Knowledge Bridging by Biotechnology Start-ups

by

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ABSTRACT

We examine how firms apply knowledge from one technical domain to innovate in another, a phenomenon we term knowledge bridging. We present a process model of knowledge bridging, thereby addressing two research questions: (1) what are the firm-level efforts associated with building knowledge bridging capacity? and (2) what are the organizational and innovative consequences of knowledge bridging activity? We build a novel dataset of all the biotechnology firms founded to commercialize recombinant DNA technology to address these questions. This empirical setting allows us to examine new ventures' knowledge bridging search behavior and consequences over time starting from a common technological event. Our results suggest that a firm's initial search direction shapes its knowledge bridging behavior. We also find that knowledge bridging capability is achieved by hiring technical personnel, more so than other boundary-spanning mechanisms. In addition, an organization's knowledge bridging capability is significantly correlated with organizational and innovative performance. The results therefore suggest that knowledge bridging can be an important organizational capability.

Keywords: knowledge exploration, technological boundary-spanning, innovation, entrepreneurship, biotechnology, patents.

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I. Introduction

Firms have a propensity to engage in "local" search, exploring knowledge that is familiar and within easy reach from their existing geographic and technological positions. This behavior has been explored at multiple levels of analysis, with explanations ranging from individual-level bounded rationality (March and Simon, 1958) to firm-level capabilities, routines, and learning myopia (e.g., Nelson and Winter, 1982; Levinthal and March, 1993). 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, Burton and Hannan, 1996; Cockburn, Henderson and Stern, 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, 1990). 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, such as by engaging in strategic alliances (Mowery, Oxley, and Silverman [1996]) and/or hiring engineers and scientists with relevant prior experience (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003).

For such mechanisms to be effective, distributed knowledge domains must be bridged. This can take place either through "porting" solution concepts from one application area to another (e.g., Baldwin and Clark, 2000) or through recombining knowledge from different arenas for productive and novel results (e.g., Schumpeter, 1934; Basalla, 1988; Hargadon and Sutton, 1997; Fleming, 2001). We use the term "knowledge bridging" to describe these phenomena of using ideas from one technical domain to innovate in another area.

We ask two related research questions in this paper: (1) What are the firm-level efforts associated with building knowledge bridging capacity? and (2) What are the organizational and innovation consequences of knowledge bridging? Our contribution is in conceptualizing and empirically testing a process model of the antecedents and consequences of knowledge bridging (Figure 1). While prior research has elucidated components of this model, our framework joins together these various streams of literature into an integrated view of the knowledge bridging process. We present an empirical test for key components of this process model, and discuss future research that can offer a more comprehensive understanding of organizational knowledge bridging.

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 bridging from their inception, while holding initial technology constant. We can then study the relative importance of various organizational mechanisms in enhancing firms' knowledge bridging capacity, as well as performance consequences of knowledge bridging capability. The empirical strategy is similar in spirit to that used by two recent papers. As in Shane (2000), who shows that individuals recognize highly varied entrepreneurial opportunities even for the same technology, we examine firms created to exploit a non-exclusively licensed technology. As in Cockburn, Henderson and Stern (2000), we look for residual organizational effects net of initial (founding) conditions.

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 launched the modern biotechnology industry (Kenney, 1986).[1] Due to generous access to detailed program records by the Stanford Office of Technology Licensing, and by combining those records with firm and patent-level data from multiple other sources, we are able to create a unique dataset of all de novo start-ups founded to commercialize this technology.

To preview the empirical results, we find that a firm's knowledge bridging behavior is shaped by its initial search conditions. In addition, knowledge bridging capability relates more strongly to some mechanisms (hiring people with different technical backgrounds and engaging in more difficult exploratory search) than others (forming alliances and affiliating with venture capital networks). We also show that there is a strong correlation between knowledge bridging and performance, both at the organizational and innovation levels, even after controlling for a variety of alternative explanations. Due to the longitudinal nature of our data, we use firm fixed effects to mitigate the risk that unobserved firm differences would overturn the results, and so the results are conservative in that they are derived from an analysis of the within-firm changes over time. The results therefore suggest that knowledge bridging can be an important organizational capability. Future research in this domain would benefit from a deeper understanding of two areas which are only hinted at in the current analysis: the differential firm-level productivity for a given level of investment in organizational knowledge bridging, as well the differential organizational costs of building knowledge bridging capabilities.

In the next section, we review the relevant literature and present a process model of knowledge bridging. Section III discusses the data and method employed, while section IV presents the empirical results. A final section concludes and discusses the results.

II. Literature and Hypothesis Development

[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, Hsu and Stern, 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).

The creative application of knowledge across technical domains has primarily been investigated at the invention or individual level of analysis (e.g., Schumpeter, 1934; Crane, 1972; Fleming, 2001; Burt, 2004). In contrast to the studies done at the invention level, a comparatively small number of papers analyze organizational-level capabilities for knowledge bridging (e.g., Hargadon and Sutton, 1997; Hargadon, 2002). Even fewer of these studies provide empirical evidence. An important reason is that it is difficult to disentangle such behavior from a variety of firm and individual level actions, especially in complex settings where the technology and business scope of each firm vary along with its organizational practices. Building upon prior research, we describe the process of knowledge bridging, and present a process model that synthesizes various antecedents and consequences of knowledge bridging, both at the individual and organizational levels (Figure 1). While we are primarily concerned with firm-level processes (as it is in this realm that the extant literature is less developed), important individual-level processes underpin these organizational phenomena.

A. What is Knowledge Bridging?

Exploratory search is important for competitive success, particularly in fast-paced environments in which technical innovation continuously reconfigures the competitive landscape (e.g., Brown and Eisenhardt, 1997; Ahuja and Lampert, 2001). The main insight from the literature is that regardless of the level of analysis, some form of boundary-spanning must take place in order to engage in any type of exploratory search, including knowledge bridging oriented search. Consider Figure 2, which shows two types of knowledge bridging. A first type involves taking knowledge from one domain and reapplying it to another. An example of this "porting" form of knowledge bridging is 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 (e.g., Nelson and Winter, 1982). The term "porting" has been used by Baldwin and Clark (2000) to describe the application of problem solving strategies drawn from one domain for use in another, which they argue is a basic operator for modular systems. Adner and Levinthal (2000) use a similar concept in their discussion of how technological "speciation" occurs, which introduces necessary variety to an organizational gene pool. More generally, Gavetti, Levinthal & Rivkin (2005) argue that problem solving through analogies, which can be a powerful tool leading to innovative thinking (but also caution that this method of problem solving can also be a pitfall for managers if taken too far).

Figure 2 also shows a second type of bridging, which involves borrowing ideas and knowledge from several areas and recombining them so as to innovate in yet another area. To illustrate this, consider the academic field of strategic management. 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. More generally, the re-application of prior problem-solving strategies into new settings is pertinent to settings such as legal research, management consulting, or computer programming where modules of problem solutions can be taken from a prior inventory of legal contracts, consulting experiences, and/or computer programs. While verbatim importing of comprehensive solutions likely represents a minority of cases in these settings, one could imagine "cutting and pasting" applicable modules to new settings for productive use.[2] Kogut and Zander (1992) apply these conceptual insights to organizational capabilities by arguing that recombinations of existing firm capabilities can result in organizational renewal, and so can be regarded as an organizational capability. While it is not our purpose to empirically distinguish knowledge bridging via porting and recombination, we have made a distinction here because each may be associated with different conceptual processes.

