THE MODERATING EFFECT OF PARTNER KNOWLEDGE DISTANCE ON THE INVENTIVE BENEFITS OF FIRM KNOWLEDGE VARIETY

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Abstract

The Knowledge Based View recognizes the virtues of hierarchy for solving complex problems but it does not address why some firms produce better solutions. We theorize that differences in solution usefulness derive from variation in firms' internal knowledge variety (IKV) and access to external knowledge. A firm's IKV delineates its ability to identify and explore promising areas on the solution landscape, and the degree to which its communication channels support cross domain knowledge flows during search. A firm's IKV thus delimits the value of the solutions it generates. We theorize that knowledge accessible at partners augments IKV-related strengths for searching rugged landscapes. We find support for these ideas in the context of drug discovery with data on invention at 229 pharmaceutical firms over 20 years.

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INTRODUCTION

As a perspective on why firms exist, and as an explanation of their boundaries, the knowledge-based theory of the firm (KBV) maintains that firms have particular advantages in governing the search for solutions to complex, ill-structured problems[1] (Conner and Prahalad, 1996; Nickerson and Zenger, 2004; Leiblein and Macher, 2009). To make the search for solutions to complex problems efficient, "theories" or perspectives on the interdependencies that can affect solution quality must be developed (Gavetti and Levinthal, 2000), and because hierarchical governance supports rich knowledge flows across disparate domains, it provides an ideal context for these theories to emerge (Grant, 1996; Felin and Zenger, 2014). Consistent with the KBV, empirical evidence suggests that firms choose to internalize the search for solutions to complex problems and that they realize performance benefits from doing so (Leiblein, Reuer, and Dalsace, 2002; Hoettker, 2005; Macher, 2006; Kapoor and Adner 2012; Macher and Boerner, 2012). However, the KBV theory does not explain why some firms produce better solutions than others, through hierarchy.

The KBV ascribes the high bandwidth communication channels supported by hierarchical governance to shared organizational identity or codes (Arrow, 1974; Kogut and Zander, 1992, 1996) and to the use of low-powered incentives and firm ownership of collaborative outputs (Williamson, 1991; Nickerson and Zenger, 2004). The presence of overlapping domain experience also facilitates knowledge exchange (Szulanski, 1996; Lane and Lubatkin, 1998) and we suggest this may be an important reason for problem solving effectiveness to vary across firms. We theorize that a firm's internal knowledge variety (IKV), which reflects the dispersion of its inventive activity across technological domains, affects the prevalence of shared domain knowledge across a firm and thereby

[1] For simplicity, we use the term 'complex' to refer to problems comprised of many elements with poorly understood interdependencies. Limited understanding of interdependencies means a problem cannot be fully decomposed to simplify solution search and firms must develop theories to guide search. Problems remain nearly or non-decomposable (i.e., ill-structured) while knowledge of interdependencies is incomplete (Rivkin 2001; Pil and Cohen, 2006).

the bandwidth of its communication channels. In turn, this affects a firm's capacity to access knowledge for problem solving.

To study complex problem solving, we focus on drug discovery, which is characterized in the literature as a search for solutions to complex problems (Henderson, 1994; Pisano, 2006; Dougherty and Dunne, 2011). The knowledge relevant to inventive search in this domain is rapidly evolving, and firms draw upon knowledge from external partners to supplement their internal knowledge. Alliance partners can expose a focal firm to novel and familiar knowledge according to differences and similarities, respectively, in the domains in which the firm and its partners invent. We capture a firm's exposure to knowledge from novel and familiar domains through alliance partners using external knowledge distance (EKD) – a metric indicating the degree to which a firm and its partners patent in the same technology classes (Jaffe, 1986; Sampson, 2007). We theorize that access to external knowledge can fill gaps in knowledge accessible internally, but only if it is made available through sufficiently high bandwidth communication channels.

We use the terminology of the NK literature, which describes solution landscapes for complex problems as rugged – comprised of peaks representing the usefulness of solutions attained with particular search elements[2] (Levinthal, 1997; Gavetti and Levinthal, 2000; Ethiraj and Levinthal, 2004). According to its level, IKV supports certain aspects of searching rugged landscapes better than others. We hypothesize how exposure to knowledge through alliances can augment a firm's strengths and attenuate its weaknesses, in solving complex problems. When firms invent with high IKV they lack domain focus and have difficulty identifying attractive peaks (i.e., they are prone to "peak picking" mistakes, frequently ending up with inferior solutions). We hypothesize that low EKD can improve a firm's ability to pick attractive starting points for search by adding to its

[2] Search elements are types of knowledge - such as heuristics, facts, or concepts - that aid the search for solutions. As part of our theory, we discuss the relevance of two kinds of knowledge: principles and functionalities, for solving complex problems like those encountered during drug discovery.

knowledge in familiar domains. Firms inventing with low IKV are extremely domain focused and have difficulty finding the highest point on the peaks they identify using familiar search elements (i.e., their capacity for "peak scaling" is limited by overly local search). Alternative perspectives on search elements from familiar domains (through low EKD) can augment local search, leading to more effective efforts to scale peaks on the landscape. When firms invent with moderate IKV, they can pick and scale peaks competently but are likely to miss opportunities to switch peak (make long jumps) in search of superior solutions. Moderate IKV supports fine-grained search over a larger portion of a solution landscape, but firm-specific experience nonetheless tends to direct search toward certain peaks and obscure others, limiting a firm's capacity for "peak switching." Exposure to novel perspectives (through high EKD) can trigger new theories about how to search the landscape and redirect attention to higher peaks.

Using data on the inventive activities of 229 publicly traded pharmaceutical firms over a 20 year period, we employ a within firm estimation to capture the influence of variation in IKV and EKD levels on the usefulness[3] of the solutions a firm produces. To test our hypotheses, we calculate differences in the effect of high and low EKD interacted with each IKV level. Consistent with our theory, we find that high (low) EKD moderates IKV in such a way that it steepens (flattens) the inverted U relationship between IKV and inventive performance. Firms with either low or high IKV benefit to a greater degree when their alliances afford access to knowledge in familiar domains (low EKD). Firms with moderate IKV benefit more when their alliances provide access to unfamiliar knowledge domains (high EKD).

[3] Patents encompass specific claims to technological novelty and utility; i.e. they represent unique solutions to particular problems. We use the number of citations that a firm's patents receive as an indication of the technological usefulness of its solutions (Fleming, et al 2007; Yayavaram and Ahuja, 2008; Schoenmakers and Duysters, 2010). Patents are not equivalent to new products, and in the pharmaceutical industry, each product is connected to an average of three patents (Ouellette, 2010).

Our study contributes to the literature in two areas. First, we extend the KBV to explain firm differences in problem solving effectiveness. We build on the KBV's focus on discriminating features of hierarchical governance, and explain how knowledge boundaries affect firm-specific communication channels and codes – features of hierarchy that are often treated as innate (Nickerson and Zenger, 2004). We identify IKV as a variable that delimits the problem solving advantages associated with hierarchy [4]. Second, we show that the contribution of IKV to success solving complex problems is conditioned by a firm's access to external knowledge through alliances (EKD). As firms explore a growing variety of open governance modes to tap into the rapidly expanding bodies of knowledge their inventive (and other) activities depend upon, it becomes increasingly important to understand the relationships between governance, knowledge boundaries, and problem solving success (Khanna, 2012; Weiblen and Chesbrough, 2015).

To lay the groundwork for our theory, we describe invention as a complex problem solving process and then introduce the relevant KBV literature. Then, we offer hypotheses on the moderating role of EKD on the inventive benefits the firm attains from its IKV. We present our longitudinal data and analyses in the pharmaceutical context, which provide empirical support for our hypotheses. We conclude with theoretical and managerial implications.

[4] To conceptualize what different levels of IKV tell us about the dispersion of a firm's domain knowledge, we visualize low, moderate, and high IKV in terms of a T-shaped configuration. The classes in which a firm patents form the horizontal (top) bar of the T and the number of patents in each class comprise vertical bars, or pillars holding up the top bar. Low IKV indicates that a firm has a distinctive (substantially longer) vertical pillar for very few of those classes, whereas high IKV means that the vertical pillars are roughly the same length all along the top bar so that it looks more like a fat top bar than a T. Moderate IKV indicates that a firm has a few well-defined vertical pillars – areas of focus that are easily distinguished, as well as pillars that indicate varied engagement with other domains comprising the top bar.

THEORY

The complexity of inventive search

Inventive search[5] begins with the identification of a need or problem to solve, and an abstract solution concept of how the problem might be solved (Arthur, 2007). Inventors then turn to a combination of experiential and theory-driven search (Maggitti, Smith, and Katila, 2013). Search proceeds through an evolutionary process of sampling from the pool of technological possibilities and adjusting the direction of search as evidence is generated and inferences derived (Levinthal and March, 1993; Katila and Chen, 2008). As traction is gained with one aspect of the solution, attention shifts to another. Problems are ultimately solved by cycling through the array of issues that surface during the search process. Representations of the solution landscape and the theories guiding search are adjusted to reflect interdependencies as they are identified.

This search process can be observed in drug discovery. This type of invention is comprised of a series of experimental stages that are guided to varying degrees by prevailing theories about appropriate drug targets and beliefs about how these targets might be affected by different compounds. For instance, to address the problem of curing Alzheimer's disease, scientists have worked for decades with a *principle* or hypothesis about what they believe is at the core of a solution (e.g. destroy amyloid and tau plaques) and explored potential mechanisms of action or *functionalities* by which that principle could be enabled (e.g. slow the production of amyloid B peptides, or their aggregation into oligomers, or accelerate their clearance from the body) (Hardy and Selkoe, 2002).

Principles are hypotheses about how a solution might be created – they succinctly describe "the method of the thing" (Arthur, 2007: p. 276), yet they cannot be fully deduced from theory, nor do they specify what functionalities (means to bring about a desired effect) should be used (Vincenti,

[5] The terms invention and innovation are sometimes used interchangeably, but they involve distinct processes: invention refers to the generation of novel ideas and innovation to their commercialization through products and new businesses (Schumpeter, 1934; Katila and Shane, 2005: p. 815; Arthur, 2007).

1990; Murmann and Frenken 2006). In drug discovery, principles and functionalities may be suggested by scientific discovery and they provide broad foci for search. Theories relating these search elements emerge through experimentation with 1000s of chemical compounds, or biologics, whose effects cannot be fully anticipated due to poorly understood interdependencies between targets and disease states, and the biochemical pathways that regulate physiological functions. This complexity is characteristic of the search for new drugs (Hara, 2003; Dougherty and Dunne, 2011).

