Knowledge Brokering and Organizational Innovation: Founder Imprinting Effects

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We empirically examine the innovation consequences of organizational knowledge brokering, the ability to effectively apply knowledge from one technical domain to innovate in another. We investigate how organizational innovation outcomes vary by founders' initial mode of venture ideation. We then compare how firms established with knowledge-brokering-based ideation differ in their methods of sustaining ongoing knowledge-brokering capacity compared with firms not established in such a manner. We do so by tracking all the start-up biotechnology firms founded to commercialize the then-emergent recombinant DNA technology (the sample of initial knowledge brokers) together with a contemporaneously founded sample of biotechnology firms that did not license the DNA technology (the sample of initial nonbrokers). Our results suggest that (a) ongoing knowledge brokering has an inverted U-shaped relationship with innovative performance in general; (b) initial knowledge brokers have a positive imprinting effect on their organizations' search patterns over time, resulting in superior performance relative to nonbrokers; and (c) initial nonbrokers rely more on external channels of sourcing knowledge, such as hiring technical staff, relative to initial brokers, reinforcing the imprinting interpretation. The described imprinting mechanism differs from extant mechanisms such as partner affiliation- and trigger-based mechanisms in explaining entrepreneurial performance differentials.

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1. Introduction

The founder imprinting literature suggests that the early choices entrepreneurs make, such as those in the domains of corporate strategy and human resource management, can affect the policies, procedures, and culture of the organization, which in turn can have long-lived effects on the organization (Stinchcombe 1965, Boeker 1989, Baron et al. 1996). We extend this literature by exploring how the basis upon which entrepreneurs ideate and conceptualize their ventures might imprint organizational development and performance by shaping the organization's exploratory search processes. To do so, we draw on Hargadon's (1998, p. 214) definition of knowledge brokering, which involves profitably "transferring *ideas* from where they are known to where they represent innovative new possibilities" (italics in original).[1] We make a distinction between initial and ongoing knowledge brokering; by *initial knowledge brokering*, we refer to situations in which founders originated venture ideas by transferring and recombining knowledge from one domain into another. (In contrast, "initial non-brokers" did not use this ideation process.) We use *ongoing knowledge brokering* to refer to the process of continuous exploratory search in which firms arbitrage and recombine knowledge across fields of technology for productive reuse.

Initial and ongoing organizational knowledge brokering are important both theoretically and practically, and so we devote our efforts to studying this particular competence. On the theoretical side, a host of papers, starting with March (1991), have argued that organizations need to strike a balance between exploiting their capabilities and exploring new terrain. Ongoing exploration is particularly important in fast-moving technological environments, which may overturn extant organizational competencies (Tushman and Anderson 1986). 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 limits the ability of exploratory search in finding global performance peaks. Local search 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). Search behavior is also perpetuated through "imprinting" by founders of new ventures (Stinchcombe 1965), and so initial knowledge brokering may play an important role in shaping subsequent exploratory activity. There has been considerable interest in the means by which firms move beyond local search (e.g., Rosenkopf and Nerkar 2001, Rosenkopf

and Almeida 2003). We regard knowledge brokering as an important means by which firms can search distantly, which conforms with the common theme in this literature that some type of boundary-spanning activity (whether technological or organizational) is necessary for organizations to tap into distributed knowledge domains.

On the practical side, knowledge brokering is one avenue of spanning knowledge boundaries that is managerially provocative. The ability to leverage knowledge and expertise in one domain to innovate in another not only economizes on research and development (R&D) expenditures (Baldwin and Clark 2000) but also offers the tantalizing prospects of yielding breakthrough innovations (Hargadon and Sutton 1997, Hargadon 1998) and quickening the pace of innovation (Kodama 1992). Whereas existing research has usefully described a process model of how knowledge brokers successfully organize their activities for product performance, we aim to build on that work by studying the imprinting effects of initial knowledge brokering.

We ask several related research questions: (1) What is the relationship between the degree of ongoing knowledge brokering at the firm level and innovation impact? (2) How does that relationship differ for initial knowledge brokers compared with initial non-brokers? And (3) how do such differences develop? At a broad level, addressing these questions allows us to bridge two parallel but heretofore-disconnected literatures, those related to founder imprinting and exploratory search/knowledge brokering. In addition, our work suggests a distinct channel in explaining heterogeneity in new venture performance compared to the current literature, which emphasizes affiliation or ties with reputable entities resulting in organizational status or legitimization (e.g., Stuart et al. 1999, Helfat and Lieberman 2002). We instead explore an imprinting mechanism for varied organizational innovation performance.

We do so by sampling a group of biotechnology firms started at or near the birth of the industry. Some of the firms were founded via licensing of an important technical invention (the Cohen–Boyer patent) of recombining DNA from two or more sources into a single target.[2] Since the technology was widely available through a nonexclusive license from Stanford University, we define initial knowledge brokers as founders who recognized the Cohen–Boyer patent as a component of an entrepreneurial opportunity. Thanks 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 data set of all de novo start-ups founded to commercialize this technology. We also assemble a set of biotechnology firms founded around the same period of time but that did not make use of this technical opportunity in ideating

their ventures. We designate this sample of firms as *initial nonbrokers*—biotechnology companies that did not transfer or recombine the newly available recombinant DNA technology into another knowledge domain as the basis for their venture ideation process. We build a longitudinal data set of these 25 firms (listed in Table 1) to trace their resource trajectories from the time of each firm's birth. This empirical strategy enables us to study the role of initial knowledge brokering for innovation performance, as well as the determinants of ongoing knowledge brokering.

We wish to note at the outset some limitations of the empirical setting that shape the interpretation of the results. First, we work with a limited sample size in our empirical analysis, which we have chosen because of the fit with answering our research questions. Second, our analysis of how ongoing knowledge brokering is bolstered and sustained does not include a full cost–benefit analysis, as we do not directly observe costs of firm actions. Third, we do not observe or measure internal firm policies (as in Henderson and Cockburn 1994), and so focus our attention on external boundary-spanning activities used by firms to build ongoing knowledge brokering capacity.

With these limitations in mind, our results suggest that variation in firm founders' entrepreneurial conjectures or theories have significant long-lasting implications for their organization's innovation performance.

Table 1   List of Firms Included in the Study

Firm	Founded	Headquarters location
Sample A: Initial nonbrokers		
CellPro	1989	Bothell, WA
Centocor Biotech	1979	Philadelphia, PA
Genetic Systems Co.	1981	Seattle, WA
Immunex	1981	Seattle, WA
Integrated Genetics	1980	Framingham, MA
Tularik	1991	San Francisco, CA
Sample B: Initial brokers		
Amgen	1980	Thousand Oaks, CA
Biogen	1978	Cambridge, MA
Celltech Group	1980	Cambridge, UK
Chiron	1981	Emeryville, CA
Creative Biomolecules	1981	Hopkinton, MA
DNA Plant Technology	1980	Oakland, CA
Enzon Pharmaceuticals	1981	Bridgewater, NJ
Genelabs Technologies	1983	Redwood City, CA
Genentech	1976	San Francisco, CA
Genetics Institute	1980	Boston, MA
GenPharm International	1988	Mountain View, CA
Genzyme	1981	Cambridge, MA
ICOS	1989	Bothell, WA
Mycogen	1982	San Diego, CA
Neurex	1986	Menlo Park, CA
New England Biolabs	1978	Ipswich, MA
Repligen	1981	Waltham, MA
Therion Biologics	1991	Cambridge, MA
VYSIS	1991	Downers Grove, IL

All of the ventures in our study exhibit an inverted U-shaped relationship between ongoing knowledge brokering and innovation performance. However, we show initial knowledge brokers systematically outperform initial nonbrokers, suggesting that the means by which entrepreneurial opportunity identification takes place has long-lasting performance consequences. Finally, we investigate how initial knowledge brokers renew and maintain their ongoing knowledge-brokering capacity over time. We find that initial nonbrokers are more reliant on channels external to the firms, such as hiring technical staff who possess skills complementary to those of the firm. This finding, coupled with the result that initial knowledge brokers outperform their counterparts on innovative output, reinforces the venture ideation imprinting perspective in which internal processes and culture, rather than external knowledge acquisition channels, are responsible for heterogeneous ongoing knowledge-brokering capacity.

Our results therefore connect the founder imprinting (via entrepreneurial opportunity discovery) literature with the exploratory search (through ongoing knowledge brokering) literature. By making this connection, we delve into an understudied mechanism generating heterogeneous new venture performance: founder imprinting as a result of entrepreneurial opportunity ideation. Finally, our finding that initial brokers outperform initial nonbrokers suggests that organizational capabilities can be both subject to founder imprinting and heterogeneous in their effects.

