventors with different technical knowledge stock	# of inventors who apply for patents at the focal firm who also have prior patenting experience in different technical areas at another organization	12.18	11.51
Venture capital inflows stock	Cumulative venture capital funding received by the firm (millions of dollars)	9.07	11.68
Number of therapeutic areas	# of therapeutic areas in which the firm participates	3.14	4.08
Funding ease dummy	Dummy = 1 if the external funding environment is in the top 10% in munificence as measured by Lerner's biotechnology index	0.34	0.48
Firm-patent measures			
External forward citations	# of external forward citations within 5 years of patent grant year	2.43	3.65
Knowledge brokering	1 – (share of primary patent class overlap between backward citing patents and the focal patent)	0.52	0.38
Pure porting	This dummy variable is set to 1 if (a) all of the patent's backward citations are to the same patent class (Herfindahl of cited patent classes = 1) and (b) that patent class is not the same as that of the focal patent (*knowledge brokering* = 1).	0.09	0.29
Pure recombination	This dummy variable is set to 1 if (a) all of the cited patents are in patent classes different than that of the focal patent (*knowledge brokering* = 1) and (b) the cited patents are not all in the same patent class (Herfindahl of cited patent classes <1).	0.10	0.30
Mixed recombination and porting	This dummy variable is set to 1 if the patent's *knowledge brokering* value is greater than 0 and less than 1.	0.48	0.50
Complexity	Fleming and Sorenson's (2004) measure of innovation complexity (see text).	0.24	0.36
References to the scientific literature	Number of patent references to the scientific literature	32.98	47.25
Inventor experience at other firms	# of patents issued to focal patent's inventors when employed by other organizations as of the application date of the focal patent	6.61	11.90

Table 3
Pair-wise Correlations of Independent Variables

A. Firm-year level of analysis

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Firm knowledge brokering stock						
(2) Overlap with initial technology focus	-0.25*					
(3) Equity alliances stock	0.47*	-0.10				
(4) Hired inventors with diff. tech. knowledge stock	0.65*	-0.36*	0.40*			
(5) VC inflows stock	0.25*	-0.12*	0.54*	0.22*		
(6) Number of therapeutic areas	0.63*	-0.35*	0.52*	0.70*	0.27*	
(7) Funding ease dummy	0.38*	-0.14*	0.21*	0.32*	0.18*	0.29*

B. Firm-patent level of analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Knowledge brokering							
(2) Complexity	0.01						
(3) References to the scientific literature	0.03	0.01					
(4) Inventor patent experience at other firms	0.10*	-0.01	0.05*				
(5) Forward citations (1976 - 2004)	-0.03	-0.13*	-0.08*	-0.11*			
(6) Pure Porting	0.44*	0.02	-0.06*	0.01	-0.02		
(7) Pure Recombination	0.46*	0.01	-0.04*	0.01	-0.02	-0.11*	
(8) Mixed Porting and Recombination	0.04*	-0.06*	0.220*	0.09*	0.01	-0.31*	-0.33*

* denotes statistical significance at the 5% level

Table 4
Factors that Affect Firm-level Knowledge Brokering
(Firm-Year Level of Analysis)

	Dep. Var.: Firm Knowledge Brokering Stock				
Estimation Method	Firm Fixed Effects OLS				
Independent variables	**(4-1)**	**(4-2)**	**(4-3)**	**(4-4)**	**(4-5)**
Equity alliances stock (t-2)	7.611*** (0.799)			3.420*** (0.715)	2.640*** (0.705)
VC inflows stock (t-2)		1.018*** (0.245)		0.086 (0.180)	0.026 (0.169)
Hired inventors with different technical knowledge stock (t-2)			1.225*** (0.068)	1.060*** (0.072)	0.806*** (0.109)
Overlap with initial technology focus	-10.912*** (2.912)	-13.299*** (3.270)	-4.128* (2.318)	-3.545 (2.209)	-2.643 (2.071)
Number of therapeutic areas					0.579* (0.349)
Funding ease dummy					7.388*** (1.217)
Firm fixed effects	Yes (18)	Yes (18)	Yes (18)	Yes (18)	Yes (18)
Constant	8.085*** (2.2450)	8.387** (3.825)	-1.929 (1.883)	-6.151** (2.663)	-5.088** (2.496)
R-squared	0.489	0.352	0.692	0.724	0.854
# observations	279	279	279	279	279

*, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Two-tailed tests are used.

Table 5
External Forward Citations within 5 Years of Patent Issue
(Firm-Patent Level of Analysis)

	Dep. Var.: External Forward Cites				*Dep. Var.*: Prob. (top 5% of Ext. Forward Cites)
Estimation Method	Neg. Binomial	Fixed Effects Negative Binomial			Fixed Effects Logit
Independent variables	**(5-1)**	**(5-2)**	**(5-3)**	**(5-4)**	**(5-5)**
Knowledge brokering	0.193** (0.083)	0.164** (0.077)	1.195*** (0.267)	1.238*** (0.277)	3.395*** (1.193)
Knowledge brokering squared			-1.036*** (0.253)	-1.043*** (0.253)	-2.567*** (1.033)
Complexity			-0.602** (0.206)	-0.475* (0.294)	-0.758 (2.069)
Complexity squared			0.159** (0.052)	0.150** (0.053)	-0.179 (1.876)
Knowledge brokering * complexity				-0.226 (0.383)	-1.494 (2.234)
References to the scientific literature			0.001 (0.001)	0.001 (0.001)	-0.000 (0.003)
Inventor experience at other firms			-0.001 (0.003)	-0.000 (0.003)	-0.002 (0.013)
Patent app. year FE		Yes (23)	Yes (23)	Yes (23)	Yes (23)
Primary patent class FE		Yes (49)	Yes (49)	Yes (49)	Yes (6)
Firm FE		Yes (18)	Yes (18)	Yes (18)	Yes (18)
Constant	0.817*** (0.054)	-0.930 (1.093)	-0.212 (1.101)	0.878 (0.840)	N/A
Log likelihood	-3913.933	-3700.300	-3683.996	-3683.820	-349.092
# observations	1883	1883	1880	1880	1832

*, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Two-tailed tests are used.

Table 6
Performance Impact of Various Types of Knowledge Brokering
(Firm-Patent Level of Analysis)

	Dep. Var.: External Forward Cites	
Estimation Method	Fixed Effects Negative Binomial	
Independent variables	**(6-1)**	**(6-2)**
Pure porting	0.139 (0.093)	0.227* (0.123)
Pure recombination	0.095 (0.096)	0.069 (0.121)
Mixed recombination and porting	0.380*** (0.059)	0.492*** (0.076)
Complexity		-0.283 (0.212)
Complexity squared		0.244*** (0.065)
Pure porting * complexity		-0.453 (0.444)
Pure recombination * complexity		0.117 (0.516)
Mixed porting and recombination * complexity		-0.791** (0.280)
References to the scientific literature		0.000 (0.001)
Inventor experience at other firms		-0.002 (0.003)
Patent app. year FE	Yes (23)	Yes (23)
Primary patent class FE	Yes (49)	Yes (49)
Firm FE	Yes (18)	Yes (18)
Constant	0.127 (0.838)	-0.001 (1.132)
Log likelihood	-4340.797	-4322.753
# observations	2239	2234

*, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Two-tailed tests are used.