B. Organizational Efforts at Promoting Knowledge Bridging

The literature on organizational search highlights several factors that lead to firms engaging in local search. Firms develop standard procedures for problem solving as an efficient managerial response to environmental pressures. The roots of organizational search in individual cognitive patterns have been long recognized, with the implication that search patterns tend to be subject to routinization (March and Simon, 1958; Nelson and Winter, 1982). Organizational repertoires persist because they tend to be efficient on average, even if they are not tailored to each specific problem at hand. If a given standard operating procedure is rarely effective, it will likely be replaced by an alternate solution scheme over time. A good share of organizational functions and their associated routines, however, may be difficult to overturn due to causal ambiguities (i.e., does Y *really* result because of X?) and managerial satisficing behavior. Within firms, individually-efficient managerial behavior can lead to fragmented organizational knowledge, which in turn can have disastrous organizational impact, such as when reacting to architectural innovations (Henderson and Clark, 1990).

In addition to search routinization, founder management team imprinting is another powerful reason for organizations' persistence in search direction (Stinchcombe, 1965). Such imprinting can be manifested in a firm's philosophies, policies and procedures as they relate to organizational culture, human resource management, and research and development practices. There could also be interactive

[2] Management scholars have also identified a process of technology melding, taking technologies from two different domains and creating a novel application (Kodama, 1992; Levinthal, 1998).

effects stemming from charter management team imprinting, so that firms develop different behavioral "styles" and organizational competencies in some activities over others.[3]

Consistent with this notion, Helfat (1994) and Henderson and Cockburn (1994) find substantial (and varied) fixed firm effects in research and development across two different industries: petroleum and pharmaceuticals, suggesting substantial within-industry heterogeneity in R&D investment strategy, and by extension, intensity of search. Cockburn, Henderson and Stern (2000) find long-lived organizational "styles" (in their case, the initial extent of science-driven drug discovery by pharmaceutical firms persisted over long periods). Their results also suggest that while such initial orientations are important, they do not fully explain the adoption of strategies that affect organizational performance. Organizational persistence of practices may extend beyond the R&D investment/search decision, into other organizational domains. For example, Boeker (1989) found that semiconductor start-ups typically maintained the corporate strategies they had at the time of founding. Given the dual forces of technological search routinization and founder imprinting, we expect:

- *H1: A firm with high knowledge bridging use at the time of its founding will persist in using that search strategy, and vice versa.*

As a firm grows and develops after founding, what are the mechanisms that facilitate knowledge bridging? At the individual level, knowledge bridging is shaped by a person's background (Shane, 2000). An individual's background is a function of her training in an academic discipline, as well as work experience. Within each scientific area, there are few individuals who can master the range of domains needed to be successful at knowledge bridging. To give a concrete example, consider George Church, a professor specializing in bioinformatics at Harvard Medical School: "Church's ability to bring together information technology and experimental genetics has made him a '*force majeure* in science,' according to Philip Leder, Andrus professor of genetics and head of the genetics department at Harvard Medical School. Far from being 'just a computer geek,' Leder says, Church is a polymath who 'has terrific ideas that nobody else would think of putting together, because of the many disciplines he has mastered.'" (Thomas, 2004)

Another important individual-level factor is the individual's social network and positioning in the social structure. An early research stream emphasized the importance of technological "gatekeepers," as boundary-spanners who facilitate inter-organizational communication and cooperation by spanning organizational and sub-unit boundaries (e.g., Allen, 1977; Tushman and Scanlan, 1981). To the extent that such actors connect structural holes in a network, they are in a privileged position as otherwise

[3] Also, individuals/founders have heterogeneous backgrounds, knowledge, and skills, and so they will likely respond to entrepreneurial opportunity windows in different ways (Shane, 2000). This implies that individual beliefs about exploiting even a common technological innovation will vary, which can account for differences in the initial position of entrepreneurial start-ups.

unconnected parties have few or no alternative routes to link themselves outside of the boundary-spanner, which can lead to economic returns for the boundary-spanner (Burt, 1992). This phenomenon may be particularly important in biotechnology, as academic inventors help embed firms in scientific networks which can have organizational performance implications (Powell et al., 1999; Murray, 2004). The benefits of connecting structural holes can also include indirect returns, such as through better idea formation (Burt, 2004).[4]

At the organizational level, various processes of acquiring, retaining, recalling, recombining, and cross-applying knowledge can be associated with building firms' knowledge bridging capability. The literature on organizational learning and memory suggests that such processes can indeed be important capabilities (e.g., Nelson & Winter, 1982; Walsh and Ungson, 1991; Huber, 1991; Kogut and Zander, 1992; Hargadon & Sutton, 1997). As is the case with other organizational capabilities, firms can differ in their ability to attract and productively recombine knowledge. This phenomenon has been examined ethnographically by Hargadon and Sutton (1997). They illustrate how a prominent product development firm, IDEO, recombines elements from its inventory of accumulated knowledge to create innovative solutions for its clients. Hargadon (2002) illustrates this phenomenon with several case studies across different settings.

Organization level knowledge bridging is more than the sum of the parts of individual level knowledge bridging capacity (in the spirit of Weick and Gilfillan, 1971; Kogut and Zander, 1992; Cohen and Levinthal, 1990). This can result from organization capabilities in orchestrating the relevant processes of acquiring, retaining, recalling, recombining, and cross-applying knowledge to solve problems in different domains. More generally, organizations can take a number of steps to leverage individual knowledge by implementing policies, procedures, and routines to build organizational capabilities. 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. Such policies may differ not only in the research latitude given to technical staff ex-ante, they also differ in tangibility of degree to which output verification is required. Such programs will also have implications for the type of individual attracted to work in such an environment.

One mechanism organizations may use to facilitate knowledge cross fertilization is hiring technical staff with expertise complementary to that already possessed by the firm (e.g., Almeida and

[4] It is interesting to speculate whether knowledge boundary-spanning primarily takes place at the individual or team level. Most of the prior literature has focused on diversity of knowledge at the team rather than the individual level. Moreover, valuable knowledge can be stored at the individual, team, and/or organization levels, with perhaps different decay rates associated with each.

Kogut, 1999; Rosenkopf and Almeida, 2003).[5] Engineers and scientists with distant technological knowledge may be hired-in on the scientific labor market, and so human capital mobility represents a means by which firms can access complementary technical talent. 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 unsuccessful integration is similar to the risk of allowing individuals unstructured time at work: people with heterogeneous backgrounds and areas of expertise may not ultimately be productive. This reinforces the argument in the literature that innovations based on local search are more certain, but that more unusual and novel combinations of knowledge, in the lower fraction of cases when they are successful, can be much more important and valuable (Fleming, 2001).