The plan for the remainder of this paper is as follows: In §2, we review the literature and develop our hypotheses relating venture ideation imprinting and ongoing knowledge brokering to innovation outcomes. Section 3 discusses the data and method employed, and §4 presents the empirical results. A final section discusses the results and implications for the literature and for practitioners.

2. Literature Review and Hypothesis Development

In this section, we first develop predictions relating knowledge brokering to innovation performance. We then examine heterogeneous imprinting effects on organizational innovation performance by degree of initial knowledge brokerage. Doing so helps bridge the theoretical gap connecting individual-level founder action to organizational outcomes. We conclude our hypothesis development by analyzing how initial knowledge brokers sustain their ongoing knowledge brokerage capacity over time.

2.1. Ongoing Firm Knowledge Brokering and Innovative Performance

As Hargadon (2002) describes, effective knowledge brokering involves a number of individual, organizational, and network-level processes that 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 1982, Walsh and Ungson 1991, Huber 1991, Kogut and Zander 1992, Hargadon and Sutton 1997). In this subsection, we theorize about the relationship between organizational knowledge brokering and innovative performance.

Work spanning the innovation and organizations literatures has highlighted the possibility that novelty in many different contexts can be derived through recombining a given set of elements. For example, Schumpeter (1934, pp. 65–66) conceptualizes the act of innovation itself as the process of carrying out new combinations, whereas Usher (1954, p. 21), in his classic work, argues, "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." Most analysts studying this phenomenon have examined it at the invention or technology level of analysis (e.g., Schumpeter 1934, Basalla 1988, Kodama 1992, Levinthal 1998, Fleming 2001). To these scholars, whether they use the term "recombination," "melding," "fusing," or "speciation event," the act of invention or technology commercialization itself involves the process of recombining existing component ideas for novel output.[3]

Fewer studies have examined the recombination phenomenon at the organizational level. Kogut and Zander (1992) generally conceptualize the act of organizational renewal as the result of recombining organizational capabilities. Hargadon and Sutton (1997) argue that successful organizational knowledge brokering involves accessing a wide range of industries with diverse knowledge bases, linking knowledge across industries and contexts, acquiring and storing knowledge into organizational memory, retrieving solutions from organizational memory, and designing solutions that recombine that knowledge. Success in this process requires a supporting organizational culture and structure. Finally, Burt (2004), taking a social network perspective within a firm, finds that compensation, positive performance evaluations, promotions, and good ideas disproportionately accrue to people whose social networks span structural holes. In that study, the focal broker is an individual but the organizational context is critical, and so we include this study as one of the few in the domain of organizational knowledge brokering.

The upshot from the disparate literature treating knowledge brokering at various levels of analysis (abstracting from the actual terminology used to describe the phenomenon of knowledge reapplication for productive use across domains) is that positive benefits accrue to such behavior. There is good reason to believe that this relationship also holds true for firms' innovative

performance up to a certain point. First, brokering ideas from disparate domains injects greater variation into an organization's internal idea pool, leading to a broader range of ideas available for recombination. This in turn enhances the likelihood that a novel combination critical for innovative performance will be reached. Second, an organizational knowledge brokering "routine" may be established along the lines Hargadon and Sutton (1997) describe for accessing, storing, retrieving, and recombining distant knowledge.

Our primary interest is in developing the argument that as firms increasingly rely on ongoing knowledge brokering, the positive relationship between brokering and innovation instead becomes a liability to innovative performance. (This perspective has not been articulated in the literature.) Before delving into the details of our arguments for this claim, it will be useful to introduce an important dimension of ongoing knowledge brokering that has heretofore been neglected: the *degree* to which the focal actor uses information and knowledge from other contexts to solve problems in the focal domain. Most studies have examined the presence (or absence) of ongoing knowledge brokering. We instead conceptualize a spectrum of brokering arrayed by how intensively knowledge is borrowed from other domains to solve problems in the focal domain.

Small to moderate amounts of ongoing brokering across contexts may lead to innovative productivity for the reasons highlighted above, as has become commonly accepted in the literature: knowledge reapplication benefits are due to the enhanced variety of insight garnered from how knowledge from the source context may apply well to the destination circumstance. However, beyond a threshold, more intensive ongoing knowledge brokering may lead to a downturn in innovative performance for two distinct reasons: recombinant exhaustion and the transfer of applicable knowledge.

First, more intensive ongoing brokering efforts may exhaust the productive search space, and so efforts at recombination beyond a critical level may prove fruitless (e.g., Katila and Ahuja 2002). Diminishing returns arise beyond a threshold, as one depletes a source domain of "good ideas" that are well suited for knowledge brokering into a destination domain. Beyond that level, there is the risk of recombining inappropriate elements, resulting in poor innovative outcomes. One specific way in which this can take place is by analogical problem solving (Gavetti et al. 2005). When relying more intensively on brokering knowledge across contexts, it may be easier to understand what is truly analogous between the source and target domains if only a small or moderate amount of material is brokered across boundaries. At higher levels of brokering, what may superficially appear to be comparable situations may in fact differ along important dimensions critical for successful brokering. As a result, wholesale reapplication of knowledge is likely to yield poor outcomes. Note that the

diminishing returns element of recombination intensity could occur with or without analogic reasoning as the instrumental mechanism.

Second, the process of reapplying knowledge can lead to an eventual downturn in innovative outcomes with higher degrees of knowledge brokering. Even with a deep understanding of the source and target contexts, translating, adapting, and tailoring the analogous materials to the problem at hand can become more challenging as the intensity of brokering increases. It can be difficult to isolate the functionality and properties of the brokered material outside of the source context, since there might be important interactions between the knowledge module and the source system. This process is especially challenging the more intensively an organization tries to broker knowledge, because a larger knowledge module likely has more system interconnections with the source context. The challenge of adapting the knowledge for use in the new context is therefore magnified, and so it is important to partition the knowledge into a portion that is functionally affected by the surrounding system and a separate portion that stands alone (Baldwin and Clark 2000). Perhaps this explains why simple replication can be surprisingly difficult, even within a firm (Szulanski 1996). For knowledge replication across organizational boundaries, the challenge can be even more severe, as illustrated by the attempt of U.S. automakers to replicate Japanese lean production systems (Womack et al. 1990). In such situations, with more intensive knowledge brokering, the possible interconnections and complexity of knowledge transfer increases, compounding the obstacles to successful knowledge brokering.

Reinforcing these ideas, Hargadon and Sutton's (1997) knowledge-brokering process model of accessing, storing, retrieving, and recombining distant knowledge is likely to work best for moderate (rather than extreme) brokering efforts because each of the organizational brokering subprocesses they describe is easier to achieve the more local the knowledge to be accessed, stored, retrieved, and recombined. This results both because of the quantities of knowledge involved and because the corresponding human resource and incentive policies require a less drastic change relative to what would be needed in a more intensive brokering effort (smaller deviations are closer to the organizational status quo).

To summarize the above arguments, some knowledge brokering can be beneficial for innovative performance, but more intensive knowledge brokering can exhaust the search space, lead to recombining inappropriate elements, and increase the risk of making mistakes during analogical problem solving. We therefore predict the following.

HYPOTHESIS 1. *Ongoing knowledge brokering will have an inverted U-shaped relationship with firms' innovation performance.*

2.2. Heterogeneous Imprinting Effects by Degree of Initial Knowledge Brokering

Whereas the above subsection analyzed the average effects of the degree of knowledge brokering on organizational innovation, we now explore how these patterns may differ based on varied modes of initial entrepreneurial opportunity recognition. In particular, we explore how firms founded by entrepreneurs who engaged in an initial knowledge-brokering process to ideate their venture differ in organizational innovation trajectory relative to nonbrokers. In doing so, we connect entrepreneurial ideation with ongoing organizational processes of innovation. We then assess the mechanisms by which initial knowledge brokers versus nonbrokers develop their ongoing organizational knowledge-brokering capacity by comparing in particular one means of accessing external knowledge, hiring technical staff from outside the boundaries of the focal organization, between initial knowledge brokers and initial nonbrokers.

2.2.1. Initial Knowledge Brokers vs. Initial Nonbrokers. The different ways in which individuals uncover entrepreneurial opportunities may have an important imprinting effect on new venture development and performance. Whereas the prior literature individually examines processes of entrepreneurial opportunity discovery and organizational imprinting, the purpose of this section is to build theory that connects the processes. In doing so, we aim to address a shortfall in the literature that Huber (1991, p. 91) aptly summarizes: "What an organization knows at its birth will determine what it searches for, what it experiences, and how it interprets what it encounters. While there seems to be universal agreement [that this early] knowledge strongly influences future learning, many of the rich details of the matter are yet to be investigated."