Conceptualizing inventive search as navigating rugged landscapes

To orient our investigation into inventive search as a context in which complex problems are solved, we draw on the language of the NK literature (Fleming and Sorenson, 2004; Nickerson and Zenger, 2004; Macher and Boerner, 2012). To solve complex problems, firms must search "rugged landscapes," defined by the presence of many locally best solutions, termed peaks, and the presence of poorly understood interdependencies amongst the variables in a solution – the search elements, that give rise to them[6] (Levinthal, 1997; Ethiraj and Levinthal, 2004).

When interdependencies are poorly understood, problem solvers have difficulty identifying all of the peaks on a solution landscape, and discerning which peaks are higher. They are also challenged to scale local peaks and to move from one peak to another. The requisite knowledge is not reliably acquired through experiential search, since small changes in the combination of solution elements deployed can dramatically alter performance outcomes (Levinthal, 1997). A more efficient

[6] Solution landscapes map alternative combinations of values that search variables (N) can take on, to the quality of the overall solution for problems being addressed. For example, N might represent a function, a principle, or an artifact used to implement them, to achieve a desired effect. Interdependence, (K) reflects the extent to which the contribution of the search variables (N) to the quality of the overall solution depends upon the values of some or all of the other variables. At higher levels of K, solution landscapes have more "peaks" and there is little correlation between the sets of variables that produce the different peaks. To simplify, we use the term 'search elements' to refer collectively to principles (what effects are relevant) and functionalities (how to bring about those effects) that problem solvers use to search for solutions, whereas the theories guiding search are proposed relationships between functionalities and principles. Experience in different technology domains provides exposure to different functionalities and principles as well as to artifacts, materials, and techniques used to implement them.

way to navigate complex solution landscapes is to draw upon cognitive representations, which organize prior experience into meaningful categories and enable problem solvers to form the theories that guide search (Gavetti and Levinthal, 2000; Gavetti, Levinthal, and Rivkin, 2005; Page, 2007; Felin and Zenger, 2014). Representations relevant to inventive problem solving encompass several types of knowledge (e.g. Garud and Rappa, 1994; Garud, 1997: Maggitti *et al.,* 2013) but for our purposes we will focus on principles and functionalities.

Inventing in different technological domains exposes problem solvers to a variety of principles: "Sometimes a principle is recalled from the past, or picked up from the remark of a colleague, or suggested by theory" but often, invention involves the integration of one or more principles that were used in prior solutions that are repurposed to address a new problem (Arthur, 2007: p. 280). Once a principle is identified, solutions are explored drawing on the firm's prior inventive experience. When firms invent repeatedly in a domain, problem solvers develop a wealth of insights into what principles or functionalities can be deployed toward particular ends and under what conditions (Arthur, 2007). This knowledge is crucial to seeing potentially useful variations on existing approaches (Boh *et al.*, 2014; Kaplan and Vakili, 2014). Immersion in a domain also reveals anomalies that can expose limitations in existing ways of thinking and prompt a search for new approaches (Constant, 1980; Kaplan and Vakili, 2014).

The relevance of firm domain knowledge for solving complex problems

The influence of domain knowledge for searching rugged solutions landscapes can be conceptualized as follows. Firms that invent in many technological domains have experience using a variety of principles and functionalities, and this affords alternative ways of conceptualizing solution landscapes. Each peak on a landscape corresponds to a unique set of search elements – one or more principles, sets of functionalities, and specific materials and artifacts deployed to bring about desired effects. Knowledge of many principles and functionalities enables problem solvers to envision more peaks on the landscape and provides multiple starting points for search. Extensive experience in the domains the firm invents in generates two additional advantages for search: (i) insight into which functionalities can be successfully used together and how – which facilitate scaling local peaks, and (ii) understanding of trade-offs associated with using different principles and sets of functionalities – which permit some evaluation of achievable performance at alternative peaks and insight into how to move from one possible peak to another.

The existence of such knowledge within a firm's boundaries suggests the types of advantages it may have in searching rugged landscapes. In keeping with theories of inventive search, we maintain that the relevance of particular bodies of knowledge to solving a complex problem is imperfectly known prior to search, and that useful knowledge is often discovered serendipitously (Arthur, 2007; Meyers, 2007; Maggitti *et al.,* 2013; Lee *et al.,* 2015). Consistent with the KBV, we note that organizational context profoundly affects the way inventive search unfolds. In the face of uncertainty, individuals turn to others to make sense of information[7] (McLaughlin, 2001; Baba and Walsh, 2010). As Arthur (2007: p. 284) notes: Social contexts "steep the originator in the lore that has built up around the problem and around previous efforts [to solve it.] They provide suggestions of useful techniques and of principles at work in other domains. They help the originator see the problem differently. Human interaction also provides needed criticism to burst fanciful bubbles, and it provides equipment and know-how to bring the concept to physical reality."

Firms comprise an important social context in which inventive search is embedded, which, according to the KBV, shapes problem solving processes in a number of important ways. Firms

[7] Along the same lines, Burt (1987: p. 1290) observed that, "When confronted with an empirically ambiguous question, a question that cannot be resolved by concrete facts, people turn to the other people with whom such questions are discussed and, in their reciprocally socializing debate, create a consensual, normative understanding of the question, resolving the question's uncertainty in their own minds, if not in fact."

encourage their members to prioritize solutions that meet certain criteria, providing anchors for search (Ocasio, 1997; Bhardwaj, Camillus, and Hounshell, 2006; Ghosh *et al.,* 2014). Firm agendas and beliefs can override social epistemologies that are sustained within scientific and professional communities, and this explains why firms seeking to solve the same problem may pursue alternative pathways (Baba and Walsh, 2010; Augier, March, and Marshall, 2015). Innovative narratives direct attention to certain kinds of problems and can lead inventors to classify them a particular way, and in the process also invoke particular representations of the solution space (Bartel and Garud, 2009). Through leadership, their use of physical space, and shared purpose, firms can overcome the homophilic tendency of social ties to conform to the boundaries of specialized fields (Henderson, 1994; Augier *et al.,* 2015), and provide a context that enables inter-disciplinary knowledge transfer and recombination (Kogut and Zander, 1992; Hakanson, 2010).

Prior research demonstrates that interactions between people with varied experience produce novel outcomes and enhance organizations' capacities to solve complex problems (Rosenberg, 2009; Lee, Walsh, and Wang, 2015). Theories to guide search emerge and evolve through routine conversations, serendipitous encounters, as well as through deliberate knowledge exchange (Arthur, 2007; Meyers, 2007; Lee *et al.,* 2015). However, the integration of knowledge for inventive search is not feasible without high bandwidth communication across domains (Lane and Lubatkin, 1998). Communication is richer when it is facilitated by shared language and domain experience (Kogut and Zander, 1992; Szulanski, 1996). Firms that have experience undertaking search across multiple domains develop communication channels and mechanisms to embrace the integration of knowledge from multiple disciplines or knowledge sources (Bartel and Garud, 2007; Grant, 1996). These channels are most effective when they encompass novel as well as common domain experience. A balance of novelty and commonality is required to facilitate the generative conversations that produce new representations of solution landscapes and theories on how to search them (Sampson, 2007; Garud, Gehman and Kumaraswamy, 2011; Heinze *et al.,* 2009).

Overlapping domain knowledge enables connections around commonly understood principles and functionalities, which can be probed further to reveal alternative ways to apply the search elements - *meaningful deviations*, which can assist peak scaling. Exposure to distant domain knowledge can produce productive recombination of search elements - *meaningful recombinations*, which trigger a reconceptualization of the solution space, revealing new peaks. Exposure to additional knowledge in domains where inventive experience is cursory improves a firm's ability to select among search elements and identify *meaningful focal points* to anchor search.
Experience dispersed across a variety of domains affords access to distinctive principles and functionalities that might be fruitfully recombined to solve problems, but concentrated domain experience underlies the capacity to recognize ways to use search elements effectively and to implement novel combinations (Kaplan and Vakili, 2014). Based on these two opposing effects, the relationship between IKV and the usefulness of a firm's solutions to complex problems should take the form of an inverted U-shape, emerging from the additive combination of costs and benefits (Haans *et al.,* 2016: p. 1179).

The benefits of communication within the firm increase with IKV, as domain variety offers greater opportunities to recombine functionalities and principles to define and solve problems - a firm gets better at *identifying peaks,* i.e. distinctive approaches to solving a problem. As the dispersion of a firm's inventive efforts equalizes, so too does the likelihood that principles and functionalities from any one of those domains inform a firm's search for solutions. As a result, a firm is able to consider a wider variety of approaches to solving problems, and this increases its chances of identifying a high peak on the solution landscape, an advantage of high IKV.

At the same time, the average cost of communication increases and the richness of conversation falls as IKV rises, since fewer of a firm's members share domain knowledge. This limits knowledge exchange pertinent to search in two ways. First, it reduces opportunities for heterogeneous experiences within a domain to be shared, which inhibits *peak scaling*. Second, the general lack of shared domain knowledge that accompanies high levels of IKV decreases opportunities to identify and evaluate combinations of search elements from multiple domains, because the conversations that enable this become costly, and this inhibits *peak switching*.

The net contribution of IKV to problem solving effectiveness thus first rises, but begins to decline after some point. The additive combination of this benefit curve and this cost curve produces an inverted U-shaped relationship between IKV and solution usefulness. The "sweet spot" exists in the range of IKV where the benefits from exposure to a variety of domains is anchored by concentration in a few domains – here, more of a firm's search efforts will be informed by communication through high bandwidth channels – where members of the organization are more likely to have some common domain experience, yet also know about search elements from disparate domains.

Although internal knowledge strongly influences solution quality (Miller *et al.,* 2007), alliance partnerships extend a firm's access to knowledge through socially embedded communication channels (Grant and Baden-Fuller, 2004; Felin and Zenger, 2014). To understand a firm's capacity to access partner knowledge, we need to understand how distant from a firm's knowledge the domain experience of its partners is. To capture this, we use the average knowledge distance between the firm and its partners, external knowledge distance (EKD), to indicate the degree that members of the firm will be exposed to knowledge from novel or familiar domains[8].