A second mechanism for accessing distant knowledge is via strategic alliances. Mowery, et al. (1996), Stuart and Podolny (1996), Baum, et al. (2000), Roy (2006) and others have examined strategic alliances as a mechanism for accessing distant knowledge. Particularly for resource-constrained start-ups, which have difficulty extending the boundaries of their organizations through vertical integration, various types of 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, Gulati and Nohria, 1998). Gomes-Casseres, Jaffe, and Hagedoorn (forthcoming) use patent citation data to provide empirical support for the link between such alliances and knowledge flows.

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.

Notice that all three boundary-spanning mechanisms discussed in this section are ways for the organization to access external ideas and resources, which may be vital for building the organization's knowledge bridging capacity. Since important innovation can take place outside the boundaries of the focal organization, and important technical knowledge may similarly reside outside the firm, the ability to

[5] The efficacy of the latter mechanism is likely to be context-specific, however. For example, Zucker, Darby and Brewer (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).

monitor and access external innovations can be important for firms' competitive advantage (Cohen and Levinthal, 1990). The discussion in this section yields three predicted mechanisms associated with knowledge bridging search:

- *H2(a): Hiring R&D personnel with different technical backgrounds increases a firm's knowledge bridging capability.*
- *H2(b): Forming strategic alliances increases a firm's knowledge bridging capability.*
- *H2(c): Venture capital involvement increases a firm's knowledge bridging capability.*

These mechanisms are illustrated in Figure 1. While strategic alliances and VC involvement are predicted to affect a firm's knowledge bridging capacity, organizational policies and routines also affect organizational knowledge bridging capability by harnessing individual level knowledge bridging, such as through hiring practices.[6]

C. Consequences of Firm Knowledge Bridging

While the main focus of this section of the paper is on the organizational impact of knowledge bridging, prior analyses have highlighted important consequences at the invention level, and so we briefly reviewing this literature. Schumpeter (1934: 65-66) conceptualized the act of innovation itself as the process of "carrying out new combinations," while Usher (1954: 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 this form of 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.[7] 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 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

[6] These mechanisms assume that some degree of information is known about the sources of relevant external knowledge. In cases where such knowledge is not known, the firm may also need to rely upon broadcast search techniques (Lakhani, 2006).

[7] 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.

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.

To the extent that knowledge bridging-oriented exploratory search is related to innovation level performance, we would expect such outcomes to positively impact organizational performance directly.[8] We posit two mechanisms exist by which individual-level knowledge bridging can have organizational effects. These mechanisms are important in aggregating invention-level outcomes to the firm level, for otherwise we would not expect invention-level results to have measurable effects at the firm level.

The first mechanism stems from evolutionary theory: ideas from other domains inject greater variation in the organization's internal idea pool. As such, there is a broader range of ideas to select from to further invest in and commercialize. Hence, knowledge bridging enhances the process of knowledge recombination described by Fleming and Sorenson (2001) and others. While it is possible to recombine ideas obtained from within the existing technical domain used to solve a particular problem, it is even better if the "gene pool" of ideas is enriched via ideas from other domains.

The second mechanism builds on our earlier discussion of structural holes. According to Burt (1992: 37), "the higher the proportion of relationships enhanced by structural holes, the more likely and able the entrepreneurial player, and so the more likely it is that the player's investments are in high-yield relationships. The result is a higher aggregate rate of return on investments." The capacity to bridge knowledge domains therefore facilitates identification and exploitation of new entrepreneurial opportunities, which leads to better organizational performance. Consider the case of serial entrepreneur Alejandro Zaffaroni, who successfully launched seven biotechnology companies across different fields of the industry. One of his former colleagues remarked about Zaffaroni: "…he is reading and thinking very widely. He is totally unafraid of any new technology in any area of human creativity. He has wonderful contacts with people in many different areas, so he sees the bridges between otherwise disparate fields"

[8] Beyond the inventive impact of knowledge bridging, 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.

(as quoted in Burt, 2004).[9] More generally, the act of new venture creation has been conceptualized as the ability to effectively recombine and/or draw productively from disparate fields. Lazear (2004) sees entrepreneurs as generalists with training in several different areas, a quality which facilitates entrepreneurial opportunity recognition. This is consistent with Biais and Perotti's (2003) argument that entrepreneurs, being non-specialists, are better able to identify functional fit across areas than specialists.

It is important to recognize that as with all types of exploratory search, attempts to bridge knowledge domains may meet with higher rates of failure. The experimentation involved in joining disparate knowledge domains is likely to be associated with higher failure rates. It is well recognized, however, that experimentation is critical for innovative progress (e.g., Thomke, 2003). While local search may be successful more often, exploratory search (including knowledge bridging) can lead to more variable outcomes, both on the negative and positive sides (Fleming, 2001; Fleming and Sorenson, 2004). The benefit of this experimental approach is that the results of "failed" experiments can be discarded. Therefore, conditional on successful knowledge bridging, we would expect to observe positive organizational and innovative outcomes:

- *H3(a): Knowledge bridging will be positively correlated with organizational-level performance*
- *H3(b): Knowledge bridging will be positively correlated with innovation-level performance*

To summarize the discussion in this section, it is useful to consider Hargadon's (2002) model of organizational learning and innovation. In this model, individuals bridge knowledge domains in a fragmented social world and bring external knowledge within the organization, so as to improve innovative outcomes. Our view is similar in spirit. Hargadon (2002) emphasizes the important roles of "converting experience into knowledge" (p. 57) and "recognizing how past learning can apply to the current situation" (p. 63), which rely on individual experience-based learning. We believe that in addition, organization-based boundary-spanning via mechanisms such as strategic alliances and labor market hiring may also be important in building firms' knowledge bridging capability (and be importantly conditioned by initial search conditions). In turn, these mechanisms lead to better innovative and organizational performance.

III. Data and Method

To test these hypotheses, we require a sample of firms that were founded to exploit a given technological opportunity. Constructing a sample of firms that is relatively uniform in the basic technology upon which they are capitalizing allows us to observe differences in initial conditions, along

[9] In our typology of knowledge bridging (figure 1), Zaffaroni and Church illustrate knowledge recombination, while the earlier example of Mullis exhibited knowledge porting in his PCR discovery.

with the subsequent evolutionary development patterns in knowledge bridging use and outcomes for these firms.

The commercialization of recombinant DNA following its discovery in 1973 by University of California-San Francisco scientist Herb Boyer and Stanford scientist Stan Cohen provides a fortuitous empirical setting. Because the history of the landmark Cohen Boyer patent 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).[10] Aside from the scientific importance of the Cohen-Boyer innovation (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.[11] We assemble a longitudinal data set of the new ventures established to commercialize the Cohen-Boyer patent. This allows us to control for unobserved time invariant firm characteristics while measuring the correlates of the antecedents and consequences of organizational knowledge bridging. This section describes our method and the variables used in the analysis.

A. Method

The first step in our method is to 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. We assemble a longitudinal data set by tracing these firms forward in time and recording information on a yearly basis.