Every organization starts with a founding decision by an individual or team of individuals. Such founding choices rest on entrepreneurial conjectures that resources could be deployed to address (Shane and Venkataraman 2000). To the extent that the conjectures turn out to be correct, ventures and their founders will profit. The critical issue is therefore what shapes the accuracy of entrepreneurial conjectures. The literature discusses the role of own experience (the lion's share of the literature) and that of entrepreneurial theorizing or imagination. These two channels of forming entrepreneurial conjectures need not be mutually exclusive in that own experience may interact with imagining possibilities to yield an entrepreneurial conjecture. An important theme in the entrepreneurial opportunity recognition literature is that prior entrepreneurial experience and domain industry experience allow individuals to engage in structural (rather than superficial) pattern recognition and to be successful in generating more accurate entrepreneurial

conjectures (e.g., Baron and Ensley 2006, Gruber et al. 2008, Grégoire et al. 2010). However, as March et al. (1991) and Felin and Zenger (2009) note, such experience is in short supply, and we know that entrepreneurs found many valuable ventures without direct experience in an industry. Moreover, particularly in the early phases of new industry development (as we will examine in our empirical analyses), there is little or no opportunity for individuals to possess direct industry experience.[4]

With or without entrepreneurial or industry experience, scholars have recognized that using analogies and metaphors can help in the venture ideation process (e.g., Felin and Zenger 2009, Cornelissen and Clarke 2010). Learning or venture ideation can take place simply by entrepreneurial theorizing without necessarily having direct experience. Felin and Zenger (2009) describe this entrepreneurial imagination process as a type of ideational trial and error that is beneficial since it avoids the costs and time required to physically experiment and await feedback. This type of mental experimentation allows individuals to ask "what-if" questions and counterfactually imagine what new products, services, and markets might emerge from venture ideas under different states of the world.

Valuable as this process may be at the venture ideation stage, most analysts suggest that it stops in the later phases of venture development. As Cornelissen and Clarke (2010, p. 545) state, summarizing the relevant literature: "After the launch, and when the venture achieves a turnover and early growth as indicators of its profit-making ability…, entrepreneurs generally become less reliant on inductive reasoning. Instead, they may shift to more calculated reasoning that is based on direct experiences and the performance of the new venture in its industry…." We instead suggest that the founding process of conjectures on entrepreneurial opportunities will affect the venture's evolution and performance outcomes.

The notion of founder organizational imprinting, the proposition that the influence of founders and founding business environment has long-lived organizational effects, has been documented in a variety of business development domains including corporate strategy (Boeker 1989), corporate governance (Nelson 2003), and management structure (Beckman and Burton 2008). The argument is that organizations become different from each other not only because of adaptation, but because policies, procedures, and culture at the time of founding shape the evolution of firms; furthermore, the persistent effects arise as a result of efficiency and/or institutionalization reasons (Stinchcombe 1965). There is mounting evidence that imprinting is not a hands-off process exogenously determined by the business environment, but rather that there is considerable role of entrepreneurial engagement or agency in shaping organizational outcomes (Johnson 2007). Such founder

imprinting may start in an even earlier phase of company development than has previously been suggested, even before organizational design and policies such as strategy, governance, and human resource systems have been set.

We propose and examine the role of founder organizational imprinting at the venture ideation and entrepreneurial opportunity recognition stage. The behavioral origins of localized organizational search in R&D have been well documented in the literature (for excellent reviews, see Stuart and Podolny 1996, Katila and Ahuja 2002). In brief, search tends to be localized because organizations rely on historic experiences, even when faced with changes in their environments. 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 facilitate efficiency, and so they can become a source of competence for the firm; hence they are not easily abandoned (Henderson and Clark 1990). For example, Cockburn et al. (2000) find organizational "styles" (in their case, the initial extent of science-driven drug discovery by pharmaceutical firms) persist over long periods of time. Therefore, ventures that arise from acts of founders' initial knowledge brokering will adopt routines that tend to institutionalize analogizing and other forms of exploratory search, whereas firms not founded in such a manner will not have the same level of knowledge brokering habitually ingrained into the organization's standard operating procedures. Such routines may set in gradually (and nonlinearly) as a result of a trial-and-error learning (Rerup and Feldman 2011). Such imprinting can be manifested and perpetuated as a result of firms' policies and procedures as they relate to organizational culture, human resource management, and R&D practices (Stinchcombe 1965, Baron et al. 1996). Once instigated, such policies and procedures are difficult to change without causing disruption, both because organizations' internal operations are highly interdependent (Milgrom and Roberts 1990) and because firms' external relations are predicated on expected advances along a development trajectory (Christensen 1997), which in turn relies on stable internal processes.

Yet a well-established literature suggests that exploratory search is important for innovation performance, particularly in fast-paced environments in which technical innovation continuously reconfigures the competitive landscape (March 1991, Brown and Eisenhardt 1997, Ahuja and Lampert 2001). Knowledge brokering is one means of exploratory search, and to the extent that entrepreneurial opportunity recognition at the venture ideation stage involved initial knowledge brokering, such processes can become entrenched in organizational memory. Furthermore, through imprinting,

organizational routines are established in which a firm's culture and incentives are geared to brokering knowledge across technical and organizational boundaries. We therefore propose the following.

Hypothesis 2A. *Firms founded via knowledge-brokering ideation (initial knowledge brokering), compared with similar firms not founded in such a manner, will subsequently exhibit superior innovative performance.*

2.2.2. Mechanisms of Building Ongoing Knowledge Brokering. If exploratory search is important for innovative performance, and initial knowledge brokers more systematically engage in habitual analogizing and recombination as their ventures evolve, an open question is how initial knowledge brokers differ from initial nonbrokers with regard to their ongoing exploratory search activity, including their ongoing knowledge-brokering activity. A main insight from the well-established body of work on exploratory organizational search is that some boundary (technical, scientific, organizational, or geographic) must be spanned for organizations to engage in ongoing exploratory search (Rosenkopf and Nerkar 2001, Rosenkopf and Almeida 2003, Ahuja and Katila 2004).

Although all firms participating in dynamic environments will likely be motivated to engage in boundary-spanning activity to keep abreast of relevant external knowledge, it is likely that firms that are not imprinted with an initial knowledge-brokering capacity will have higher incentives and motivation to engage in extramural, boundary-spanning activity. This is because initial knowledge brokers have more internal capacity and organizational routines associated with actively and habitually seeking opportunities to reapply knowledge from one domain to innovate in another area, thereby mitigating the need for them to use external channels as extensively as initial nonbrokers.

Although there is a range of external mechanisms of accessing knowledge, we focus on one such channel, hiring technical staff (engineers and scientists) with expertise complementary to that already possessed by the firm (e.g., Almeida and Kogut 1999, Rosenkopf and Almeida 2003, Singh and Agrawal 2011). We do so not only because technical labor mobility has been the subject of a wide range of studies in the management and innovation literature but also because this mechanism involves tapping into direct, experience-based knowledge. This can be especially important if the relevant knowledge is complex, specialized, and/or tacit. Consistent with Polanyi's (1966) observation that individuals know more than they can articulate as a result of the tacit nature of knowledge, Zucker et al. (1998) find that in the early biotechnology industry, the specialized knowledge possessed by highly accomplished university scientists made them scarce and valuable resources. That

these scientists were for the most part geographically immobile helps explain the observed concentration of the industry near academic centers of excellence in biology and chemistry, as well as why this concentration has persisted over time. There is therefore little substitute for direct personnel involvement, particularly to "unstick" highly specialized and tacit technical knowledge. These same factors have led to the widely held belief that transferring knowledge (even with the availability of codified sources such as scientific publications or patents) is extremely difficult absent the movement of skilled individuals (e.g., Teece et al. 1997). The emphasis of hiring "star" scientists likewise stems from the same phenomenon.[5]

Hiring inventors with prior experience in different technical areas allows a firm to introduce those areas into its existing repertoire of knowledge. Apart from the new employee's direct knowledge being applied within the context of the firm's routines, it also creates opportunities for existing employees to become engaged with and borrow from the ideas put forth by the new employee. Firms can also hire inventors with a track record of brokering knowledge across domains.