[8] As an example, consider two firms, A and B, each with two alliances. Firm A has two partners and each devotes 50% of its inventive efforts to the same technological domains as the focal firm. Firm B has two partners; one devotes 10% and the other 90% of its inventive efforts to the same technological domain as the focal firm. Firm A and Firm B

Hypotheses

Search Advantages from IKV and the Augmentative Role of External Knowledge

High IKV and Peak Picking. Given the path dependent character of search (Helfat, 1994; Nerkar and Parchuri, 2005; Katila and Chen, 2008), the starting points a firm selects can greatly influence what solutions are ultimately reached. When problem solvers can conceptualize a variety of solution approaches, a firm can initiate search near a number of different peaks. To select effectively between different starting points requires an understanding of when and how certain principles and functionalities are useful, and this knowledge accumulates through immersion in a domain (Fleming, 2001; Dane, 2010; Boh *et al.,* 2014; Kaplan and Vakili, 2014). Firms that invent in many domains, without concentrating on any of them, are likely to have less of such knowledge. When inventive efforts are widely dispersed across domains, attention within the firm is fragmented and domain knowledge overlaps to a lesser degree throughout the firm (Ocasio, 1997; Miller *et al.,* 2007). Even if the firm integrates some knowledge across domains, its lower bandwidth communication channels means useful domain knowledge is less often transferred and recombined throughout the firm (Szulanski, 1996). Without focus, the chances of inappropriately transferring the lessons learned from prior search are also greater (Ghosh *et al.,* 2014).

Role of EKD with high IKV. High IKV firms have the potential to begin their search near high peaks on the landscape, but the variance in the set of options they can consider is high (Singh and Fleming, 2010). Among firms inventing with high IKV, those embedded in low EKD alliance relationships might offset their weakness in peak picking since they have access to additional knowledge in familiar domains. Overlap in domain knowledge, between a firm and its partners, increases the accessibility of this knowledge.

overlap an average of 50% with their partners. Accordingly, we expect that the odds that Firm A's and Firm B's members will interact with members of partner firms who possess experience in the common domains are approximately the same – even though exposure for Firm B comes primarily through one partner. This approach is in line with similar studies in the literature that examine the role of external partners on invention (cf. Sampson, 2007).

With fortified domain knowledge, problem solvers stand a better chance of selecting fruitful starting points for search. This facilitates the surfacing of critical knowledge regarding principles and functionalities, and increases a firm's capacity to identify *meaningful focal points* for search. Low EKD partnerships also support lower cost, richer knowledge transfers as partners have domain knowledge in common. By adding to a firm's domain understanding, low EKD partnerships provide a more robust basis for evaluating alternative search elements, allowing the firm to reject inferior starting points on solution landscapes (Singh and Fleming, 2010). This leads to the following hypothesis:

Hypothesis 1: Firms with high IKV produce more useful solutions on average (i.e. achieve higher inventive performance) when they can access familiar domain knowledge through their collection of alliance partners (i.e. EKD is low), as compared to when their access to knowledge through alliance partners is primarily in unfamiliar domains (i.e. EKD is high).

Low IKV and Peak Scaling. The way in which a solution landscape is explored also affects the outcome a firm arrives at. Since the height of each peak (i.e., the level of performance attainable through the search elements a firm is working with) is not fully predictable at the outset, a firm's capacity to scale the peak(s) it focuses on offers a chance of producing a useful solution.

Firms inventing with low levels of IKV have an advantage in scaling peaks because their intensive focus in a few domains provides insight into when and how to use search elements effectively. High bandwidth communication channels cultivated by focused problem solving activities support rich and frequent transfers of domain knowledge, and increase the degree to which relevant domain knowledge is accessed for search. On the other hand, search is likely to proceed along familiar paths unless compelling evidence that alternative principles or functionalities should be considered is presented (Henderson and Clark, 1990; Audia and Goncalo, 2007; Dane, 2010).

Narrow focus can limit problem solvers' ability to work through bottlenecks[9] and stall efforts to scale local peaks (Arthur, 2007; Boh *et al.,* 2014).

Role of EKD with low IKV. Alliances with partners that concentrate on at least some of the same domains can prompt firms inventing with low IKV to consider alternative ways to approach search. Partners that invent in common domains provide a balance of shared conceptual understanding and heterogeneous (though within domain) experiences. Engaging with partners that work in the same domain is thus more likely to expose problem solvers to *meaningful deviations* in how familiar search elements are being utilized and to counterfactuals, leading to greater flexibility in how domain knowledge is applied (Dane 2010: p. 581).

Meaningful deviations can prompt conscious evaluation of alternative implementations of search elements (Audia and Goncalo, 2007; Dane, 2010; Singh and Fleming, 2010). Search thus becomes less automatic and more deliberate, increasing the reliability with which a firm can deploy domain knowledge to scale local peaks. Access to distant domain knowledge is unlikely to augment search efforts in the same way when IKV is low, because the firm's attention is narrowly focused on certain theories and not on integrating unfamiliar ones. We hypothesize:

Hypothesis 2: Firms with low IKV produce more useful solutions on average (i.e. achieve higher inventive performance) when they can access familiar domain knowledge through their collection of alliance partners (i.e. EKD is low), as compared to when their access to knowledge through alliance partners is primarily in unfamiliar domains (i.e. EKD is high).

Moderate IKV and Peak Switching. In addition to selecting peaks and attempting to scale them, problem solvers can arrive at better solutions by making "long jumps" that relocate search to a new peak. This entails exploring solutions based on different principles or functionalities (Kauffman, 1993; Levinthal, 1997). Firms inventing with moderate IKV are better able to engage in long jumps,

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[9] Dane (2010) describes several variants of cognitive inflexibility, including functional fixedness, where individuals associate functionalities with a narrow range of purposes, limiting how they consider using them.

because they possess the benefits of familiarity with a broad range of solution elements, as well as substantial insight into when and how to deploy them (Fleming, 2001; Schoenmaker and Duysters, 2010; Ghosh *et al.,* 2014). Further, moderate IKV fosters a balance of overlapping and novel domain experience within the firm, which can support rich knowledge transfers as well as generative discussions that reveal opportunities to recombine prior search elements (Simonton, 2009; Garud, Gehman, and Kumaraswamy, 2011).

Role of EKD with moderate IKV. Firms with moderate IKV have a more comprehensive perspective on the solution landscape and are in a better position to select new peaks for exploration. This level of knowledge variety supports rich communication channels to transfer knowledge within and across domains, enabling firms to efficiently update theories guiding search as they acquire new information about solution landscapes. Alliance partners with inventive experience stemming from distant domains can introduce novel ideas and challenge assumptions prevalent in the firm's focal domains (Phene *et al.,* 2006; Jeppesen and Lakhani, 2010). Actors that are marginally connected with the firm's focal domains likely employ different principles and have experience with different functionalities (McLaughlin, 2001). Access to these insights enables the firm to extend its understanding of the solution landscape in productive ways (Jeppesen and Lakhani, 2010).

Too much reuse of familiar combinations of solution elements can produce weaker solutions (Fleming, 2001; Audia and Goncalo, 2007), implying that firms with moderate IKV must continually be on the lookout for meaningful ways to recombine what they have learned within and across domains. Although firms with moderate IKV have many feasible ways to recombine their domain knowledge, their challenge is to counteract the tendency of search to gravitate to familiar paths (Fleming and Sorenson, 2004). Exposure to novel perspectives and unfamiliar search elements can "shake up" established patterns of communication (Kanter 1988; Nemeth, 1995; Zhou and Li, 2012), alerting a firm to *meaningful recombinations* of domain knowledge (Augiers, March, and Marshall, 2015). Alliance partners that collectively provide access to distant domains provide such opportunities. Accordingly, we hypothesize:

> *Hypothesis 3: Firms with moderate IKV produce more useful solutions on average (i.e. achieve higher inventive performance) when they can access unfamiliar domain knowledge through their collection of alliance partners (i.e. EKD is high), as compared to when their access to knowledge through alliance partners is primarily in familiar domains (i.e. EKD is low).*

Table 1 summarizes our theory.

<u>Insert Table1 about here</u>

METHODS

Research setting

We test our hypotheses in the pharmaceutical industry, specifically focusing on the early stages of research through which new drug candidates are discovered. This setting is an ideal context in which to test our hypotheses, as drug discovery is inherently a complex process, and the solution landscapes over which search occurs are rugged (Pisano, 2006; Dougherty and Dunne, 2011; Khanna, 2012). Patenting behavior in this industry provides insight on which firms are more successful, and tells us a great deal about the technological knowledge pharmaceutical firms bring to the search process. Patents are classified as belonging to particular technological domains, indicated by class codes. Patent classes designate the technological composition of an invention, and they correspond well to distinctive pools of solution elements and domains of technological expertise (Benner and Waldfogel, 2008; Yayavaram and Ahuja, 2008; Strumsky, Lobo, van der Leeuw, 2012). As a firm invents repeatedly in a particular class, it accumulates familiarity with more of the various material compositions, methods of use, and processes that class encompasses.

Sample and data

To test our hypotheses, we restrict our analyses to public US pharmaceutical firms (SICs 2833-2836), enabling us to control for key financial data. We focus on the 20 year period from 1984 to 2004 – a period of unprecedented growth in scientific and technological knowledge relevant to pharmaceutical invention, and the extensive use of alliances for R&D (Henderson, 1994; Pisano, 2006). We obtained a list of 529 active public pharmaceutical firms and their consolidated financial data from the 2007 Compustat database, which provided complete financial data for 400 firms. Of these 400, 36 firms had only one observation and 135 firms had no patents during the study period, leaving us with a sample of 229 firms and 2332 firm-year observations[10].