We conduct two analyses, the first examining firms' efforts at promoting knowledge bridging capacity, and the second concentrating on organizational and innovation consequences of knowledge

[10] 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).

[11] 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.

bridging capability. To do this, we collect annual data for each firm, the details of which we will discuss below. Several of the variables are constructed from patent data for each firm, and so it is worth briefly describing the procedure we use in gathering such data.

Using the U.S. patent database, we identified all 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 bridging.[12] 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.[13] 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 found in Table 1, and a pair-wise correlation matrix of the independent variables is found in Table 2.

B. Measuring Knowledge Bridging

Since the main concept in the paper is knowledge bridging, it is worth elaborating on its measurement. Before doing so, it will be useful to discuss prior measures of organizational search, most of which follow Jaffe (1986) in characterizing firms' technological position using patent class data. These measures of organizational search aim to capture the concept of local versus more distant search relative to the firm's knowledge base. These measures are divided into those that use focal patent information and those that use backward patent citation-based data. Several authors have used focal patent class information (either primary patent class or subclass) to measure the different technological inputs and recombinations utilized to derive the focal invention (Fleming, 2001; Fleming and Sorenson, 2004). A second group of authors have used patent class information of firms' backward cited patents to measure

[12] 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.

[13] 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.

the degree of firm-level R&D search. A pair of studies employs measures of knowledge overlap across firms. Mowery, Oxley and Silverman (1996) examine the degree to which a given firm overlaps with another firm's technical knowledge. Another study analyzes the extent a firm's technical knowledge overlaps with a common stock of scientific knowledge in a network-centric sense (Stuart and Podolny, 1996). Rosenkopf and Nerkar (2001), in the context of optical disk drive firms, use citations to non-disk patents as a measure of technological exploration (and non-self citations as a measure of organizational exploration).

Our conceptualization of knowledge bridging search emphasizes the overlap between the technical domain a firm relies upon and the technical area in which it produces new knowledge. Therefore Rosenkopf and Nerkar's (2001) measure of boundary-spanning search comes closest in spirit to our preferred measure of knowledge bridging. Since the patent classification system reflects technical rather than product categorization, and 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 the following simple measure of knowledge bridging. The variable, *patent knowledge bridging*, is defined as [1 – (share of cited patents that are in the same primary class as the focal patent)] (mean = 0.52). The extent to which a focal patent cites patents in different technical areas relative to the focal invention indicates the degree of knowledge bridging. The measure is therefore 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). High measures of *patent knowledge bridging* imply substantial use of scientific knowledge originating from outside the focal patent area. This measure is aggregated to the firm-year level by calculating *patent knowledge bridging* based on a firm's portfolio of patent portfolios in a given year.[14] We create a stock measure of this firm level measure, called *knowledge bridging stock* (mean = 41.52).

While backward patent citations have been validated as a (noisy) measure of knowledge flows in the economics literature (e.g., Jaffe and Trajtenberg, 2002), such citations are also subject to interpretational challenges (see the discussion in the concluding section). Therefore, citation-based patent measures should be used when there is a clear conceptual motivation.[15] We believe that employing a

[14] Note that we do not use subclass information in the measure. Our choice is guided by two reasons, one computational, the other conceptual. Because of the large number of potential subclasses in both the focal and the backward cited patents, calculating a relative measure using all the subclass information becomes computationally difficult (as a many-to-many patent subclass mapping quickly becomes quite complex). As well, because we wish to capture the concept of taking knowledge from one domain to innovate in another at a coarse rather than subtle manner, we confine ourselves in this study to primary three digit patent classes rather than more fine-grained sub-class information.

[15] 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.

relational measure comparing focal patent class (knowledge output) to backward citation patent classes (knowledge inputs) captures the concept of knowledge bridging.

C. Analyzing Firms' Efforts at Promoting Knowledge Bridging Capacity

We first investigate organizational efforts to promote knowledge bridging capacity at the firm-year level of analysis. We regress the knowledge bridging 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 lasting organizational effects based on initial conditions. In the empirics, we adopt Cockburn, Henderson, and Stern'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 firm's patents with the same technology classes with those applied for in the firm's first three years since a firm's founding.

A second group of right hand side variables contain three measures of various types of organizational boundary-spanning. The first, *stock of equity alliances* as of *t*-2 (mean = 1.05), is a proxy for the extent to which firms engage in boundary-spanning via tightly-coupled alliances. The alliance data come from the Recombinant Capital database. A second measure, *stock of venture capital funding* as of *t*-2 (mean = 9.07), is a measure of the degree to which VCs, who may offer ventures access to an extended resource network, are involved with the entrepreneurial firm. The VC data come from the Venture Economics database. Finally, *stock of hired inventors with different technical knowledge* as of *t*-2 (mean = 12.18), 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. We then transformed this flow variable into a cumulative stock of new hires with different technical knowledge for each firm-year.

A final set of right hand side variables serve as important controls. Using the insight that truly novel inventions recombine technical components that have historically not been recombined, Fleming and Sorenson (2004) develop a measure of uniqueness of patent subclass recombination. We adopt their variable nomenclature, *coupling*. This measure is defined in a two-step process. First, 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 measure of the difficulty of component combination in creating a patent, as 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. *Coupling* is an important control variable, as it implicitly adjusts for the technological distance of the focal invention, at least at the level of the focal patent classes.[16] We use this measure both at the firm-patent level (*coupling*; mean = 0.89) and aggregate the measure to the firm-year level and compute its stock (*stock of firm coupling*; mean = 6.00).

The *number of therapeutic areas* (mean = 3.14) indicates the number of therapeutic areas in which a firm operates, and is therefore a proxy for the firm's scope of operations. Finally, the variable *funding ease dummy* (mean = 0.34) 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.

D. Analyzing the Consequences of Knowledge Bridging

A second analysis examines the consequences of knowledge bridging. At the firm-year level of analysis, two dependent variables measure organizational outcomes, FDA product approval and IPO hazard. At the firm-patent level of analysis, two variables measure innovative outcomes, patent forward citations and patent generality.

FDA product approval (mean = 0.17) is an indicator variable taking a value of one if the focal firm experienced an FDA product approval in year t (and zero otherwise). The variable *initial public*

[16] Constructing an analogous control for the frequency of focal patent class-backward citation as compared to the population of all observed historic citing-cited patent class information would have been ideal. We use the coupling measure here both because it is likely to be correlated with the ideal measure and because it has been validated by prior research (Fleming and Sorenson, 2004). More pragmatically, developing a control for historic citing-cited patents is a very complex task that probably merits an entire paper unto itself.

offering (mean = 0.03) equals one if the firm experienced an IPO in year t (and zero otherwise). The variable *external forward citations* (mean = 2.43) 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 second measure of innovative impact is *patent generality* (mean = 0.54). This variable is defined as: $G_i = \left[1 - \sum_{j=1}^{J}\left(\frac{N_{ij}}{N_i}\right)^2\right]\left(\frac{N_i}{N_i - 1}\right)$, where i indexes the patent, j indexes patent classes, and N represents counts of forward citations. The expression outside of the square brackets adjusts for bias associated with small numbers of forward patent counts (Hall and Trajtenberg, 2005). *Patent generality* measures the diversity of patent classes among forward citations (Henderson, Jaffe, and Trajtenberg, 1998). A high generality score suggests that a focal patent is being cited by other patents from a broader range of technological classes, and is likely to be more general-purpose or fundamental in its application. One might interpret a high generality score as a form of positive spillovers induced by the knowledge-originating firm.