Our prediction is that initial knowledge brokers, compared with initial nonbrokers, will rely less heavily on external boundary-spanning mechanisms such as hiring external technical staff with complementary knowledge domains to bolster their ongoing knowledge-brokering capacity. In contrast, initial nonbrokers are more reliant on such external channels because they do not have the same boundary-spanning internal processes and routines. An example of a possible internal mechanism would be a policy that allows technical staff within private firms to engage in open science by allowing them to publish portions of their research findings in professional journals (Henderson and Cockburn 1994) or set aside dedicated time for exploratory research.[6] We therefore predict the following.

HYPOTHESIS 2B. *Firms founded via knowledge-brokering ideation (initial knowledge brokering), compared with similar firms not founded in such a manner, will rely more on internal rather than external mechanisms (such as hiring technical staff from the labor market) to develop their ongoing knowledge-brokering capacity.*

3. Data and Method
To test these hypotheses, we need an empirical setting in which there is variation in the degree to which venture founders use initial knowledge brokering in their venture ideation process, as well as variation in the degree to which firms engage in ongoing knowledge brokering. It will be useful to examine an empirical context in which the sample comprises entirely new ventures, as the literature suggests that established firms

have developed sets of organizational routines and may already be on differing resource attainment trajectories. A common stage of industry evolution will also be desirable as varied opportunities to bolster ongoing knowledge-brokering capacity may be present in the business environment at different stages of industry life cycle. 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 data set tracking their activities over time.

The birth of the biotechnology industry provides a fortuitous empirical context in light of our study requirements. A key event in the early development of the biotechnology industry was the discovery of recombinant DNA in 1973 by University of California, San Francisco scientist Herb Boyer and Stanford scientist Stan Cohen. Because the history of the discovery and patenting of the landmark technology is recounted in detail elsewhere (e.g., Reimers 1987, Hughes 2001), we will not duplicate those efforts here. Instead, we merely note that Stanford University conducted an open, nonexclusive licensing program of the recombinant DNA 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).[7] 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 \$200 million in licensing revenues, which implies product sales based on the innovation of some \$40 billion.[8]

We designate start-up licensees of this patent as initial knowledge brokers, as these founders recognized the entrepreneurial opportunity afforded by this invention. We further assemble a group of new biotechnology ventures founded contemporaneously but that did not make use of the recombinant DNA technology as a comparison non-initial-brokering group. The remainder of this section describes our sampling method and how we constructed the variables used in our analysis.

3.1. Sample
As background before discussing our sampling approach, it is important to realize that we cannot measure or systematically study entrepreneurial ideas that were abandoned and never commercialized. Our solution to constructing a sample of new ventures with variation in the process by which they employed initial knowledge brokering at the birth of their ventures must therefore involve studying a set of firms that were actually founded. We also wish to study comparable biotechnology firms founded in the same (early) stage of industry

life cycle as the Cohen–Boyer patent licensees. At the birth of the biotechnology industry, virtually all of the firms were founded with the assistance of university scientists (Kenney 1986), which explains the typical pattern of geographic colocation of biotechnology firms with academic centers of excellence in the underlying disciples (Zucker et al. 1998).

We define two subsamples: (1) *Initial knowledge brokers* are entrepreneurial firms that licensed the Cohen–Boyer patent (19 firms).[9] (2) *Initial nonbrokers* are defined as firms that did not license the recombinant DNA patent despite being founded contemporaneously to the sample of Cohen–Boyer patent licensees (six firms). In accordance with our conceptualization, initial brokers arbitraged and/or recombined knowledge related to their focal domain with recombinant DNA technology, whereas initial nonbrokers did not follow this same ideation process for their venture initiation. We identified initial brokers using data from the Stanford Technology Licensing Office and applied the following criteria: (1) the firm is de novo (as opposed to an established pharmaceutical firm), and (2) the firm licensed the Cohen–Boyer patents at the time of founding or within two years after founding. To identify initial nonbrokers, we researched business and oral histories of the early biotechnology industry including Kenney (1986), Robbins-Roth (2000), and Powell and Sandholtz (2012), and online resources such as the oral history collection on bioscience and biotechnology of the Bancroft Library at Berkeley.[10] We conducted Web research on the founders of these companies and the founding circumstances. For example, Tularik was cofounded by David V. Goeddel when he left Genentech after growing disenchanted by recombinant DNA-based cloning techniques and specifically to pursue alternative approaches.[11] Table 1 lists the firms in each of these subsamples, denoted as "initial brokers" and "initial nonbrokers" respectively, along with each firm's founding year and location.

We assemble a longitudinal data set of these firms by tracing firms forward in time and recording information on a yearly basis. 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 data set of 4,155 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 a measure of ongoing knowledge brokering (discussed in the next section).[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 data set contains 29,143 backward citations and 25,690 forward citations. For each focal patent, we also record the names and addresses of each inventor (3,276 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 allow 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 pairwise correlation matrix is shown in Table 3.

3.2. Key Measures

We follow an established approach of using patent class data to identify the technological position of each invention (e.g., Jaffe 1986). Ongoing knowledge brokering emphasizes the overlap between the technical domain a firm relies on 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 nondisk 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 and measure ongoing brokering at the level of the firm instead of each invention, we develop a more general version of the Rosenkopf and Nerkar measure.

We define *ongoing firm knowledge brokering* as the percentage of citations made to patents applied for (and subsequently granted) that are in primary U.S. classes that the firm did not also receive patents in in each year.[14] For firm i in year t, *ongoing firm knowledge brokering* is defined as the number of backward citations to patents in primary U.S. classes firm i did not patent in during year t divided by the number of backward citations made by firm i in year t.[15] High measures of *ongoing firm knowledge brokering* suggest substantial use of technical knowledge originating from outside the firm's own technological base. To better approximate the time of invention, we use the application year of each patent to compute this measure, rather than the year the patent was granted.

For the regression analysis, we also create a stock measure of this firm-level measure, *ongoing firm knowledge-brokering stock*. Since *ongoing firm knowledge brokering* 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 (*ongoing firm*

Table 2   Summary Statistics and Variable Definitions

	Definition	Mean	SD
Variables used in Table 4			
External forward citations	Number of external forward citations received by a patent within five years of patent grant year	2.47	3.64
Ongoing firm knowledge brokering	For each firm in a given year, this is the percentage of citations made by patents applied for (and subsequently granted) that are to primary U.S. classes that the firm did not also receive patents in that year	0.20	0.19
Firm knowledge stock	For each firm, this is the number of patents granted (by application year)	24.9	27.6
Patent originality	1 − Herfindahl of each patent's backward citations (Henderson et al. 1998), adjusted for bias, as per Hall and Trajtenberg (2005)	0.54	0.33
Patent complexity	For each patent, this is Fleming and Sorenson's (2004) measure of innovation complexity (see the fifth paragraph of §3.2)	0.23	0.35
Patent references to the scientific literature	For each patent, the number of references made to the scientific literature; a measure of dependence on scientific knowledge	31.1	45.1
Additional variables used in Table 5			
Ongoing firm knowledge-brokering stock	Stock of firm-year aggregation of *ongoing firm knowledge brokering* (see the third paragraph of §3.2)	14.52	15.49
Alliances stock	Stock of number of strategic alliances formed by each firm in a given year	15.31	26.96
Venture capital inflows stock	Cumulative venture capital funding received by the firm in a given year (millions of dollars)	9.68	14.83
Hired inventors with different technical knowledge stock	Number of inventors who apply for patents at the focal firm in a given year who also have prior patenting experience in different technical areas at another organization	11.03	10.56
Funding ease dummy	Dummy = 1 (in a given year) if the external funding environment is in the top 10% in munificence as measured by Lerner's (1994) biotechnology index	0.34	0.48
Overlap with initial technology focus	Share of firm's patents in a given year that are in the same technology classes as those applied for by the firm during the first three years since its founding	0.60	0.37

*knowledge brokering$_{it}$ × number of patents$_{it}$).[16] Follow-ing 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 (2006) 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).