Pharmaceutical firms use alliances extensively, driven in part by the diversity and multi-disciplinary nature of the knowledge that is required for invention (Brusoni, Criscuolo, and Geuna, 2005; Hoang and Rothaermel, 2005). We focus on alliances related directly to research, development, and co-development. To identify each firm's R&D alliance partners, we drew on Recombination Capital (Recap) Inc., a comprehensive source of pharmaceutical alliances (Schilling, 2009). We extracted patent data from the U.S. Patent and Trademark Office (USPTO) Cassis database to develop our measures for IKV and EKD and inventive performance. According to the concordance between the U.S. Patent Classification System and the Standard Industrial Code System[11], 64 three digit patent classes correspond to pharmaceutical inventions. Focusing on these classes enabled us to capture comparable differences in domain knowledge across firms (Benner and Waldfogel, 2008). To ensure that we assigned alliances and patents to the correct entity, we constructed family trees of all 529 public firms using the Corporate Affiliations database compiled

[10] The fixed-effects negative binomial model that we use (Hausman, Hall, and Griliches, 1984) conditions the joint probability of the counts for each group on the sum of the counts for the group. This restricts the data to those firms with at least one patent across two years. Using the full sample of 400 firms and a random effect negative binomial model produced no substantive change in our results.
[11] The concordance links US patent classes with 55 unique Standard Industrial Codes (SICs) and is available on the website: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/brochure.htm#Patent_Data.

by the LexisNexis Business Data Group. We validated subsidiary information using company websites and SEC 10-K filings. We relied on the family trees to allocate all patents granted for pharmaceutical inventions (a total of 54,854) to the 529 public firms that could comprise the alliance networks of the 229 firms that are the focus of our analysis during the time period under study.

Dependent Variable

To assess the usefulness of a firm's solutions to complex problems, we examine patenting outcomes. Patents are granted to inventions that satisfy the USPTO's novelty, usefulness, and non-obviousness criteria. While every patent embodies some new knowledge, the usefulness of individual patents varies greatly. Citations to a firm's patents originate when researchers solving new problems, perceive them as useful to their own problem solving efforts. Following prior work on invention, (Fleming, *et al.,* 2007; Yayavaram and Ahuja, 2008; Schoenmakers and Duysters, 2010), we define our dependent variable, *firm inventive performance*, as the number of citations that a firm's patents receive[12]. Patents receive the highest number of citations somewhere between the year after they are issued (grant date) and three to four years after the patent application date (Jaffe, Trajtenberg, and Henderson, 1993; Jaffe and Trajtenberg, 2002; Mehta *et al.*, 2010) or, in the case of drugs and medicine, five years after their application date (Hall *et al.,* 2001). The likelihood that a patent will receive citations declines in the fourth year after the grant date (Mehta *et al.*, 2010: p. 1192). We measure this performance via the sum of all citations received in years t+1 to t+3 to all the firm's patents granted in year t. For patents granted in the final year of our study, 2004, we collected citation data through 2007. We use the grant date rather that the application date because empirical evidence suggests that a patent's "citation clock" does not start until it is issued (Mehta *et al.*, 2010).

Independent variables

[12] Operationally, citations are generally incorporated by a firm's lawyers as they seek to define the intellectual lineage and novelty of the patent. Citations can also be added by patent examiners investigating novelty and usefulness of claims (Alcacer, Gittelman, and Sampat, 2009).

We constructed knowledge variety and distance measures relying on patent classes to indicate technology domains (Sampson, 2007; Phelps, 2010; Strumsky, Lobo, van der Leeuw, 2012). All independent variables are lagged by one year. Like our dependent variable, IKV and EKD are based on patents granted in a particular year, but IKV and EKD use patents granted in time t-1, whereas citations are to patents granted in time t.

Internal knowledge variety (IKV). We measure IKV as the distribution of patents across all 64 pharmaceutical patent classes, using the inverse of the nonbiased Herfindahl Index (HHI) proposed by Hall (2002: p. 3, equation 6). This approach adjusts for bias caused by the size of firms' patent portfolios by increasing the value of the resulting Herfindahl index for firms with fewer patents (Hall, 2002). The computational formula is: $IKV_i = 1 - \left[\frac{N_i * HHI_i - 1}{N_i - 1}\right]$ where, $HHI_i = \sum_{k=1}^{k}\left[\frac{N_{ik}}{N_i}\right]^2$

i= focal firm; k=patent classes; N_{ik}= number of patents in class k by the focal firm i; N_i= total number of patents in all classes by the focal firm i. The index rises with the number of domains (patent classes) a firm invents in and the equality of its efforts across classes. Its value can range from 0 to 1, with a smaller value indicating that, adjusting for the size of the overall patent portfolio, a firm has lower levels of internal knowledge variety[13].

External knowledge distance (EKD). We measure EKD by estimating the angular separation between a firm and all of its partners' patent portfolios (Jaffe, 1986; Sampson, 2007). Angular separation measures the degree to which a firm and its partners patent with the same intensity in the same classes and it thus captures the distance between a firm's knowledge and the domain experience of its partners. We adjust for the fact that partners with larger portfolios will have greater influence on the EKD measure by dividing each firm's number of patents in a given class *k*, by the highest number of patents held by the firm or its partners in class *k* to obtain each partner's relative

[13] For example, a firm with 1 patent in each of the 64 patent classes would have IKV of 1 and a firm with 10 patents in each of the 64 classes would have IKV of .986.

contribution to that domain. The external knowledge distance between a firm and each of its partners' patent portfolios is measured by $EKD_{ij} = 1 - \frac{S_i{'}S_j}{\sqrt{S_i{'}S_i}\sqrt{S_j{'}S_j}}$ where i≠ j; i= focal firm; j=partner firms; S_i= vector of adjusted number of patents granted to a focal firm; and S_j= vector of adjusted number of patents granted to a focal firm's partners. The vectors represent patent portfolios, $S_i = (S_i^1 \ldots S_i^k)$, where S_i^1 represents the adjusted number of patents granted to firm i, in class k. We calculate this measure for each focal firm and partner dyad and then take the simple average. Averaging the EKD measure allows us to aggregate the dyadic distance to the firm level and captures the likelihood of a firm's members identifying potential insights they can draw upon at alliance partners. In the instance where firms do not patent, the vectors contain all 0 values and following Sampson (2007), we set the EKD measure equal to 1[14]. EKD values range from 0 to 1, where 1 indicates the greatest possible external knowledge distance and 0 indicates no distance.

Control variables

We control for *Firm patent stock* using the count of patents a firm has received in time t, so that coefficient estimates for other independent variables capture marginal contributions to the mean impact of a firm's inventions. To control for annual variability in patenting we also estimated our models with the number of patents granted in the previous three years. The estimates are consistent with those reported here. Partners with more patents could have stronger research skills and a larger stock of knowledge, and hence may contribute more to a firm's inventive performance (Stuart, 2000). We control for *Partner Patent Stock* with the total number of patents a firm's partners received during the preceding three years. Prior experience with a partner could enhance a firm's inventive performance because familiarity improves collaboration (Reuer, Zollo, and Singh, 2002). We determined whether a partner had collaborated with the focal firm at any time in the preceding years

[14] We have 808 observations in which we set EKD at 1 because of lack of patenting (the total number of observations in our analysis is 2,332). Excluding these 808 observations yields results consistent with those reported here.

under analysis ("established partners"). *Partner experience* is calculated as the ratio of established partners in year t to the total partners in year t.

Firms that work with partners that differ from each other – i.e. exhibit greater *Network Knowledge Distance (NKD)* might find that this increases both the opportunities and challenges associated with exploiting external knowledge for invention (Phelps, 2010). We controlled for differences amongst a firm's partners' knowledge, using the computational formula for EKD, but this time we exclude the focal firm to assess the distance among firms that constitute the focal firm's network: $\mathrm{NKD_i} = \frac{[\sum_h \{\sum_j \boldsymbol{d_{hj}}\}]}{\frac{m_i*(m_i-1)}{2}}$ $\quad Equation\ (1)$ where $\mathrm{d_{hj}} = 1 - \frac{S_h{}'S_j}{\sqrt{S_h{}'S_h}\sqrt{S_j{}'S_j}}$ $\quad Equation\ (2)$

i= focal firm; h= partner firms; j= partner firms; m= number of partners; S_h= vector of number of patents granted to a focal firm's partners; S_j= vector of number of patents granted to a focal firm's partners. The index *h* in Equation 1 is over particular partners and *j* indexes over all partners excluding the focal firm. The second summation (over h) corrects for double counting. When calculating the average NKD for firm i, the term: $\frac{m_i*(m_i-1)}{2}$ captures the number of potential relationships among the firm's partners.

Firms that engage in a large number of R&D alliances can access a large volume of technological information, which could positively affect a firm's inventive performance (Ahuja, 2000). However, managing many relationships can also complicate knowledge transfer (Van Wijk, Jansen, and Lyles, 2008). *Network size* is measured as the total number of R&D alliances that a firm is engaged with each year (Freeman, 1979), and can include multiple agreements with a given firm. *Network efficiency* is the degree to which a firm's partners occupy unique structural positions in a network, or lack ties to the same other firms in the network (Burt, 1992). Partners that connect a firm to different nodes transmit more diverse information to the firm, and this could augment its inventive performance (Ahuja, 2000).

Annual *R&D expenditure* in US dollars (logged) helps control for the size of firms' research efforts. *Firm age* can affect the types of invention a firm invests in, with older firms preferring incremental inventions and younger firms betting on riskier technologies (Sorensen and Stuart, 2000). Large firms can attract talent and technology, but they also tend to act slowly, which may reduce their capacity to produce significant inventions. We control for *Firm size* with the log of annual sales revenue. *Slack resources* allow firms to explore opportunities outside their core technology domains and thus sustain their ability to develop important inventions (Ahuja and Lampert, 2001). However, agency problems could increase with slack and dampen inventive performance (Tzabbar, 2009). We use current assets divided by current liabilities to control for slack resources (Singh, 1986). *Year dummies* capture systematic differences in citation patterns across annual patent cohorts.

Analyses and results

We employ the fixed effects negative binomial model with the conditional likelihood estimator suggested by Hausman, Hall, and Griliches (1984) because our dependent variable is constrained to be a non-negative integer and its values are over-dispersed. Fixed effect estimation controls for potential bias from omitted intangible factors, such as organizational culture or corporate vision, which could influence inventive performance and our IKV and EKD variables (Greene, 2003). Random effects results are consistent with those we report.

We present basic statistics in Table 2 and we report the results of our negative binomial regression analyses in Table 3. As Table 2 shows, some correlations are above 0.5. To assess potential multicollinearity, we conducted sensitivity analyses by estimating our models without the firm patent stock, age, and size variables[15]. Coefficients on the remaining variables do not change.

[15] O'Brien (2007) states that common treatments of multicollinearity, such as eliminating variables or combining them into a single index may yield a model that suffers from omitted variable bias. We act conservatively and report our models with all the variables included in the regression model to avoid any concern of omitted variable bias.