The right hand side variables in the organization-level regressions include a subset of those described in the prior section, with one addition: the key independent variable, *stock of knowledge bridging* as of *t*-2. The analogous knowledge bridging measure in the firm-patent analysis is the *patent knowledge bridging* measure.[17]

A number of other right hand side variables are used in the firm-patent analyses. A first set measures patent scope by counting the *number of primary patent classes* (mean = 2.27) and the *number of patent subclasses* (mean = 6.16). While our measures of patent scope are based on US patent classes, our results are robust to a measure of scope based on international patent class, which has been correlated with economic value (Lerner, 1994). Another control variable is for the *number of references to the scientific literature* (mean = 32.98), which may indicate the degree of reliance on more fundamental scientific knowledge. *Inventor patent experience at other firms* (mean = 6.63) 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 (mean = 6.6). The measure aims to capture the degree to which inventors at a focal organization have patenting experience at other firms.

[17] An alternate definition of knowledge bridging in the firm-patent analysis is the variable *patent originality* (mean = 0.53). This variable is defined similarly to *patent generality*, but uses backward citations instead (Henderson, Jaffe, and Trajtenberg, 1998). The higher a patent's originality score, the more diverse are the citations made by that patent to different technological classes. While *patent originality* is related to *patent knowledge bridging*, the conceptual difference is important: *patent originality* measures the breadth of patent classes cited, while *patent knowledge bridging* measures the overlap between a patent's own class and those it cites.

IV. Empirical Results

A. Efforts to Promote Knowledge Bridging

The analysis of firms' efforts to promote knowledge bridging is presented in Table 3. The dependent variable is *knowledge bridging 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. The first column shows a specification with a single right hand side variable: *overlap with initial technology focus*. That variable is negative and statistically significant at the 1% level, suggesting that the more a firm overlaps in the same technical invention classes as its initial years, the less accumulated knowledge bridging stock the firm tends to have. This supports *H1*, which suggested that a firm's initial search direction will importantly affect its knowledge bridging use (though in the fully specified model, the estimated coefficient is no longer significant).

A second specification, (3-2), examines three boundary-spanning mechanisms: two year lagged stock values of *equity alliances*, *VC inflows*, and *hired inventors with different technical knowledge*. While the equity alliances variable is positive and statistically significant at the 10% level, the VC inflows variable is statistically indistinguishable from zero. The technical staff labor market effect is positive and statistically significant at the 1% level.

The third specification, (3-3), is a fully specified model with the right hand side variables from the first two specifications and the following controls: *stock of firm coupling* (*t*-2), *number of therapeutic areas*, and *funding ease dummy*.[18] The firm coupling variable is positive and statistically significant at the 1% level, suggesting that firms with more "difficult" inventions are associated with knowledge bridging behavior. The negative (and statistically significant) coefficient on the therapeutic areas variable suggests that the more areas the firm is involved in, the *less* knowledge bridging it undertakes. This result is contrary to a hypothesis of economies of scope associated with a higher stock of knowledge bridging technological search. As for the main right hand side variables, the overlap with initial technology focus variable, while estimated with a negative coefficient, is no longer statistically significant. The positive *hired inventors with different technical knowledge* effect persists at the 1% level, while the *stock of VC inflows* (*t*-2) effect is now estimated with a negative and statistically significant coefficient. The latter result suggests that on balance, a higher level of VC investment is *negatively* associated with knowledge bridging search. This might result from a VC selection effect in which on average, VCs are selecting start-ups which are not using knowledge bridging based search. This in turn may result from the time

[18] The number of observations in the first and third specifications of Table 3 is 15% less than the second specification because several firms did not patent within the first three years of founding, which is an input to the variable *overlap with initial technology focus*.

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. We are unable to empirically distinguish between these explanations, though they are both consistent with the estimated results.

B. Firm Performance Impact of Knowledge Bridging

In this sub-section, we examine correlates of two organizational performance variables, the probability of an FDA drug approval and the hazard rate of an IPO (both analyses are contained in table 4). The unit of analysis in the table is again a firm-year.

We begin with the regressions of the likelihood of developing an FDA-approved drug in a given year. Because the dependent variable is an indicator variable, and because we control for fixed firm effects across the panel, we employ fixed effects logit regressions. In the first column of Table 4, we show a parsimonious specification with only the variable *knowledge bridging stock* (lagged two years) and firm fixed effects on the right hand side. The accumulated stock of knowledge bridging represents a firm level aggregation of the knowledge bridging variable, based on patents granted as of two years ago. The estimated coefficient is positive at the 10% significance level.

A second specification, (4-2), adds controls variables for the degree of innovative difficulty associated with the stock of firms' patents evaluated as of two years ago (*stock of firm coupling*), a proxy for the size and scope of the firm (*number of therapeutic areas*), and an indicator variable for time periods in which entrepreneurial funding is relatively easy as measured by the upper 10% of the Lerner biotechnology index (*funding ease dummy*). The coefficient on *knowledge bridging stock* is quantitatively larger relative to model (4-1), though it is still significant only at the 10% level. The results reported in this table are largely unchanged if all of the stock variables are depreciated at an 18% rate using an exponential decay rate as suggested by the literature (e.g., Argote et al., 1990).[19]

In the final two columns of Table 4, we explore the relationship between organizational knowledge bridging and the hazard of an IPO (conditional on not having undertaken an IPO by the last time period). The public markets are a significant source of entrepreneurial funding for firms in the biotechnology industry, and so examining the timing of an IPO is highly relevant in this context. Firms in the analysis start being "at risk" for an IPO at the time they are founded. The same right hand side variables and specification structure as used in the prior two columns are employed here. The reported coefficients in the final two specifications of Table 4 are hazard ratios, and so values significantly larger

[19] The notable difference is that the *number of therapeutic areas* variable in regression (4-2) is no longer statistically significant at the 10% level.

than one represent increases in the hazard of an IPO, while the opposite is true for estimates significantly less than one. In both specifications (4-3 and 4-4), we find that knowledge bridging increases the hazard of an IPO.

The overall results from the table can be easily summarized. First, the *knowledge bridging stock* variable is consistently positive at the 1% level across the specifications. Second, the *number of therapeutic areas* measure is positive and significant at the 1% level. As before, the interpretation could be either a true scope effect, or could simply proxy for firm size and/or stage of development.

C. Innovative Impact of Knowledge Bridging

In the remaining two empirical tables, we examine the innovative impact of knowledge bridging at the firm-patent level, and so the unit of observation in Tables 5 and 6 is a 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 bridging across organizational boundaries.[20] 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: patent knowledge bridging 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 class fixed effects. 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.[21] While the knowledge bridging effect is slightly diminished when the fixed effects are included, the statistical significance of the knowledge bridging variable remains significant at the 5% level.