A measure that is distinct from *ongoing firm knowledge brokering* but that is often used in the literature is *patent originality*. This variable is defined as $o_i = [1 - \sum_{j=1}^{J}(N_{ij}/N_i)^2](N_i/(N_i - 1))$, 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). The higher a patent's originality score, the more diverse are its backward citing patents' technological classes. Although

Table 3   Pairwise Correlations

Variables used in Table 4	(1)	(2)	(3)	(4)	(5)
(1) *External forward citations*					
(2) *Ongoing firm knowledge brokering*	0.055*				
(3) *Firm knowledge stock*	−0.014	−0.398*			
(4) *Patent originality*	0.073*	0.071*	0.043*		
(5) *Patent complexity*	−0.073*	0.020	−0.006	−0.064*	
(6) *Patent references to the scientific literature*	−0.015	−0.053*	0.096*	0.027	0.015

Variables used in Table 5	(1)	(2)	(3)	(4)	(5)
(1) *Ongoing firm knowledge-brokering stock* (t)					
(2) *Alliances stock* ($t-2$)	0.760*				
(3) *Venture capital inflows stock* ($t-2$)	0.078	0.204*			
(4) *Hired inventors with different technical knowledge stock* ($t-2$)	0.672*	0.701*	0.201*		
(5) *Funding ease dummy*	0.527*	0.213*	0.076*	0.255*	
(6) *Overlap with initial technology focus* ($t-2$)	−0.218*	−0.293*	−0.128*	−0.369*	−0.156*

*Statistical significance at the 5% level.

patent originality is related to knowledge brokering, there are two important differences. First, originality is a patent-level measure, whereas our measure of knowledge brokering is at the firm level. Second, *patent originality* measures the breadth of patent classes cited, whereas *ongoing firm knowledge brokering* measures the overlap between a firm's own patent classes and those it cites. For example, imagine two firms each with only one patent. Suppose that both patents have *patent originality* values at the minimum of 0, with the first patent having all its backward citations concentrated in the same class as the focal patent, whereas the second patent has all its backward citations concentrated in a different class relative to the focal patent. Despite having the same value for *patent originality*, the first case exhibits no *ongoing firm knowledge brokering*, whereas the second one does. Our analysis includes *patent originality* as a control variable, to explore whether *ongoing firm knowledge brokering* is significant after controlling for *patent originality*.

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 (2001) 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:

$E_i =$ (No. of subclasses previously combined with

subclass i)/(No. of previous patents in subclass i).

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

$$K_j = \text{(No. of subclasses on patent } j) \Big/ \sum_{j \in i} E_i.$$

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:

$$C_i = K_j/N_j$$

$$= \text{Coupling of patent } j/\text{No. of subclasses on patent } j.$$

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) NK model it is based on. 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.

3.3. Variables Used in Analyzing the Innovation Consequences of Knowledge Brokering

We examine the innovation consequences of ongoing 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 (Jaffe and Trajtenberg 2002, Hall et al. 2005). We restrict the forward citation count to those made by external entities (by excluding self-citations) to explore the role of ongoing knowledge brokering across organizational boundaries, though the results are generally robust to inclusion of self-forward citations.

The main right-hand-side variable of interest is the *ongoing firm knowledge brokering* measure. In examining the consequences of knowledge brokering, we utilize the flow of this variable, so we test whether the level of *ongoing firm knowledge brokering* for a firm at the time a patent application was filed is correlated with the number of forward citations subsequently received by that patent. We discuss our rationale for this below. We also include the squared term of this variable to test for a quadratic relationship (Hypothesis 1). These results are inclusive of controls for *patent originality* and *patent complexity*. In addition, we control for the *number of references to the scientific literature*, which indicates the degree of reliance on fundamental scientific knowledge. Sets of dummy variables are included to control for patent application years and primary U.S. patent classes.[17]

In our analysis of innovation performance trajectories as a function of the degree to which venture founders use initial knowledge brokering in their venture ideation process, we employ these same variables and specifications. The analyses only differ by the subsamples used to estimate the effects.

3.4. Variables Used in Analyzing the Mechanisms of Developing Knowledge Brokering

We investigate organizational factors that shape ongoing knowledge brokering at the firm-year level of analysis. We regress *ongoing firm knowledge-brokering stock* on our primary measure of organizational boundary spanning (beyond a set of firm fixed effects and organizational controls described below). The key dependent variable is *hired inventors with different technical knowledge stock* ($t - 2$), 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 U.S. 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 from the ones the firm received patents in within the past five years.[18] We then transformed this flow variable into a cumulative stock of new hires with different technical knowledge for each firm-year.

We control for two other means by which organizations may be accessing external knowledge, with the understanding that interpreting the relative effects of these additional channels may be difficult since each mechanism may be employed for disparate reasons. *Alliances stock* $(t-2)$ is a proxy for the extent to which firms engage in boundary-spanning via alliance relationships. The measure is based on count data, which are sourced from Recombinant Capital (a specialist in biotechnology industry data) and triangulated with the SDC Platinum database. We use a two-year lag structure, although the results are similar using a one-year lag. A second variable, *venture capital inflows stock* $(t-2)$, is a measure of the degree to which venture capitalists (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.

Our analysis includes several additional control variables. A *funding ease dummy* is based on Lerner's (1994) index of the biotechnology industry funding environment (including funds from VCs, 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 1 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 they may therefore experiment and engage in more exploratory search.

A second control variable addresses the role of firms' initial search conditions and orientation. Several theories predict long-lasting organizational effects based on initial conditions (e.g., Stinchcombe 1965, Baron et al. 1996). In the empirics, we adopt the philosophy of Cockburn et al. (2000) of examining organizational strategy while taking into account the impact of imprinting of initial conditions. We do this by constructing the variable *overlap with initial technology focus*, which is defined as the share of firms' patents with the same technology classes as those applied for in its first three years since

founding. We select the three-year time period to allow for a sufficient window of patent observability; allowing for one- or two-year time periods yield qualitatively similar results.

As a robustness test, we also include a control for the *number of therapeutic areas*, which 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. These data are not available for all firms, so we do not report it with the main results.

4. Empirical Results

4.1. Innovation Impact of Knowledge Brokering

In Table 4, we examine the impact of firm knowledge brokering on its innovative performance, with the unit of observation a firm–patent pair. The dependent variable in Table 4 is the number of external forward citations within five years of patent issue, a well-established measure of innovative impact (Jaffe and Trajtenberg 2002). Specifying a citation window of five years after patent issue allows for a meaningful citation comparison across observations. Since the dependent variable in the analysis is a nonnegative count, we estimate Poisson models, as in Hausman et al. (1984) and Hall and Ziedonis (2001). We include both firm- and patent-level variables, so a random effects Poisson model is appropriate and preferable to a negative binomial model (Hilbe 2008, Chapter 10).[19]

The baseline model, Model 4-1, reports a parsimonious specification with *ongoing firm knowledge brokering* and its squared term as the main right-hand-side variables. Using a flow rather than a stock variable for the innovative impact of knowledge brokering matches the dynamic conceptualization of brokering as an organizational competence that can change over time. The estimated coefficient for *ongoing firm knowledge brokering* is positive and significant ($p < 0.001$), whereas *ongoing firm knowledge brokering*^{2} is negative and significant ($p < 0.001$). The positive direct effect and negative quadratic term jointly imply an inverted U-shaped relationship between firm knowledge brokering and innovation performance, thus supporting Hypothesis 1. This 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. In the specification, we control for *patent originality*, which is positive and significant, and sets of dummy variables for patent application years and primary patent classes. Because of the censoring of forward citations, it is important to include the patent application year dummies to take into account patent cohorts, each of which have different baseline forward citation rates.[20]

Model 4-2 adds controls to the baseline specification for scale effects via the variable *firm knowledge stock* (as

Table 4 Impact of Ongoing Knowledge Brokering on Innovation (External Forward Citations Within Five Years of Patent Issue) Using a Random Effects Poisson Model

Variable	Sample			
	All (Model 4-1)	All (Model 4-2)	Initial brokers only (Model 4-3)	Initial non-brokers only (Model 4-4)
Ongoing firm knowledge brokering	0.874*** (0.250)	0.782*** (0.258)	1.026*** (0.281)	0.752 (0.830)
Ongoing firm knowledge brokering^2	−1.137*** (0.309)	−1.132*** (0.312)	−1.323*** (0.347)	−1.962* (1.010)
Firm knowledge stock		−0.002*** (0.001)	−0.002** (0.001)	−0.014 (0.012)
Patent originality	0.410*** (0.500)	0.395*** (0.051)	0.395*** (0.053)	0.430*** (0.158)
Patent complexity		−0.565*** (0.100)	−0.527*** (0.105)	−1.758*** (0.541)
Patent references to the scientific literature		0.001** (0.000)	0.001** (0.000)	0.010*** (0.003)
Dummy for each patent application year	Yes (23)	Yes (23)	Yes (23)	Yes (23)
Dummy for each primary U.S. patent class	Yes (49)	Yes (49)	Yes (49)	Yes (49)
Constant	0.349*** (0.081)	0.516*** (0.087)	−0.626** (0.262)	0.956*** (0.278)
Log likelihood	−4,498.85	−4,462.93	−4,093.20	−308.24
No. of observations	1,631	1,628	1,498	130

Note. The dependent variable is *external forward citations*.