Model 1 in Table 3 reports the estimates for the control variables. Firms possessing higher patent stocks and firms with high network efficiency exhibit greater inventive performance. However, in the presence of these and other controls, having more alliances reduces the impact of firms' inventions. Consistent with prior empirical work, R&D expenditure and partner experience are associated with superior inventive performance. In line with prior research in the bio-pharmaceutical industry, we do not observe firm age effects (Arora *et al.*, 2009; Sosa, 2009). We also find that network knowledge distance, firm size, and slack resources do not influence inventive performance.

Insert Tables 2 and 3 about here

In models 2, 3, and 4 (Table 3) we include the individual and simultaneous effects of IKV and EKD on inventive performance. Since prior studies suggest an inverted U-effect of both IKV and EKD on inventive performance (e.g. Henderson and Cockburn, 1996; Sampson, 2007), we include the first and second order of the IKV and EKD variables in all models. In models 2 and 4, the coefficient of IKV is positive while the coefficient of its squared term is negative, replicating the inverted U-shape relationship to inventive performance identified in the literature. To confirm the inverted U-effect of IKV and EKD on inventive performance we calculate the turning points for IKV and EKD curves following the approach suggested by Haans, Pieters, and He (2016). The turning point at which IKV begins to exhibit a negative effect on inventive performance occurs at 0.4, within the data range, and 71 percent of observations have IKV values below that level. Since we have a nonlinear model, we tested for the significance of the marginal effects of IKV on inventive performance and find they are significant for all the values of IKV before and after the turning point. In the region (0, 0.4) the slope of IKV curve is positive and significant while it is negative and significant in the region (0.4, 1). The coefficient of EKD is positive while the coefficient of its squared term is negative, supporting prior findings in the literature. The turning point at which EKD begins to exhibit a negative effect on inventive performance occurs at 0.7, within the data range. Five percent of the EKD values fall below the EKD turning point. The marginal effects of EKD on inventive performance are significant for all the values of EKD before and after the turning point. In the region (0, 0.7) the slope of EKD curve is positive and significant but in the region (0.7, 1) the slope is negative and significant.

In model 5, we include all main effect and interaction variables. As noted above, since both IKV and EKD have an inverted U-shape effect on inventive performance we must include four components in our regression model to assess their interaction: (a) IKV * EKD, (b) IKV squared * EKD, (c) IKV * EKD squared, (d) IKV squared * EKD squared. To visually present the effect of the significant non-linear interactions in model 5, we follow an approach commonly used in the strategy literature (cf. Sampson, 2007; Lahiri, 2010; Kotha, Zheng, and George, 2011; Haans *et al.*, 2016). We take the coefficient estimates from model 5, and calculate the predicted value of inventive performance ($e^{\beta' X}$) over the entire range of values for IKV when EKD is low and again when EKD is high (one SD below and above the mean, respectively). The outcome is graphed in Figure 1. The slope of the inverted U-shaped curve showing the relationship between IKV and inventive performance is steeper when EKD is high than when EKD is low.

Although our theory centers on EKD moderation affecting the steepness of the inverted U-shaped curve for IKV, Haans *et al.* (2016), recommend testing for the possibility of a second type of moderation – namely one that leads to a shift in turning point. We calculated the turning point of the IKV curve when EKD is low and when EKD is high, following the method outlined in Haans *et al.* (2016). We find that the turning point of the IKV curve occurs at 0.4 for both low and high levels of EKD.

<u>Insert Figure 1 about here</u>

While Figure 1 provides an indication of how EKD affects the relationship between IKV and inventive performance at different levels of IKV, in a nonlinear model the significance of EKD's marginal effect can vary for each value of IKV (Ai and Norton, 2003; Hoetker, 2007; Wiersema and Bowen, 2009; Zelner, 2009). This marginal effect --also referred to as the true interaction effect-- is given by the cross partial derivative of the regression equation (cf. Ai and Norton, 2003; Hoetker, 2007; Zelner, 2009). Using the delta method to calculate standard errors (Wooldridge, 2001; Kotha *et al*., 2011), we find that the marginal effect values at low, moderate, and high IKV levels are significant when EKD is at the low or the high level. They are not significant for 67 firm year observations in the moderate IKV range (between 0.356 and 0.447). An Appendix that includes a plot of the true interaction effects, marginal effects calculated for a representative sample of IKV values at high and low EKD, and associated Stata code is available from the authors.

To test our hypotheses, we identify the cutoff points for low, moderate, and high levels of IKV, needed for our hypothesis tests. First, we calculate the predicted inventive performance at each IKV value when EKD is at the low level. Then, we calculate the predicted inventive performance at each IKV value when EKD is at the high level. At IKV values of 0.15 and 0.6, firms attain similar inventive performance at low and high levels of EKD. These IKV points correspond to the crossover points in Figure 1, which indicate where the dominant drivers of the IKV*EKD relationship to inventive performance have shifted. We take these points as our cutoff points. Hence, we set low IKV as $0 \leq IKV \leq 0.15$, moderate IKV as $0.15 < IKV \leq 0.6$, and high IKV as $0.6 < IKV \leq 1$. Of the data in our sample, for low, moderate, and high IKV values we have 566, 299, and 1,467 observations, respectively. As noted above, the low and high levels of EKD (the moderator variable) are one standard deviation below and above the mean EKD value, respectively. Similar to Sampson (2007), the majority of observations (1527) have high EKD values, 190 have low EKD values, and 615 are in the moderate range of EKD that we do not focus on.

Collectively, the true interaction effect and marginal effect analyses results confirm that *low* and *high* EKD moderates the relationship between low and high IKV levels and inventive performance and that inventive benefits of different levels of IKV depend on EKD. In line with Zelner's (2009) recommendations to examine predicted values of the dependent variable associated with theoretically meaningful changes in the independent variables, we assess whether predicted values for inventive performance at low, moderate, and high levels of IKV are statistically different when EKD is low versus when EKD is high. Table 4 includes the predicted values of inventive performance at all levels of IKV when EKD is low, and when EKD is high.

Insert Table 4 about here

We rely on results presented in Table 4 to test our three hypotheses. In line with Hypothesis 1, we find that firms with high IKV levels attain higher inventive performance when they have low EKD than when they have high EKD. In line with Hypothesis 2, we find that firms with low IKV attain higher inventive performance when they have low EKD than when they have high EKD. In line with Hypothesis 3 we find that firms with moderate IKV values (which include IKV values around the IKV turning point 0.4), attain better inventive performance if they also maintain partnerships that confer a high level of EKD than a low level of EKD. While the difference is statistically significant, as mentioned earlier, the marginal effect of IKV is not significant for 67 firm year observations in the moderate IKV firms when firms have low and high levels of EKD, and our support for Hypothesis 3 should be accepted with some caution.

Robustness checks

Alternative explanations

We considered other factors that could explain our results. One possibility is that patents in certain classes were inherently more likely to receive citations. We re-estimated our final model using a control for growth in each of the 64 patent classes in which these firms invent. First, for each firm year we counted the patents granted in each of 64 classes. Second, we divided each firm/year patent count in each class by the total count of patents granted in each class to all firms. This normalization helped us adjust for the fact that some classes may have more patents than other classes. Third, we summed the normalized patent counts for each firm year to obtain a normalized patent count by each firm year. We used these normalized patent counts to calculate:

$$\text{Technological domain growth}_{it} = (\text{Nomalized patent counts}_{it} - \text{Normalized patent counts}_{i,t-1}) / \text{Normalized patent counts}_{i,t-1}$$

When controlling for this growth, the coefficients for IKV and EKV remain significant and in the hypothesized direction.

Although we believe there is substantial support for our theoretical mechanisms in the literature, we also sought to validate them by examining the prior art citations on a firm's patents as an indication of its reliance on familiar versus unfamiliar knowledge components as building blocks for invention using the approach outlined by Katila and Ahuja (2002). We used a five year window in determining whether citations are familiar or new, following research which indicates organizational memory generally declines at this rate in high technology industries (Katila and Ahuja, 2002). We measure repetitive use of familiar knowledge components (prior art patents) for inventive solutions as follows: $\textit{Familiar knowledge}_{it} = \frac{\sum_{t-5}^{t-1} \textit{count of repeated citations}_{i}}{\textit{total all citations}_{it}}$, where count of repeated citations is equal to the sum of annual citations that were repeatedly cited by firm *i* in the previous 5 years. We measure unfamiliar knowledge components for invention as follows $\textit{Unfamiliar knowledge}_{it} = \frac{\textit{total new citations}_{it}}{\textit{total all citations}_{it}}$, where total new citations $_{it}$= count of cited patents by firm *i* in year *t*, which were not cited in the past five years (t-1 to t-5); total all citations$_{it}$= count of all cited patents by firm i in year t. We examined the influence of IKV on familiar and unfamiliar knowledge use in two separate regressions, including the control variables from our original analysis. As our theory would suggest, IKV affects the use of both familiar and unfamiliar knowledge in an inverted U-shape. Firms with moderate IKV reuse familiar and unfamiliar knowledge components in their inventive search to a greater degree than do firms with low or high IKV[16].

Alternative measures

Prior research has measured external knowledge distance between a focal firm and its partners in different ways. To assess whether the main results of this study are sensitive to these differences, we assessed alternative ways to measure EKD and NKD. Following Tzabbar (2009), we created vectors for each firm and its partners, comprised of the distribution of patents granted in each class, and measured EKD as the angular distance between the focal firm and its partners. Following Rodan and Galunic (2004) and Phelps (2010), we created an alternative measure of NKD by incorporating both the dyadic distance from a focal firm to each of its partners and the distance between each of the partners. Substituting these EKD and NKD measures generates results consistent with those reported in Table 3. We also estimated our models with IKV and EKD measures based on the International Patent Classification system (at the 8 digit class level), and the results are consistent with those we report[17]. Our results are insensitive to whether we include all citations to a firm's patents in the dependent variable, or exclude self-citations.

Selection bias

To determine whether our results are affected by selection bias resulting from dropping firms that do not patent in the fixed effects specification, we estimated a Heckman selection model (Cameron

[16] We also divided our sample into subsamples based on the annual IKV values and compared the t-statistics, which we calculated for each group mean difference, to the critical value for a two-tailed t-test and the 95% confidence interval. We found that the mean familiar knowledge and unfamiliar knowledge values for low IKV (unfamiliar mean=.2, std dev=.3; familiar mean=.5, std dev=1.1) and high IKV (unfamiliar mean=.2, std dev=.3; familiar mean=.6, std dev=2.2) were statistically different from those for firms with moderate IKV (breadth mean=.4, std dev=.3; depth mean=2.5, std dev=4.9). This is consistent with the regression results.