The next specification, (5-3), adds control for a host of additional patent qualities. The first group controls for patent scope via measures of *number of patent classes* and *number of patent subclasses* (these are based on USPTO classes, though results using international patent class-based proxies for patent scope are consistent). The *number of patent subclasses* is correlated with forward citations. These scope

[20] The results are also generally robust to inclusion of self forward citations.

[21] 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 (the NUS patent project allows us to access more recent patent data), we do not use these deflators in our analysis.

variables are important controls, as different inventions may have different forward citation possibilities due to differences in the technical terrain they cover.

Within specification (5-3), a second group of variables aim to control 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 used as an important control variable. 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.

A third set of variables in specification (5-3) controls for the "innovativeness" of a particular patent. We use Fleming and Sorenson's (2004) measure, *coupling*, which measures the degree to which a focal patent uses subclass combinations that have historically been rarely observed. *Coupling* is an important control variable, as it 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 *coupling* tests the linearity of the *coupling* effect (this variable is positive and statistically significant).

The next specification, (5-4), substitutes *patent originality* as the measure of patent level knowledge bridging which maintaining all of the patent controls from the prior specification. The originality measure is defined as the Herfindahl-Hirschman concentration index of the backward cited patent classes of the focal patent. A more original patent is therefore one with a higher diversity (lower concentration) of backward patent classes. In contrast to our measure of *patent knowledge bridging*, however, *patent originality* does not comparatively evaluate the focal patent class in relation to the patent classes of the backward cited patent classes. Using the originality measure as an alternate measure of the bridging concept yields a positive and statistically significant estimate (at the 1% level), controlling for the same effects as the prior specification.

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 bridging 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 10% of the forward citation distribution in specification (5-5). We employ the same right hand side variables as in specification (5-3), and find that knowledge bridging is positively associated with being in the top 10% 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.

In Table 6, we examine the impact of knowledge bridging on *patent generality*, an alternative measure of innovative performance. 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, Jaffe, Trajtenberg (1998) and others as a proxy for innovative performance, especially as related to the production of more "fundamental" or "general" inventions. We use fixed effects OLS models in these analyses, and employ a parallel empirical specification structure as that used in Table 5.

The first two columns in the table, models (6-1) and (6-2), show that patent knowledge bridging is correlated with *patent generality* with or without firm, patent class, or patent application year effects. In both cases, the main knowledge bridging effect is statistically significant at the 1% level. The same groups of patent controls are included in the third column as found in Table 5, with the addition of one variable: forward citation from 1976 through 2004. This variable controls for the possibility of different profiles of patent generality merely as a consequence of different counts of forward citation rates over the time period in which electronic records of patent data are available to us. The bridging measure continues to be significant at the 1% level in the regression.

In specification (6-4), we substitute the variable *patent originality* for the measure of knowledge bridging. The net effect is similar, both statistically and quantitatively.[22] Finally, we investigate whether patent knowledge bridging is correlated to the likelihood of being in the top 10% of the generality distribution (within this sample) using a fixed effects logit model in specification (6-5). We find statistical support for the bridging effect at the 1% level, as before.[23]

V. Discussion and Conclusions

In this paper, we conceptualize a process model of knowledge bridging in which individual and organizational level processes act to influence a firm's capacity to conduct knowledge bridging search and to capitalize on that capability. The process model combines and elucidates several components discussed by organizational theorists. Moreover, we design and empirically test important parts of the model. The commercialization of recombinant DNA technology via non-exclusive licensing offers 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

[22] This may not be so surprising given the 58% correlation between the two variables. If we enter patent knowledge bridging and patent originality into the same specification (together with the full set of control variables), the patent knowledge bridging variable is still estimated with a positive coefficient, albeit at a reduced level. The same does not hold true for a similar right hand side specification in a negative binomial specification of the number of external forward citations within five years of patent issue. Presumably the collinearity of the bridging and originality measures is more severe in the forward citation regression relative to the generality regression.

[23] The results become statistically noisier with higher thresholds of being in the extreme right tail of the innovative performance distribution, though the results on the probability of being in the upper 5% of the external forward citation and generality distributions are robust at the 10% and 5% levels, respectively.

efforts of firms in building knowledge bridging capability and its performance implications, without the potential confounding effects of diverse initial technologies or firms at different stages of their life cycle. We find that the practice of hiring technical staff with a diverse technical knowledge base is associated with higher knowledge bridging use, as is engaging in more "difficult" inventions as measured by historic combinations of patent classes. Those firms with a high level of VC funding tended to use knowledge bridging *less* often, as did firms operating in a larger number of therapeutic areas. The VC effect may result either from a selection effect by VCs (and their investment preferences) or as a consequence of VC involvement in focusing new ventures on product development and commercialization. Unfortunately, we are unable to distinguish these effects using our data.

In the analysis of organizational consequences of knowledge bridging at the firm-year level, we find that knowledge bridging is correlated both with the hazard of an initial public offering as well as the likelihood of FDA drug approval. We also examine the innovative impact of knowledge bridging at the firm-patent level of analysis. We find firms' inventions that exhibit knowledge bridging garner higher levels of external forward patent citations, and are more "general" in nature, being cited by a more diverse array of future patents.

While these results help give us a better understanding of the knowledge bridging phenomenon, two interpretational issues merit discussion. These involve: (1) firms' efforts to promote knowledge bridging, and (2) inference based on patent data. Each is discussed in turn.

There are a number of issues related to interpreting firms' efforts at promoting knowledge bridging. First, a more comprehensive analysis addressing possible omitted variable bias and causality would be worthwhile. Our empirical strategy in this paper was to include firm fixed effects in the regression analyses. If there are firm-specific, temporally changing variables which significantly affect knowledge bridging 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 may trigger organizational search (Cyert and March, 1963; Bromiley, 1991). Another issue is the causal direction of the results. Our empirical strategy relies on a temporal sequencing argument to infer causality (knowledge bridging stock as a function of time-lagged values of firms' boundary-spanning activity). However, knowledge bridging could still be a cause rather than a consequence of these boundary-spanning activities; ideally, one would like to uncover more fundamental "triggers" of knowledge bridging oriented search. Future efforts may wish to apply more sophisticated tools (e.g., instrumental variables regressions) to better understand causality and/or better understand the origins of knowledge bridging behavior.

A second area related to promoting knowledge bridging 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 bridging. Firms may face different costs when accessing, storing, recombining and cross-applying knowledge. Bridging highly disparate knowledge domains can lead to valuable recombinations, but making the investment may not be worthwhile for the average individual or organization.[24]

A third interpretational issue relating to firms' efforts to promote knowledge bridging is the process by which knowledge bridging-oriented invention takes place. The debate on the extent to which social interaction is necessary for invention (including knowledge bridging 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.

A separate set of issues surround 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). The main issue here is whether our knowledge bridging measures adequately capture the phenomenon of re-applying technical knowledge from one domain to innovate in another. We believe that the measures we employ and develop are reasonable proxies, though as with any measures, they may be imperfect. Measures similar to ours are used in the scientometric literature: journal articles that cite work from a variety of fields are more likely to have borrowed, recombined and extended knowledge from a broader range of academic disciplines than journal articles that cite only other studies from the same knowledge domain.