*Statistically significant at the 10% level; **statistically significant at the 5% level; ***statistically significant at the 1% level.

measured by the number of patents granted to each firm by application year). Another group of control variables address patent-level heterogeneity, including the *number of references to the scientific literature* (as opposed to references to prior patents), which Fleming and Sorenson (2004) argue can aid in the technological search process. We also control for Fleming and Sorenson's (2004) *complexity* measure to account for whether brokering is especially important for innovation in complex technical environments. The *complexity* variable 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 the level of the focal patent classes. The estimated coefficient of this variable is negative and statistically significant at the 1% level, consistent with the notion that more complex knowledge resists transfer. The main variables of interest, however, are *ongoing firm knowledge brokering* and its squared term. The former variable is positive and significant ($p < 0.001$), whereas the latter is negative and significant ($p < 0.001$), as before, net of additional controls for invention and firm characteristics.

We performed a number of (unreported) robustness checks to validate our main results. First, we controlled for firm scale effects beyond that captured by *firm knowledge stock* by controlling for the number of therapeutic

classes each firm's products spanned each year. Second, we controlled for differences in the contemporaneous external boundary-spanning mechanisms (*hired inventors with different technical knowledge stock, alliances stock*, and *venture capital inflows stock*) associated with each firm, because such differences could generate varied innovation output. In each case, the main results of the inverted U-shaped relationship between *ongoing firm knowledge brokering* and forward patent citations held. Finally, we tested the robustness of our results to alternative estimation methods and functional forms. We found that the general empirical pattern is robust to a piecewise spline function, a finite mixture model, and a quantile regression according to the deciles of the innovation outcome distribution, and so we can rule out, for example, a threshold activation/deactivation process.

4.2. Heterogeneous Imprinting and the Degree of Initial Knowledge Brokering

We now turn to analyzing the predicted organizational innovation imprinting effects of founder choices. We do so by separately estimating the full model of Model 4-2 on each of the *initial knowledge brokers* and *initial non-brokers* subsamples.

Model 4-3 shows the results for *initial knowledge brokers*. The estimated coefficient for *ongoing firm knowledge brokering* remains positive and significant ($p < 0.001$), whereas its squared term remains negative and significant ($p < 0.001$). Both variables have

magnitudes that are slightly larger than in Model 4-2, which included all the firms. This suggests that for initial brokers, the quadratic relationship between *ongoing firm knowledge brokering* and innovation performance is stronger than that that holds for the entire sample. The remaining variables in Model 4-3 yield estimates that are very similar to those in Model 4-2.

The final column of Table 4 shows the results for the subsample of *initial nonbrokers* (Model 4-4). Here, we see a key difference compared to specifications 4-2 and 4-3. The coefficient estimate for *ongoing firm knowledge brokering* is positive but no longer statistically significant ($p > 0.1$). Furthermore, its squared term is negative and of a much higher magnitude than in the other two models, but it is only statistically significant at the 10% level. Overall, this suggests a weaker quadratic relationship between *ongoing firm knowledge brokering* and firm performance among initial nonbrokers. The other variables in Model 4-4 remain of the same sign, although several of them are less statistically significant.

The implied effects of these regression results is illustrated in Figure 1, which plots the predicted number of forward patent citations within a five-year window against *ongoing firm knowledge brokering*, holding the other variables at the means of their distributions. The continuous line is for initial knowledge brokers, whereas the dashed line is for initial nonbrokers. As we move along the horizontal axis away from the origin and

towards the right, both of these lines exhibit a positive slope at low to moderate levels of *ongoing firm knowledge brokering*, but they both slope downward at higher levels of *ongoing firm knowledge brokering*. It is striking that the plot for initial brokers begins with a steeper positive trajectory and remains above that of initial nonbroker firms throughout the entire range of *ongoing firm knowledge brokering*. It also extends upwards further along the *ongoing firm knowledge brokering* axis, reaching a maximum value of 2.6 citations at around 0.4 along the horizontal axis. In contrast, the initial nonbrokers exhibit a maximum value of only 2.1 citations at an *ongoing firm knowledge brokering* level of around 0.2. With all else being equal, initial knowledge brokers have a higher predicted innovation impact than initial nonbrokers, and this gap persists across all levels of *ongoing firm knowledge brokering*, in support of Hypothesis 2A. As with the earlier model, we performed robustness checks by including boundary-spanning variables, the number of therapeutic areas, and testing for threshold and spline effects.

4.3. Determinants of Ongoing Firm Knowledge-Brokering Capacity
The analysis of firms' efforts to promote ongoing knowledge brokering is presented in Table 5. The dependent variable is *ongoing firm knowledge-brokering stock*, and the estimation method is firm fixed effects ordinary least

Figure 1   Predicted Relationship Between Ongoing Firm Knowledge Brokering and Forward Citations (at the Mean Value of Other Variables)
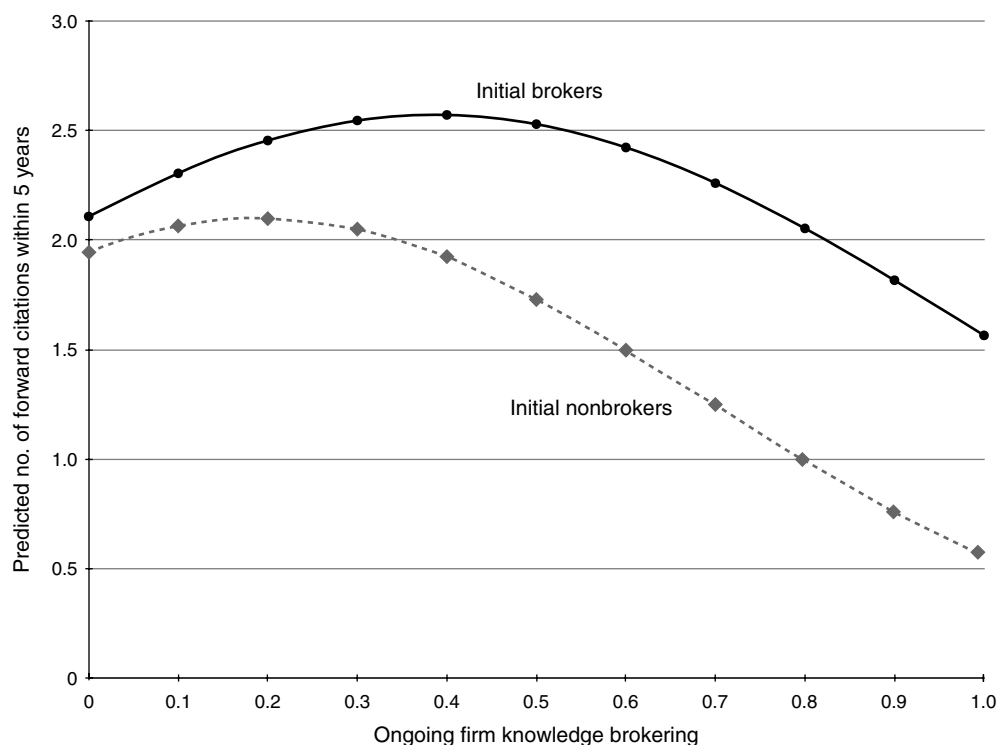
Table 5 Determinants of Ongoing Knowledge-Brokering Capacity (Firm-Year Level of Analysis) Using Firm Fixed Effects OLS

Variable	Sample		
	All (Model 5-1)	Initial brokers only (Model 5-2)	Initial nonbrokers only (Model 5-3)
Hired inventors with with different technical knowledge stock $(t-2)$	0.171*** (0.056)	0.146** (0.056)	1.376*** (0.281)
Alliances stock $(t-2)$	0.426*** (0.019)	0.434*** (0.019)	0.658*** (0.099)
Venture capital inflows stock $(t-2)$	0.110* (0.062)	0.122 (0.093)	0.019 (0.073)
Funding ease dummy	3.472*** (0.708)	2.907*** (0.761)	0.696 (1.837)
Overlap with initial technology focus	−2.751** (1.100)	−1.770 (1.248)	0.838 (2.223)
Firm fixed effects	Yes (24)	Yes (18)	Yes (5)
Constant	−0.205 (1.232)	−1.446 (1.512)	−7.039* (3.085)
Adjusted R^2	0.891	0.905	0.784
No. of observations	337	279	58

Note. The dependent variable is *ongoing firm knowledge-brokering stock*.