[17] To conduct these analyses, we pulled data from the NBER patent data base for the decade spanning 1990 to 1999. To match these patent data with the Compustat data, we relied on assignee, which generally corresponds to the subsidiary or business unit level. This yielded a sample of 141 assignees for whom we pulled alliance data from Recap and SDC. Knowledge variety and distance measures were computed based on 3 year moving windows of patents, and the citation counts used for the dependent variable were cumulative (we controlled for average patent age), covering up to a six year window following patent issue date.

and Trivedi, 2005). We used probit regression to estimate the likelihood of patenting in the first stage. We incorporated parameter estimates from the first stage into a second stage regression model to predict inventive performance. We used network size and efficiency, R&D expenditures, firm size, and slack resources for the first stage model. The inverse mills ratio was significant in the second stage, and the signs and significance levels of these results were consistent with those reported in Table 3, Model 5. We also estimated the random effects negative binomial model, which does not truncate the data by excluding zero outcomes, and the results do not change substantively. The standard deviation on our dependent variable is large, so we estimated our models after dropping outliers; again the results are consistent with those reported in Table 3.

Endogeneity

It is conceivable that omitted variables, such as the content of a firm's R&D strategy, could influence IKV, EKD, and a firm's inventive performance (Ahuja and Novelli, 2011). We account for this unobserved heterogeneity by employing a fixed effects analysis. We used instrumental variable regression analysis to assess endogeneity statistically. We used alliance portfolio functional diversity, the number of therapeutic areas in which a firm actively invents and maintains alliances, and partner patent stock to instrument IKV and EKD. Each instrument was found to be relevant and valid, according to first stage F-tests, and the second stage Hansen J statistic, respectively. Having validated these instruments, we conducted the Davidson and MacKinnon (1993) test of regressor exogeneity using Model 4 from Table 3. We are able to reject the null of endogeneity suggesting that IKV and EKD, as well as their squares, are exogenous (IKV X^2=.071, p-value=.790; IKV_sq X^2=.323, p-value=.570; EKD_sq X^2=.179, p-value=.672). In addition, the results of the IV regression are qualitatively similar to the reported results for Model 4 in Table 3.

DISCUSSION

Contributions to Theory

The knowledge-based theory of the firm advances the idea that a key role for managers is to choose the problems that a firm solves, and to align governance with attributes of those problems – particularly their complexity (Nickerson and Zenger, 2004; Leiblein and Macher, 2009). Two central predictions of the KBV have received empirical support: firms internalize complex problems and outsource solution search for decomposable sub-problems, and there are performance advantages to aligning governance with problem complexity in this manner (Hoetker, 2005; Macher, 2006; Jeppesen and Lakhani, 2010; Kapoor and Adner 2012; Macher and Boerner 2012).

Yet the KBV provides little guidance as to why firms differ in their ability to utilize hierarchy to generate useful solutions to complex problems. Indeed, as Nickerson and Zenger point out, "knowledge-based arguments tend to highlight the virtues of hierarchy, [but] not its limits in forming and transferring knowledge" (2004: p. 2). There is some evidence within the KBV literature that the capacity to experiment with potential solutions plays an important role in firms' problem solving capacities (Macher 2006). Likewise, the delineation of appropriate knowledge boundaries for particular governance modes appears to be important (Brusoni, Prencipe, and Pavitt, 2001; Kapoor and Adner, 2012). Yet the KBV provides little guidance as to how governance and knowledge interact to influence problem solving. To address this, we explored the joint contribution of knowledge variety governed through hierarchy and knowledge accessible at alliance partners, to a firm's success in solving complex problems related to invention. The steps we have taken to explore this issue contribute to theory in two areas.

First, in the KBV literature, a firm's problem solving capacity is its ability to effectuate alignment between governance and problem attributes (Nickerson and Zenger, 2004; Leiblein and Macher, 2009). We extend this tenant of KBV by theorizing that hierarchical problem solving effectiveness also reflects firms' knowledge boundaries. Relative to other forms of governance, hierarchy better supports high bandwidth communication channels that facilitate the rich, cross domain knowledge flows essential to discerning interdependencies and forming theories to search rugged solution landscapes (Felin and Zenger, 2014). Whereas the KBV attributes this advantage to discriminating features of hierarchy, such as reliance on low powered incentives (Williamson, 1991), we theorize that it also reflects the dispersion of firms' inventive efforts across technology domains. Inventive focus produces greater overlap in the domain experience of a firm's members (raising channel bandwidth) while highly diffuse invention limits such shared experience and generates greater heterogeneity (providing recombinative opportunity) in members' domain knowledge. Problem solving is enabled by a balance of both.

Second, to solve complex problems, firms often need to access knowledge from other organizations. Alliances may be particularly useful for complex search because they too support high bandwidth communication channels (Kogut and Zander, 1992; Heiman and Nickerson, 2004). As a firm's members interact with its alliance partners, they are exposed to different ways of looking at problems and to novel principles and functionalities (Hohberger *et al.,* 2015). This exposure can shape the theories used to search rugged landscapes, augmenting the benefits derived from IKV. We theorized that EKD fills different gaps in a firm's capacity to search rugged landscapes – helping it to select, scale, or switch peaks - according to its level of IKV. Our results demonstrate joint effects of IKV and EKD on the usefulness of a firm's solutions that are consistent with this theory.

We contribute empirical findings which complement and extend work on governance choice and problem solving outcomes downstream from the invention process (Hoetker, 2005; Macher, 2006; Kapoor and Adner 2012; Macher and Boerner, 2012). The results qualify earlier findings regarding which levels of IKV (Henderson and Cockburn, 1994, 1996), or EKD (Sampson, 2007) are most beneficial to firms' inventive efforts, by demonstrating how the joint effects of IKV and

EKD vary with the level of IKV. Our findings for high IKV are consistent with the importance of focus for capitalizing on variety (Ghosh *et al.,* 2014).

Henderson and Clark (1990) theorized that as a firm's communication channels, information filters, and problem solving strategies become routinized, they constrain the firm's product design capacities. Later termed the mirroring hypothesis, the theory contends that products come to reflect the organizations that generate them (Colfer and Baldwin, 2010). "Organizations' governance structures, problem solving routines, and communication patterns constrain the space in which it searches for new solutions." (MacCormack, Baldwin, and Rusnak, 2012: p. 1309). Inflexible mental models and habitual patterns of interaction limit organization members' exposure to alternative perspectives, minimizing provocation to question the status quo as well as opportunities to come across fruitful ways to recombine familiar search elements or utilize new ones (Henderson and Clark, 1990). In essence, the mirroring hypothesis describes a down side of the very things the KBV theorizes underlie innate advantages of hierarchy for problem solving. Distinctive governance structures and shared histories support rich communication and help to make search efficient, but these features of hierarchy may also limit the usefulness of the solutions a firm can generate by constraining search to certain peaks on a solution landscape.

Research suggests that narrowly focused organizations, such as those developing a single technology or relying on one business model, are especially vulnerable to constricted solution search. Firms with broad domain focus might avoid this ossification (Argyres and Silverman, 2004; Miller *at al,* 2007; Leiponen and Helfat, 2012). To sustain their problem solving agility, authors urge firms to maintain a "T-shaped" portfolio of skills and knowledge – e.g. by fostering deep competence in a few domains and the capacity to transfer knowledge and recombine expertise from those domains (Bingham and Eisenhard, 2011; Wladasky-Berger, 2015). We find that wider domain experience yields benefits, yet too much variety without focus (i.e., highly dispersed domain experience) makes it difficult to compare alternative search paths in an effort to select the highest peaks (Ghosh *et al*, 2014). We have argued this has implications for the usefulness of the solutions that firms with different levels of IKV tend to generate, and also for the benefits they derive from knowledge available through alliance partners.

Managerial Implications and Next Steps

Our theory has implications for managers' decisions regarding where to locate the search for solutions. Felin and Zenger (2014: p. 917) propose that, "as problems become more complex, firms will adopt governance forms that facilitate the extensive knowledge sharing required to form theories and heuristics to guide search." We theorize that the capacity for such exchange is influenced by the knowledge boundaries that a governance form encompasses, as well as its discriminating features. Managers should consider not only whether domain knowledge they believe to be relevant is present, but also whether a problem solving effort can benefit from a variety of perspectives as well as a common focus and understanding. A central tenet of KBV is that firm-specific codes and language enable the transfer of rich knowledge across domains – but perhaps equally important to some search efforts is the fact that heterogeneous insights into common domains may be gained when problem solving unfolds in different organizational contexts. Regardless of governance form, problem solving efforts might benefit from perspectives shaped by multiple social and technological contexts, which catalyze novel associations and could potentially overcome limitations described by the mirroring effect (Page, 2007; Skarzynski and Gibson, 2008).

An additional challenge that managers face in aligning governance with problem complexity is that when interactions between search elements are poorly understood, it can be difficult to discern which domains are most relevant to identifying a solution. Felin and Zenger (2014) suggest that this dilemma can be overcome through open forms of governance, in which firms broadcast problems externally and encourage individuals and organizations with relevant expertise to self-identify.

However, to convert complex, ill-structured problems into the decomposable problems amenable to broadcast, firms must commit to high level design parameters which bound the search space in some fundamental way (Sieg, Wallin, and von Krogh, 2010; Felin and Zenger, 2014). Locating a search for solutions externally has the advantage of tapping into a much wider variety of domain expertise than might be accessible inside a firm (Jeppesen and Lakhani, 2010), but it also imposes significant constraints. As firms lock-in key architectural parameters, they sacrifice flexibility to redefine problems and revise the theories guiding search as more is learned about the solution landscape.[18] Open governance might yield important benefits, even with the boundaries that are placed on search. To successfully engage an external population of problem solvers with unknown expertise, a firm must define its need in language that is not contextually-dependent, and this could further facilitate knowledge sharing within the firm (Sieg *et al*, 2010; Jeppesen and Lakhani, 2010).

Alliances offer access to knowledge through contextually rich communication channels and this makes them well suited to supporting the formation of theories to guide search (Zollo *et al.* 2002; Felin and Zenger, 2014). Once theories take shape, managers may avail themselves of a burgeoning array of open governance forms to support an internal search for solutions – to help solve sub-problems, for example, as parts of the solution space become better understood (for interesting examples of open governance forms now being used in the pharmaceutical industry see Khanna, 2012; Wang, Plump, and Ringel, 2015). Alternatively, firms can rely on open governance to inform efforts to formulate the theories that will guide search, such as by holding contests for

[18] This is one reason that modular design practices are most applicable to well understood technologies (Baldwin and Clark, 2000).

hypotheses about how to solve a complex problem like curing diabetes (King and Lakhani, 2013: p. 4).