A second 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

[24] Efforts at bridging, 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.

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 third issue relates to the reliability of patent citations as a measure. Alcacer and Gittelman (forthcoming) argue that patent examiner-imposed citations may be an important phenomenon. If true, then our calculation of the knowledge bridging 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.[25]

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 (which of course is a pre-requisite to using any form of boundary-spanning activity), we believe that this issue needs more systematic attention in this literature. This relates to differential organizational costs of building knowledge bridging capabilities discussed above, as well as to differential firm-level productivity for a given level of investment in organizational knowledge bridging capability. Second, while we purposefully investigated knowledge bridging in a well-controlled empirical setting, and so believe that the reported results are conservative, 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 (reassuringly, Roy's [2006] empirical results, which address related concepts, are broadly consistent with those reported here). Finally, a micro-level analysis of how firm managers facilitate or encourage knowledge bridging would be interesting. 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) or setting aside time for engaging in scientific endeavors (such as at 3M or Google Labs) result in more knowledge bridging? Exploring these and other firm-level mechanisms would deepen our understanding of knowledge bridging.

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

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Figure 1: Process Model of Knowledge Bridging

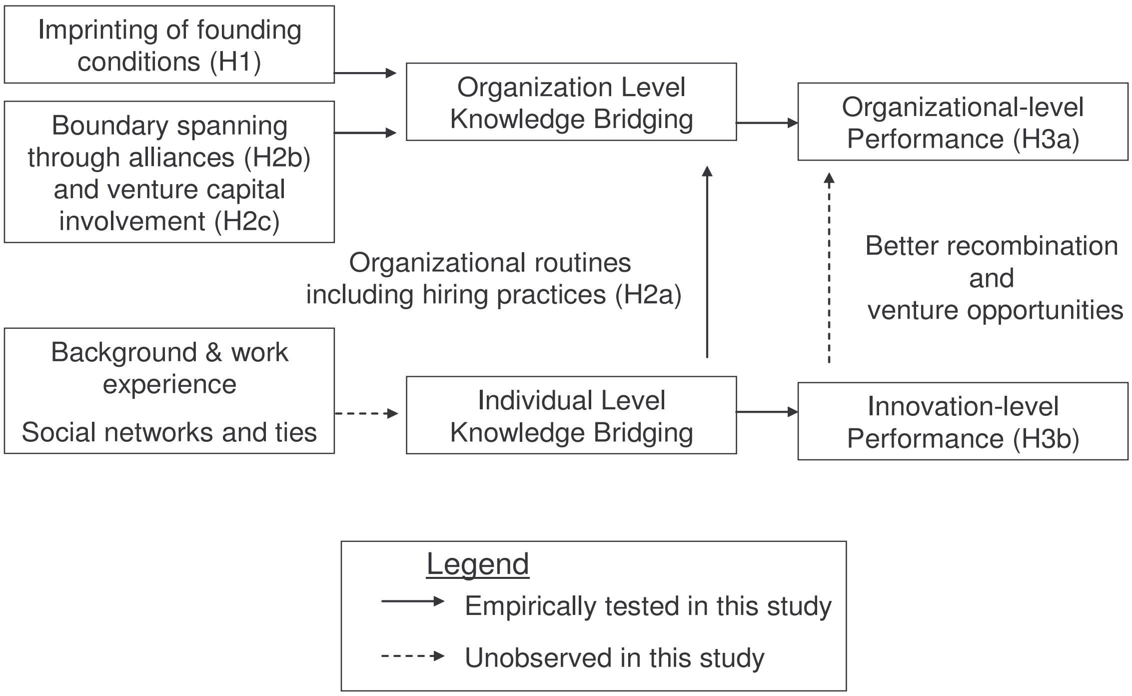

Figure 2: Modes of Knowledge Bridging

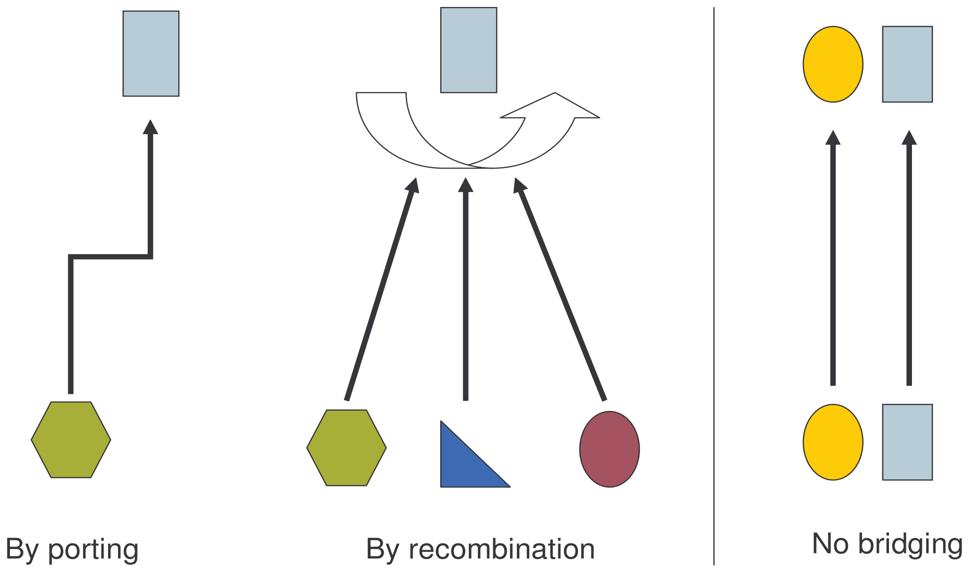

Table 1
Summary Statistics and Variable Definitions

VARIABLE	DEFINITION	MEAN	SD
Firm-year measures			
Stock of firm knowledge bridging	Stock of firm-year aggregation of *patent knowledge bridging* (see below)	41.52	73.02
FDA Drug Approval	Dummy = 1 if a firm had a drug approved by the US Federal Drug Administration (FDA) in year *t*	0.17	0.37
Initial public offering	Dummy = 1 if the firm went public (IPO) in year *t*	0.03	0.16
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
Stock of equity strategic alliances	Stock of equity-based strategic alliances	1.05	1.52
Stock of hired inventors with different technical knowledge	# 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
Stock of venture capital funding	Cumulative venture capital funding received by the firm	9.07	11.68
Stock of firm coupling	Stock of firm-year aggregation of *coupling* (see below)	6.00	4.58
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
Patent generality	Concentration (HHI) of forward-citing patent classes (see Jaffe and Trajtenberg, 2001), adjusted as per Hall (2005)	0.54	0.33
Patent originality	Concentration (HHI) of backward-cited patent classes (see Jaffe and Trajtenberg, 2001), adjusted as per Hall (2005)	0.54	0.33
Patent knowledge bridging	1 – (share of primary patent class overlap between backward citing patents and the focal patent)	0.52	0.38
# primary patent classes	# of primary USPTO classes assigned to the patent, evaluated as of Dec. 2004	2.27	1.00
# patent subclasses	# of USPTO sub-classes assigned to the patent, evaluated as of Dec. 2004	6.16	3.88
# references to the scientific literature	# of patent references to the scientific literature	32.98	47.25
Coupling	Fleming and Sorenson's (2004) measure of the historic difficulty of recombining patent subclasses (see the text)	0.89	0.68
Inventor patent 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	6.63	11.92
# forward citations (1976 – 2004)	# of forward patent citations between the years 1976 - 2004	6.63	14.70