*Statistically significant at the 10% level; **statistically significant at the 5% level; ***statistically significant at the 1% level.

squares (OLS) regression, which allows us to mitigate the risk of unobserved time-invariant firm characteristics, such as initial founding team quality, overturning the results. It is worth noting at the outset that we use stock variables for both the dependent and key independent variables. Using stock rather than flow variables recognizes the cumulative nature of search processes and R&D efforts. Because our level of analysis is a firm-year within a firm fixed effects framework, the estimates essentially reflect the impact of changes in the flows of the key independent variables on the flow of *ongoing firm knowledge brokering*. We lag the independent variables by two years because current period ongoing knowledge-brokering capabilities likely reflect actions taken in the recent past. Although the coefficients we report have not been depreciated (to reflect organizational decay of knowledge and capability), the results are similar for depreciation rates of up to 20%.

The first column of Table 5 shows the hypothesized boundary-spanning mechanism, *hired inventors with different technical knowledge stock*, for the full sample. The estimated hiring effect is positive and statistically significant at the 1% level ($p < 0.001$) even when controlling for two other possible boundary-spanning mechanisms, *alliances stock* and *venture capital inflows stock*. The estimates from Model 5-1 imply that a 1% increase in *hired inventors with different technical knowledge*

stock corresponds to a 0.48% increase in *ongoing knowledge-brokering stock* (evaluated at the means of the other right-hand-side variables).

As robustness checks, we substituted *hired inventors with different technical knowledge stock* with the stock of all hired inventors (unconditioned on having prior work experience in different technical domains). The estimated coefficient remains positive and significant at the 1% level but has a slightly smaller magnitude. We also retain our original stock variable of hired inventors with different knowledge domains and add a flow measure of the number of fired inventors. The original variable remains positive and significant.

The control variables in Table 5 are the *funding ease dummy* and *overlap with initial technology focus*. The *funding ease* variable is positive and significant ($p < 0.001$), so a munificent funding environment is consistent with ongoing knowledge-brokering activity. The *overlap with initial technology focus* variable is negative and significant at the 5% level, which is consistent with the local search and founder imprinting literatures suggesting that firms' initial orientation importantly shapes its subsequent R&D behavior—in this case, ongoing knowledge brokering.

The second and third columns of Table 5 (Models 5-2 and 5-3) present the results for the same empirical specification as Model 5-1 but for the subsamples of *initial brokers* and *initial nonbrokers*, respectively. For both subsamples, the estimated coefficients for *hired inventors with different technical knowledge stock* is positive and significant at the 1% level. Interestingly, the coefficient for the hiring variable is much higher for the *initial nonbrokers* than for *initial brokers* (1.38 versus 0.15). An F-test shows these estimates are statistically different from each other ($F = 22.7$, $p < 0.001$).[21] For *initial nonbrokers*, a 1% increase in the hiring variable implies an estimated 0.60% increase in *ongoing knowledge-brokering stock*, whereas for *initial brokers* it implies a 0.21% increase in *ongoing knowledge-brokering stock*. These results suggest that hiring inventors with different technical knowledge has a higher marginal effect for *initial nonbrokering* firms than for *initial brokers*. We examine these results in light of the results of Table 4, which shows that the payoff from engaging in ongoing firm knowledge brokering is lower for *initial nonbrokers* than for *initial brokers*, in support of Hypothesis 2B. Together, these results suggest that although *initial nonbrokers* could in principle increase their level of ongoing brokering by hiring across technical domains, they have less of a reason to do so because they are unable to capture the benefits of brokering as effectively as *initial brokers*. Initial brokers are therefore less reliant on external channels yet are able to generate greater innovative output. This pattern is consistent with an imprinting interpretation of initial brokers, in which internal processes

of routinized exploratory search via reapplying knowledge from one domain for productive reuse in another has become embedded in the organization.

5. Discussion and Conclusions

We contribute to two literatures, knowledge brokering/exploratory search and founder imprinting, which had not previously been linked. We theorize and provide empirical evidence for an inverted U-shaped relationship between ongoing knowledge brokering and innovation performance. This nonlinear association provides an understanding for why firms may devote different effort levels to acquiring and exercising ongoing knowledge-brokering capacity. In addition, founders who exercised knowledge brokering at the birth of their ventures (*initial knowledge brokers*) maintained long-term innovation trajectory advantages relative to initial nonbrokers, suggesting an important founder "imprinting" effect. Reinforcing the interpretation of founder imprinting, we find that in developing ongoing knowledge-brokering capacity, initial nonbrokers are more reliant on external boundary-spanning mechanisms such as hiring technical staff from outside the organization. This suggests that initial brokers more productively employ internal channels of maintaining and renewing their ongoing knowledge-brokering capacity. We therefore conclude that organizational capabilities can be both heterogeneous in effect and subject to founder imprinting.

The early phase of the biotechnology industry provides a useful context to examine initial and ongoing knowledge brokering by new ventures. In this empirical setting, we are able to largely factor out differences in firm development life cycle and biotechnology industry life cycle as explanations for performance differentials while exploiting useful firm-level variation in the degree of initial and ongoing knowledge brokering. In this concluding section, we discuss our contributions to research and the limitations of our study, highlighting potential avenues for future work on the subject.

5.1. Contributions to Research

We make contributions to two related literatures. A first set of contributions relate to the founder imprinting literature. We find that the manner in which founders ideate their venture opportunities has organizational innovation consequences far beyond the immediate, and so we extend the literature on opportunity discovery by linking it with the founder imprinting literature. One interpretation of our results is that although various types of organizational imprinting may exist during the early stages of a firm, knowledge brokering is one form of imprinting that may be sufficient to generate persistent heterogeneity among firms. Furthermore, whereas the existing literature finds that founder imprinting can influence a wide array of organization designs and policies such as corporate strategy and human resource management practices,

our results suggest that imprinting can occur at the earliest phase of venture development, enterprise ideation and entrepreneurial opportunity discovery.

This very early-stage imprinting has implications for understanding the mechanisms shaping heterogeneous organizational innovation performance. Perhaps the most common mechanism in the literature explaining uneven new venture performance is a transfer of human or social capital. Prior studies have suggested a number of ways in which this may happen, including from "parent" to spinoff firms (e.g., Helfat and Lieberman 2002), through alliance or venture capital affiliates of the focal new venture (e.g., Stuart et al. 1999), or via the prior work ties of new ventures' top management teams (e.g., Burton et al. 2002). Another class of mechanisms explaining differences in managerial behavior, and therefore organizational performance, invokes thresholds or triggers due to the business environment or personal managerial aspiration cues (e.g., Mintzberg et al. 1976, Greve 1998). Our work broadens the mechanisms generating new venture performance heterogeneity to include venture ideation-based founder imprinting.

A deeper understanding of mechanisms holds practical as well as academic importance. Each of the three mechanisms discussed above implies different prescriptive advice for entrepreneurial managers. For example, an affiliation-based mechanism of performance entails much different investments and managerial actions relative to an imprinting-based one. Conceptualizing and empirically assessing both initial and ongoing knowledge-brokering processes allows us to better understand the means by which venture ideation-based imprinting operates. Our finding that initial nonbrokers rely more on external boundary-spanning mechanisms such as hiring technical staff from other organizations to build their ongoing knowledge-brokering capacity (though yielding worse outcomes in innovation performance) suggests that the internal channel used by initial knowledge brokers bears more fruit with regard to innovation performance.

Our results also contribute to the knowledge-brokering literature. Whereas the prior literature put forward the view that more ongoing knowledge brokering is better with respect to a number of organizational outcomes, we theorize and affirm the proposition that the relationship is not straightforward. We conceptualized one spectrum of ongoing knowledge brokering arrayed by how *intensively* knowledge is borrowed from other domains to solve problems in the focal domain, and explored theoretically and empirically the effect of increasingly intensive ongoing knowledge brokering on innovative performance. We devote considerable attention to theorizing a curvilinear relationship between brokerage and innovative performance. Although ongoing knowledge brokering yields beneficial effects, we argue and empirically affirm an eventual downturn in innovative performance with increasing levels of ongoing knowledge brokering.

The nonlinear relationship between ongoing brokering and innovation impact provides an understanding for why firms may devote different effort levels to acquiring and exercising ongoing knowledge-brokering competence. More generally, these results illustrate the theme that organizational capabilities themselves are not homogeneous in performance consequence because knowledge brokering is not an unfettered good, as the prior literature suggests. The nonlinear relationship that we find also informs a large body of work on managing multidisciplinary research (e.g., Jannsen and Goldsworthy 1995) in which an important issue is the value of cohesion versus diversity (the former is associated with research along disciplinary lines, the latter with interdisciplinary research).