We encourage further research to understand how open governance augments the benefits of internal knowledge variety – or a firm's capacity to transfer knowledge in ways that improve solutions, particularly when the relevant domains are unclear. Such inquiry could build on a robust body of work investigating factors, such as organizational climate (Bertels, Kleinschmidt, and Koen, 2011), star scientists (Tzabbar, 2009; Hess and Rothaermel, 2011), and internal networks (Nerkar and Paruchuri, 2005; Grigoriou and Rothaermel, 2016) that affect a firm's capacity to benefit from external knowledge for innovation. Additional research in this vein could extend what we have learned about knowledge boundaries to illuminate how "engineered" differences in firms' communication channels interact with degrees of governance alignment to affect problem solving outcomes.[19]

Limitations

Although we took many steps to assure the robustness of our findings, researchers can make different methodological choices. So that appropriate inferences are drawn from this study, and to clearly identify gaps future research could address, we have tried to comprehensively lay out the limitations associated with our choices. First, we estimated fixed effects regression models to test our hypotheses because it enables us to rule out unobservable firm level factors and thereby attenuates some important concerns regarding endogeneity. However, even with year dummies and

[19] For example, in addition to the level of IKV and EKD a firm invents with, communication channels and knowledge flows can be augmented through the creative use of physical space, work design, and incentives to encourage people from different units to interact (Rivkin and Siggelkow, 2003; Heinze *et al.,* 2009; Augier, March, and Marshall, 2014). Nonetheless, the literature also suggests that there is some degree of equifinality in how various bundles of practices affect search, and that a firm's approach to search changes slowly in response to changes in policy on this front (e.g. Henderson, 1994; Henderson and Cockburn, 1994). When new best practices become apparent they diffuse gradually and inertial forces slow their influence on the day to day behavior of a firm's members even after their adoption (Henderson, 1994; Holweg and Pil, 2004). Moreover, firm approaches to search reflect idiosyncratic histories, and the beliefs and narratives that have developed through these histories (Henderson, 1994; Bartel and Garud, 2009; Baba and Walsh, 2010). We control for these inertial differences in search using firm fixed effects.

theoretically relevant time varying factors controlled for, these models may not have completely eliminated omitted variable bias. We used instrumental variable regression analysis to assess endogeneity statistically. As discussed earlier, the results of the IV regression are qualitatively similar to the reported results for Model 4 in Table 3. We also talked with people in the industry to uncover managerial choices that might simultaneously drive IKV and EKD as well as citations to a firm's patents, but identified none[20]. Nevertheless, future studies that adopt alternative approaches to addressing endogeneity could help to clarify the case for interpreting our results as indicative of an associative or a causal relationship between the joint effects of IKV and EKD and solution usefulness.

Second, to test our interaction effects, we needed to identify appropriate cut off points for the levels of IKV we theorize about. We used Figure 1 to identify the cross over points for this purpose. Statistically, firms attain similar inventive performance at low and high levels of EKD when IKV takes on the values of 0.15 and 0.6, and hence these points were taken as the cutoff points for low, moderate, and high levels of IKV. These cutoff points may differ in other samples or when alternative heuristics are used to identify theoretically relevant ranges of IKV[21].

Additionally, authors have elaborated several of the virtues of patent classes for understanding firms' knowledge boundaries, including consistency in the definitions used to

[20] The managers we spoke with maintain that their focus is on identifying the best solutions to therapeutic problems and state that patenting in specific classes is not a goal of their research efforts. Patent strategies might affect the distribution of patents across classes: a patent can make many claims or claims can be made in separate patents; however, controlling for the average number of claims per patent produced no change in our models. Firms in this industry form alliances to benefit from partners' complementary resources (e.g. expertise in different value chain activities) and also from expertise in similar technology domains (e.g. as indicated by citations to the same patents or to a partner's patents as prior art) (Rothaermel and Boeker, 2007). Hence, depending upon project needs, managers might expect low (Lane and Lubatkin, 1998), moderate (Sampson, 2007) or high EKD (Phelps, 2010) to contribute to better technological solutions.

[21] We conducted a robustness test to see if our results change when we employ a different method to calculate cutoff points for low, moderate and high levels of IKV. A widely used heuristic is to take 1 SD above and below the mean value of the variable of interest. Applying this heuristic to IKV produced the following ranges:
Low: $0 \leq IKV \leq 0.2$; Moderate: $0.2 < IKV < 1$; and High: $IKV = 1$, which substantially widens the range of IKV values treated as moderate and limits the high IKV value to 1. With these values, Hypotheses 1 and 2 are still supported but Hypothesis 3 (for moderate IKV) does not hold for IKV levels between 0.6 and 0.9.

delineate technological differences and the ability to trace firms' inventive activities over long time periods (e.g. Benner and Waldfogel, 2008; Yayavaram and Ahuja, 2008; Strumsky, Lobo, van der Leeuw, 2012). However, classes might be regarded as a rather coarse way to understand differences in what firms actually know. A well-known limitation of patent-based knowledge measures is their inability to reflect solutions created but not patented and to capture tacit knowledge that might be instrumental in solving problems. Patent classes might encompass different degrees of heterogeneity in the kinds of technologies that fall within them, adding some noise to the IKV and EKD measures and reducing the statistical power of these variables in regression models. Citations to common patents has been used to provide a more fine-grained measure of the similarity in firm's knowledge (e.g. Rothaermel and Boeker, 2007; Lowe and Velosi, 2015). Our theory revolves around firms' access to a variety of broadly different domains from which different principles and functionalities could be drawn to shape search, so these metrics may be too fine-grained for our purposes. In our robustness analysis we did use 8 digit IPC classes which define domains at a more fine-grained level, and obtained results consistent with those reported here.

Fourth, we rely on citation weighted patents as our measure of solution usefulness. The question remains whether patent citations in the pharmaceutical industry ultimately lead to more approved products. Graham and Higgins (2007) use data from Pharmaprojects and NDA Pipeline from 1990 to 2001, to link pharma-related patents to FDA approved products. They conclude that "…more highly cited patents are more likely to be associated with an FDA-approved product. This finding is economically meaningful since these patents protect the revenue streams of approved products" (Graham and Higgins, 2007: p. 30). In a separate study of four high tech sectors (aerospace and defense, computer and office machinery, pharmaceuticals, and electronics and communications) Hagedoorn and Cloodt (2003) find that patent citations and new products in the pharmaceutical industry are correlated at .382. Further, they look at four different indicators, R&D

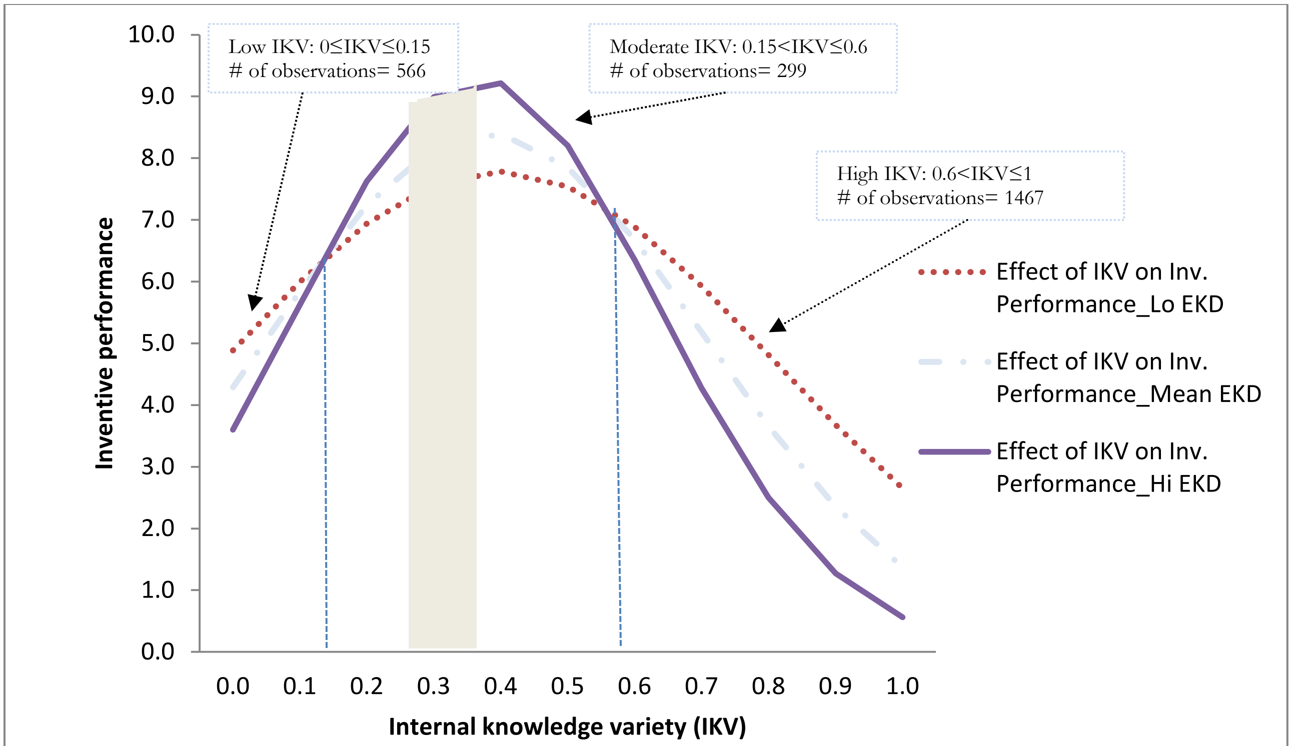
expenditures, patent counts, patent citations, and new product introductions, and find …"that the overlap between each of these four indicators is that great …that in high-tech sectors any of these four indicators could be taken as a measure of innovative performance in the broad sense"(p. 1375).