Table 2
Pair-wise Correlations of Independent Variables

A. Firm-year level of analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Knowledge bridging stock								
(2) Overlap with initial technology focus	-0.25*							
(3) Stock of equity alliances	0.47*	-0.10						
(4) Stock of hired inv. w/ diff. tech. knowledge	0.65*	-0.36*	0.40*					
(5) Stock of VC inflows	0.25*	-0.12*	0.54*	0.22*				
(6) Stock of firm coupling	0.62*	-0.28*	0.32*	0.50*	0.21*			
(7) Number of therapeutic areas	0.63*	-0.35*	0.52*	0.70*	0.27*	0.56*		
(8) Funding ease dummy	0.29*	-0.14*	0.21*	0.32*	0.18*	0.65*	0.29*	

B. Firm-patent level of analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Patent knowledge bridging								
(2) Patent originality	0.58*							
(3) # primary patent classes	0.19*	0.18*						
(4) # patent subclasses	0.03	0.08*	0.52*					
(5) # references to the scientific literature	0.03	0.03	0.04*	0.07*				
(6) Coupling	0.00	-0.06*	-0.07*	-0.17*	0.06*			
(7) Inventor patent experience at other firms	0.09*	0.10*	0.07*	0.11*	0.05*	-0.04*		
(8) Forward citations (1976 - 2004)	-0.03	0.01	0.08*	0.09*	-0.08*	-0.23*	-0.11*	

* denotes statistical significance at the 5% level

Table 3
Firms' Effort to Promote Knowledge Bridging
Firm Fixed Effects OLS Regressions
(Firm-Year Level of Analysis)

	Dep. Var.: Knowledge Bridging Stock		
Independent variables	**(3-1)**	**(3-2)**	**(3-3)**
Overlap with initial technology focus	-58.761*** (14.481)		-6.395 (10.057)
Stock of equity alliances (t-2)		5.688* (3.417)	0.861 (3.463)
Stock of VC inflows (t-2)		-0.175 (0.642)	-2.247*** (0.843)
Stock of hired inventors with different technical knowledge (t-2)		4.193*** (0.366)	3.164*** (0.540)
Stock of firm coupling (t-2)			8.515*** (0.880)
Number of therapeutic areas			-5.795*** (1.716)
Funding ease dummy			-2.264 (6.602)
Firm fixed effects	Yes	Yes	Yes
Constant	68.624*** (8.544)	132.486*** (19.595)	-11.895 (12.093)
R^2	0.34	0.59	0.72
# observations	279	328	279

* and *** denote statistical significance at the 10% and 1% level, respectively.

Table 4
Organizational Performance Regressions
(Firm-Year Level of Analysis)

	Drug Approval Firm Fixed Effects Logits		Time to IPO Firm Fixed Effects Cox Hazard Regressions	
	Dep. Var.: Prob.(FDA Drug Approval)		*Dep. Var.*: Initial Public Offering *Note: coefficients are hazard ratios*	
Independent variables	**(4-1)**	**(4-2)**	**(4-3)**	**(4-4)**
Knowledge bridging stock (t-2)	0.004* (0.002)	0.007* (0.004)	1.189*** (0.078)	1.418*** (0.184)
Stock of firm coupling (t-2)		-0.165* (0.095)		0.805 (0.187)
Number of therapeutic areas		0.139* (0.079)		2.550*** (0.745)
Funding ease dummy		0.295 (0.504)		0.267 (0.809)
Firm fixed effects	Yes	Yes	Yes	Yes
Log Likelihood	-90.628	-88.643	-24.351	-15.431
# observations	187	181	127	127

* and *** denote statistical significance at the 10% and 1% levels, respectively.

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 10% of Ext. Forward Cites)
Estimation Method	Neg. Bin.	Fixed Effects Negative Binomial			FE Logit
Independent variables	**(5-1)**	**(5-2)**	**(5-3)**	**(5-4)**	**(5-5)**
Patent knowledge bridging	0.193** (0.083)	0.164** (0.077)	0.156** (0.079)		0.501** (0.243)
Patent originality				0.252*** (0.092)	
Number of primary patent classes			-0.005 (0.032)	-0.043 (0.034)	-0.035 (0.097)
Number of patent subclasses			0.015* (0.008)	0.029*** (0.008)	0.029 (0.024)
Number of references to the scientific literature			0.001 (0.001)	0.001 (0.001)	-0.001 (0.002)
Coupling			-0.642*** (0.153)	-0.656*** (0.174)	-0.420 (0.489)
Coupling squared			0.174*** (0.041)	0.162*** (0.048)	0.180 (0.139)
Inventor patent experience at other firms			-0.001 (0.003)	0.000 (0.003)	-0.001 (0.010)
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)	0.278 (0.831)	-0.026 (1.107)	-14.540 (1544.528)	
Log likelihood	-3923.584	-3708.973	-3694.538	-3010.703	-528.789
# observations	1887	1887	1884	1525	1874

*, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 6
Patent Generality
(Firm-Patent Level of Analysis)

	Dep. Var.: Patent Generality				*Dep. Var.*: Prob. (top 10% of Patent Generality)
Estimation Method	OLS	Fixed Effects OLS			FE Logit
Independent variables	**(6-1)**	**(6-2)**	**(6-3)**	**(6-4)**	**(6-5)**
Patent knowledge bridging	0.203*** (0.022)	0.167*** (0.040)	0.140*** (0.035)		0.890*** (0.335)
Patent originality				0.157*** (0.023)	
Forward citations (1976-2004)			0.001** (0.000)	0.001 (0.001)	-1.345*** (0.139)
Number of primary patent classes			0.055**** (0.017)	0.058*** (0.020)	0.285** (0.132)
Number of patent subclasses			-0.006 (0.005)	-0.007 (0.005)	-0.007 (0.033)
Number of references to the scientific literature			0.000 (0.000)	0.000 (0.000)	-0.001 (0.002)
Coupling			0.005 (0.075)	0.031 (0.095)	0.044 (0.542)
Coupling squared			0.006 (0.016)	-0.002 (0.019)	0.098 (0.158)
Inventor patent experience at other firms			0.000 (0.001)	-0.000 (0.001)	-0.010 (0.011)
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	0.442*** (0.014)	0.203* (0.107)	0.134 (0.141)	0.227 (0.214)	
R^2 or Log likelihood	0.060	0.177	0.197	0.204	-260.130
# observations	1495	1495	1495	1258	1463

*, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.