Our results also suggest heterogeneous innovation effects stratified by whether founders utilize initial knowledge brokering in the venture ideation process. These results are consistent with the notion that although there are a myriad of ways of recombining knowledge elements (many of which likely yield no value), knowledge-brokering capacity provides guidance to firms in better understanding structural rather than superficial similarities and differences between situations to increase the likelihood that relevant knowledge is applied appropriately to produce innovative output. We therefore move beyond the general characterization in prior research of innovation as a recombination of elements by analyzing a specific context featuring industry birth and following new venture development and innovation performance longitudinally. By doing so, we illustrate Kogut and Zander's (1992) arguments that the recombination of organization routines gets embedded in organizational, rather than individual memory, which explains how firm skills of combinative capabilities persist even in the face of turnover of founders and top executives. Our work is also complementary to this view in that we link individual actions (founder enterprise ideation) with organizational outcomes (firm innovative performance).

5.2. Limitations and Future Directions

Several limitations of our paper point to interesting future research directions. We discuss three sets of limitations in this section. The first deals with sampling and inference issues, the second set concerns interpreting our patent-based measures, and the final set regards interpreting the results of our analysis of ongoing knowledge-brokering capacity development. We discuss future research opportunities throughout this section.

A first issue is the limited sample size we employ in our empirical analyses. We purposefully chose the empirical setting for its desirable institutional features as explained in §3. Ideally, future work will replicate and extend this work in the context of a larger sample.

A second set of limitations concern interpreting patent data. Whereas the costs and benefits of patent-based

measures have been extensively discussed elsewhere (see, e.g., Jaffe and Trajtenberg 2002), we highlight a few issues especially relevant to our context. First, 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 overcite 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.

Another issue concerning patent data relates to the reliability of patent citations as a measure. Alcácer and Gittelman (2006) argue that patent examiner-imposed citations may be an important phenomenon. Hence, our knowledge-brokering measures may not accurately represent search behavior by scientists and organizations. On the one hand, patent examiners may "fill the gaps" and add citations to knowledge that inventor(s) did not actually rely on, biasing our measure. On the other hand, patent examiners may include similar citations that simply track those of the inventor(s), but do not add any bias. 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. Work by Criscuolo and Verspagen (2008) suggests that although examiner-imposed citations are significant in terms of the geographic concentration of knowledge, the difference between examiner and inventor citations is not statistically significant in terms of technological similarity, after self-citations are removed. Further detailed research will be needed to determine what bias (if any) is introduced by examiner-imposed citations on our measures of knowledge brokering.[22]

A final set of limitations concern interpreting how firms with different initial brokering origins build their ongoing knowledge-brokering capacity. Our method of inference involved examining the productivity of external boundary-spanning channels, most notably hiring technical staff with knowledge complementary to a focal firms' own,[23] across initial brokering type. Although we note that internal strategic reorientation may be rare in organizations, this does not mean that such efforts do not take place, and so examining efforts to bolster knowledge brokering is a fertile area for future research. Our hope is that future research will more comprehensively study the benefits and especially costs of both internal and external channels of building knowledge-brokering

capability. 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 within-firm knowledge-sharing mechanisms result in more ongoing knowledge brokering, and with what costs? It would be interesting to study how firms differ in the costs they face when accessing, storing, retrieving, and brokering knowledge. In the present analysis, not only do we not have information about the costs of our external boundary-spanning mechanisms; each of the inputs may enable access to different types of external knowledge. For example, involvement in venture capital networks may yield knowledge about outside management practices or strategic direction, whereas hiring technical staff may yield qualitatively different external knowledge (yet it is unclear ex ante what type of external information may be best suited to bolster ongoing knowledge-brokering capacity).

Finally, we end with a call for a better understanding of the interaction between individual- and organizational-level knowledge brokering. Firms 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 and instituting policies and organizational design choices. Individuals, however, are the ones carrying out inventive activities; they generate the organization's knowledge schema through a process of trial and error (Rerup and Feldman 2011). Establishing a "baseline" amount of knowledge brokering will be important, as serendipity and other factors may give rise to organic brokering. Exploring these and other multilevel knowledge-brokering mechanisms would deepen our understanding of this form of R&D search.

Acknowledgments

Endnotes

[1] When we use the term "broker," we do not necessarily mean it in the social network sense of bridging structural holes (Burt 1992). We are concerned with using ideas from one domain to innovate in another, which may take place with or without the presence of structural holes.

[2] The biotechnology industry is technologically dynamic, which makes knowledge brokering and other channels of innovation particularly important. For example, in the 1998–2003 time period, about two-thirds of drugs discovered in the United States were discovered in nonpharmaceutical firms, mostly in biotechnology firms (Kneller 2005).

[3] Gavetti et al. (2005) consider the process of strategists' decision making and problem solving via analogical reasoning, which is related to this discussion in that partial analogies can be construed as a form of idea recombination. We return to the concept of analogical reasoning shortly.

[4] The venture prehistory and spin-off literature (e.g., Helfat and Lieberman 2002) also examine the role of entrepreneurial experience and the privileged position of descendants of industry incumbents.

[5] A managerial challenge of hiring from disparate domains, however, is to productively integrate such staff into the organization (e.g., by effectively 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, and assumptions), not to mention possibly entrenched organizational power and politics supporting extant organizational processes. These risks can be partially mitigated by developing an organizational culture that promotes experimentation (Thomke 2003).

[6] 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 they can have implications for accessing external knowledge.

[7] 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 formed the core 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.

[8] Stanford offered licenses to the patent for a modest fee ($10,000 annual payments, with 0.5% royalty rates on end products). In addition, between 1980 and 2000, the patent was cited 235 times by other patents, whereas 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.

[9] Within this group, in unreported robustness tests, we further distinguished licensees of the patent who were not inventors of the technology they sought to commercialize (designated *moderate brokers*) and those who both licensed the patent and sought to commercialize their own inventions (designated *specialized brokers*). The results from this bifurcation of the initial

knowledge brokers group are consistent with the results we report.

[10] We thank Martin Kenney for suggesting sources and companies that would meet our sampling criteria.

[11] For a brief account, see http://www.nytimes.com/1997/11/23/magazine/success-is-like-a-drug.html (accessed May 30, 2013).

[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. Consequently, our data set contains *all* backward citations regardless of dates.

[13] We found 23,418 patents awarded to inventors with these or similar names. A research assistant was assigned the arduous task of filtering this data set row by row, identifying each unique inventor based on the inventor's name 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 42 such inventor names in our database, accounting for 1,086 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.

[14] We thank an anonymous reviewer for proposing this measure. The results reported here are consistent with another measure we used in an earlier version of this paper, which is the angular separation between a vector containing the focal firm's patent classes each year and another vector containing the patent classes of its backward citations.

[15] We do not use patent 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 subspecialty to another of the focal patent's technological area. We therefore confine ourselves to primary three-digit patent classes rather than subclasses. There is also the issue of how to treat patents without prior patent references as prior art. Such cases are very rare in our data set. The empirical results are robust to including an indicator variable for such instances.

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

[17] The analysis is 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 tables presented because they are likely to be an intermediate outcome of the ongoing knowledge-brokering process. We thank an anonymous reviewer for pointing this out.

[18] We used the five-year window to capture the idea that firms would hire people with fairly recent knowledge in different areas 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.

[19] In unreported random effects negative binomial models, we find similar results, though with slightly larger standard errors. The random effects in these models refer to patent effects. A Hausman test is agnostic between a random and fixed effects model.

[20] 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 by Jaffe and Trajtenberg (2002). Because we do not use the National Bureau of Economic Research data set for our patent data (this allows us to include more recent patents), we do not use these deflators in our analysis.

[21] A similar effect arises in the *alliances stock* variable, though we conceptualized that variable as a control. As with the hiring variable, an F-test shows that the *alliances stock* coefficient for initial nonbrokers is higher than for initial brokers ($F = 12.4$, $p < 0.001$).

[22] Thompson and Fox-Kean (2005) raise concerns regarding the patent matching procedure used by Jaffe et al. (1993). In their study of the geographic localization of knowledge spillovers, Jaffe et al. (1993) use patent citations to create a matched sample, which they use to control for the preexisting distribution of inventive activity. The empirical design in our paper does not rely on constructing such patent citation-based matched samples.

[23] Our work is consistent with that of Singh and Agrawal (2011), who relate firms' inventor recruitment to use of those recruits' prior ideas.

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