In this study we relied on R&D alliances to examine the role of external knowledge. However, firms can also access external knowledge through different institutional arrangements, including contests, crowdsourcing, user communities, sponsored research, and open data (Felin and Zenger, 2014; Jeppsen and Lakhani, 2010). Following the time period of our study, pharmaceutical firms are placing greater reliance on a broad spectrum of channels through which they access knowledge to inform their drug discovery efforts (Khanna 2012; Wang *et al*, 2015). Likewise, we are focusing on a context where patenting is a particularly salient indicator of problem solving (Cohen et al., 2000). An important issue for future research is to determine whether the theory holds for complex problem solving in other industrial and problem solving contexts, particularly where different metrics of success are important (e.g. process development speed, Macher, 2006; product development speed, Macher and Boerner, 2012; value-chain related problems such as service delivery or supplier problems, Heiman et al., 2009).

Table 1: Summary of the Theory Linking IKV and EKD to Problem Solving Effectiveness

Mechanisms	**Low IKV (focused)**	**Moderate IKV (balanced)**	**High IKV (diffuse)**
Communication channels	Largely overlapping domain knowledge supports rich intra-domain knowledge flows, increasing accessibility of domain knowledge for problem solving, but limiting variation in perspectives.	A balance of common and different domain knowledge supports rich intra- and cross-domain knowledge flows, increasing opportunities for productive recombination of search elements.	Minimal overlapping domain knowledge limits accessibility of domain knowledge and opportunities for productive within- and cross- domain knowledge transfer and recombination.
Search elements (principles, functionalities, and other domain-specific knowledge used to form theories to guide search)	Focus permits reuse of domain-specific principles and functionalities and provides insight into when and how they produce desired effects. This helps to *scale local peaks* but increases the susceptibility of search to inflexible cognitive representations of solution landscapes.	Balance permits fruitful experimentation and adaptation of theories guiding search by recombining principles and functionalities from different domains. This enables a firm to identify and *switch to higher peaks*. Better peaks are revealed by shaking up cognitive representations.	Broad coverage of design variables enables a firm to locate multiple places to initiate search but coarse depiction of their relevance, and limited intra- and inter-domain knowledge flows hinders the firm's capacity to select the most fruitful starting points for search.
EKD's role in augmenting the benefits of IKV, for solving complex problems	Interaction with low EKD partners reveals *meaningful deviations* in the use of familiar search elements. This leads to more effective peak scaling.	Interaction with high EKD partners reveals *meaningful recombinations* of solution elements from disparate domains. This helps firms redirect attention to higher peaks.	Interaction with low EKD partners reveals *meaningful focal points* to anchor search (e.g. around certain sets of solution elements). This helps firms to reduce peak picking mistakes.

Figure 1. The Moderating Effect of EKD on the IKV - Inventive Performance Relationship[a,b]



[a] Interaction graph is based on Model 5 coefficients (Table 3), at the median value of control variables.
[b] The marginal effect values at low, moderate, and high IKV levels when EKD is at *low* or high *level* are significant (at p≤0.001), except the shaded area representing 67 firm year observations (3% of the sample).

Table 2. Descriptive Statistics and Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Inventive Performance	1												
2	Firm Patent Stock	0.769	1											
3	Partner Patent Stock	0.312	0.381	1										
4	Network Knowledge Distance	-0.278	-0.312	-0.450	1									
5	Network Size	0.409	0.580	0.498	-0.411	1								
6	Network Efficiency	0.215	0.206	0.194	-0.109	0.201	1							
7	Firm Age	0.606	0.557	0.304	-0.314	0.376	0.101	1						
8	Firm Size (log sales)	0.616	0.620	0.298	-0.273	0.428	0.181	0.706	1					
9	R&D Expenditure (log R&D)	0.610	0.647	0.368	-0.287	0.487	0.449	0.567	0.746	1				
10	Slack Resources	-0.073	-0.069	-0.022	0.035	-0.048	0.027	-0.109	-0.146	-0.090	1			
11	Firm's Partner Experience	0.294	0.314	0.230	-0.178	0.251	0.480	0.209	0.312	0.474	-0.009	1		
12	Internal Knowledge Variety	-0.027	0.040	0.080	-0.033	0.044	0.113	0.014	0.065	0.119	0.016	0.079	1	
13	External Knowledge Distance	-0.312	-0.388	-0.490	0.420	-0.344	-0.156	-0.261	-0.288	-0.345	0.036	-0.263	-0.065	1
	Obs	2332	2332	2332	2332	2332	2332	2332	2332	2332	2332	2332	2332	2332
	Mean	251.801	47.961	36.975	0.988	25.925	0.4911	21.866	2.958	2.734	7.435	0.333	0.634	0.971
	Std. Dev.	684.583	145.692	115.760	0.074	84.698	0.211	21.426	2.702	1.868	20.771	0.322	0.406	0.104
	Min	1	0	0	0	0	0	1	0	0	0.0002	0	0	0
	Max	5281	1689	1150	1	923	0.791	129	10.869	9.408	661.216	0.947	1	1

Table 3. Results of fixed effects negative binomial analysis for inventive performance [a]

Variables	Model 1 Controls	Model 2 IKV	Model 3 EKD	Model 4 IKV & EKD	Model 5 Interactions added
Firm Patent Stock	0.0007 (0.0002)	0.0009 (0.0001)	0.0007 (0.0002)	0.0009 (0.0001)	0.001 (0.0001)
Partner Patent Stock	0.0002 (0.0002)	-0.0002 (0.0002)	0.0001 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Network Knowledge Distance	-0.116 (0.221)	0.028 (0.168)	0.082 (0.241)	0.111 (0.178)	-0.021 (0.180)
Network Size	-0.001 (0.0003)	-0.0007 (0.0002)	-0.001 (0.0003)	-0.0006 (0.0002)	-0.0007 (0.0002)
Network Efficiency	0.644 (0.169)	0.571 (0.157)	0.671 (0.170)	0.585 (0.157)	0.582 (0.157)
Firm Age	-0.0005 (0.002)	-0.0009 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Firm size (log sales)	-0.017 (0.020)	-0.020 (0.019)	0.017 (0.020)	-0.020 (0.019)	-0.019 (0.019)
R&D Expenditure (log R&D)	0.279 (0.025)	0.171 (0.027)	0.274 (0.027)	0.169 (0.026)	0.169 (0.027)
Slack Resources	0.001 (0.001)	0.0005 (0.001)	0.001 (0.001)	0.0004 (0.001)	0.0003 (0.001)
Partner Experience	0.175 (0.080)	0.067 (0.070)	0.150 (0.081)	0.056 (0.070)	0.040 (0.070)
Internal Knowledge Variety		3.757 (0.222)		3.749 (0.222)	7.116 (4.701)
Internal Knowledge Variety Squared		-5.043 (0.225)		-5.032 (0.225)	-10.821 (4.817)
External Knowledge Distance			3.724 (1.216)	2.182 (1.030)	2.460 (3.170)
External Knowledge Distance Squared			-2.704 (0.805)	-1.496 (0.681)	-2.018 (2.045)
Internal Knowledge Variety × External Knowledge Diversity					-20.720 (12.578)
Internal Knowledge Variety Squared× External Knowledge Distance					31.972 (12.908)
Internal Knowledge Variety × External Knowledge Distance Squared					17.575 (8.083)
Internal Knowledge Variety Squared× External Knowledge Distance Squared					-26.444 (8.297)
Year Dummies	Included	Included	Included	Included	Included
Log Likelihood	-8890.743	-8468.815	-8883.534	-8466.197	-8443.371
Likelihood ratio test X^2, improved fit relative to models indicated		model 1 $X^2(2)$= 843.86	model 1 $X^2(2)$ = 14.42	models 1, 2, 3 respectively $X^2(4)$=849.09 $X^2(2)$=5.24 $X^2(2)$=834.68	model 4 $X^2(4)$ = 45.65

[a] Independent variables are lagged by one year with respect to the dependent variable

Table 4. Predicted values of inventive performance at representative levels of IKV for low and high EKD

IKV	Predicted value of inventive performance when EKD is low[a] (standard error)		Predicted value of inventive performance when EKD is high[a] (standard error)	
0.000	1.399	(0.153)	1.176	(0.059)
0.075	3.077	(0.365)	2.879	(0.280)
0.098	1.273	(0.131)	1.234	(0.097)
0.133	3.176	(0.325)	3.274	(0.291)
0.199	1.569	(0.147)	1.658	(0.125)
0.200	3.278	(0.471)	3.477	(0.467)
0.206	2.533	(0.452)	2.692	(0.486)
0.208	6.027	(0.798)	6.407	(0.806)
0.222	1.936	(0.154)	2.076	(0.128)
0.233	3.244	(0.283)	3.499	(0.240)
0.246	5.838	(0.866)	6.335	(0.880)
0.248	2.995	(0.236)	3.253	(0.187)
0.250	3.057	(0.257)	3.329	(0.224)
0.262	3.458	(0.299)	3.791	(0.288)
0.285	2.481	(0.206)	2.734	(0.181)
0.290	2.173	(0.238)	2.400	(0.249)
0.303	3.075	(0.275)	3.403	(0.256)
0.327	3.393	(0.547)	3.768	(0.578)
0.337	2.005	(0.187)	2.228	(0.179)
0.351	2.215	(0.165)	2.462	(0.145)
0.356	7.058	(1.320)	7.840	(1.412)
0.363	7.701	(1.076))	8.555	(1.133)
0.373	1.712	(0.148)	1.899	(0.141)
0.383	5.196	(0.581)	5.758	(0.635)
0.395	3.490	(0.286)	3.857	(0.283)
0.400	7.866	(1.340)	8.682	(1.511)
0.410	4.345	(0.395)	4.786	(0.399)
0.423	2.557	(0.457)	2.805	(0.486)
0.504	5.678	(0.751)	5.959	(0.793)
0.650	5.150	(0.659)	4.628	(0.565)
0.750	3.472	(0.362)	2.654	(0.248)
0.752	1.713	(0.160)	1.304	(0.107)
0.754	2.994	(0.592)	2.273	(0.449)
0.800	2.172	(0.221)	1.501	(0.144)
0.850	1.717	(0.147)	1.046	(0.060)
0.861	1.132	(0.119)	0.683	(0.058)
0.872	2.406	(0.435)	1.393	(0.237)
0.879	2.273	(0.347)	1.315	(0.181)
0.887	1.322	(0.141)	0.725	(0.048)
0.900	1.686	(0.330)	0.920	(0.162)
0.924	1.254	(0.169)	0.645	(0.064)
1.000	0.742	(0.096)	0.308	(0.016)

[a]All predicted values are significant at 0.001 level.
Predicted values are calculated at the mean value of control variables.

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