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Organizational Learning and Knowledge Structures: The Interplay Between Experiential And Cognitive Search

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Abstract

Organizational Learning and Knowledge Structures: The Interplay Between Experiential And Cognitive Search Arusyak ZAKARYAN, SKEMA Business School Enrolment: 4th year; expected graduation year: 2018 Email: arusyak.zakaryan@skema.edu This study seeks is to identify internal search processes that enhance the inventive outcomes of experiential learning – i.e., learning from distributed technological experience accumulated inside organization's boundaries – and, knowledge structures that facilitate such learning processes. We build upon the argument that learning from experience unfolds through cognitive search, which is based on cognitive representations, and experiential search which is based on feedbacks from prior actions. We further suggest that internal search that builds upon technologically distant knowledge allows firms to effectively combine these two search logics and attenuate their pitfalls, thus, enhancing inventive impact. Moreover, the impact of inventions generated through such search is higher when firm's knowledge structure is highly decomposable. Using a longitudinal dataset from global photographic equipment and supplies industry covering 89 firms from 1975 to 2008 we find statistical support for our arguments. Our study contributes to literature on experiential learning by specifying technological characteristics of built-upon knowledge and organizational factors that improve organization's ability to leverage its technological experience. Keywords: Organizational learning; experiential learning; distant search; cognition; knowledge networks.

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INTRODUCTION

‘If only HP knew what HP knows’ (Sieloff, 1999, p. 47).

This statement made by an R&D executive in HP reflects the challenges incumbent firms face with respect to effective knowledge management and learning. This is especially relevant for multi-business organizations with distributed experience on diverse technological domains for which ‘experiential-based knowledge can be an important basis of competitive advantage’ (Levinthal and March, 1993, p. 96; Cohen and Leventhal, 1990, Hargadon, 2002). However, organizations often fail to retain, retrieve and extract lessons from their broad technological experience due to complications inherent in the nature of experience itself (i.e., paucity, redundancy, ambiguity), cognitive and inferential limitations of its members and various organizational factors (i.e., disciplinary and departmental boundaries) (Levitt and March, 1988; Levinthal and March, 1993; March, 2010). As Hargadon (2002) remarked ‘the central questions guiding the study of knowledge in organizations are, ultimately, why it is so difficult for organizations to learn from their experiences and why it is so difficult for them to forget these lessons when faced with a changed environment (p. 42)’.

To comprehend the processes through which experience translates into improved (or diminishing) performance one needs to examine organization’s search behavior (March, 1991; Fleming, 2001; Phene, Fladmoe-Lindquist and Marsh, 2006; Miller, Fern and Cardinal, 2007). We employ the term ‘internal search’ (Rosenkopf and Nerkar, 2001) to encompass the knowledge sourcing activities organizations engage in which build upon internally generated knowledge (Rosenkopf and Nerkar, 2001). With this respect, research remains inconclusive about the technological characteristics of experiential knowledge - local vs distant - that inventors should search for in order to overcome the challenges associated with experiential learning. Moreover, inventive outcomes from internal search are conditional on the way in which experiential knowledge is structured in organization's memory – knowledge network structures (Walsh and Ungson, 1991; Yayavaram and Ahuja, 2008). In this regard, prior research has not examined how this particular organizational factor influences the learning outcomes from internal distant search.

We question, hence, in this paper (i) what internal technological search strategies – i.e., search for local vs distant knowledge - enhance learning outcomes in terms of invention impact? and (ii) whether and how knowledge structures moderate the relationship between internal distant search and invention impact? Understanding the mechanisms that can improve experiential learning processes offers rich theoretical and practical implications, since it can provide established firms with long-lasting competitive advantage.

We draw upon literature on organizational learning, search and recombinant invention to build our theoretical arguments. Research in this tradition argues that experiential learning combines two logics of search: cognitive – based on actor's (i.e., individual, research subunit, organization) representation of the problem space – and experiential – based on routines drawn from immediate feedbacks of actions (Gavetti and Levinthal, 2000; Gavetti, 2005; Gavetti, Levinthal and Rivkin, 2005; March, 2010). Both mechanisms have their limitations which complicate experiential learning (Gavetti and Levinthal, 2000; Starbuck, Barnett and Baumard, 2008; March, 2010). More specifically, cognitive search that misperceives cause-effect relationships between actions and outcomes results in faulty interpretations of experiential knowledge – i.e., "superstitious learning" -, whereas experiential search, that reinforces inefficient routines and limits experimentation, constrains inventive efforts at local optima – i.e., "competency traps". Hence, to enhance inventive outcomes from experiential learning organizations need to allocate equivalent efforts to both learning processes and address their pitfalls (Gavetti and Levinthal, 2000; Kim, Kim and Miner, 2009; March, 2010).

We argue in this paper that internal search that builds upon technologically distant knowledge provides learners with a more heterogeneous experience pool for conducting experiential search, reducing, therefor, dangers of competency traps. Furthermore, it improves cognitive search by stimulating learners to regularly upgrade their cognitive representations as response to actual feedbacks from actions, reducing, thereby, risks of superstitious learning. Hence, we expect that distant search inside organization's technological experience increases inventive outcomes of experiential learning.

The use of technologically distant knowledge, however, acts as a double-edged sword: it both enables to avoid cognitive inertia, but it also complicates the interpretation of experiential knowledge, heightening the dangers of superstitious learning. We seek, thereby, to identify subsequently organizational factors that alleviate the hurdles of internal distant search. We focus on the structure of organization's knowledge networks and its level of decomposability, in particular, which reflects the extent to which knowledge elements inside its knowledge base are coupled to each other or isolated from each other in separate clusters (Yayavaram and Ahuja, 2008; Schilling and Green, 2011; Wang, Rodan, Fruin and Xu, 2014). We suggest that highly decomposable knowledge networks facilitate mindful retrieval and interpretation of relevant experiential wisdom from a distant field. Moreover, experiential and cognitive search produces higher inventive outcomes under highly decomposable knowledge networks since the requisite variety maintained in such structures (Simon, 1962; Yayavaram and Ahuja, 2008) allows to overcome cognitive inertia and avoid competency traps. We hypothesize, thus, that the level of decomposable of knowledge structures positively moderates the relationship between internal distant search and inventive outcomes from experiential learning.

The empirical setting for testing our hypothesis covers global photographic equipment and supplies industry from 1975-2008. We construct a longitudinal dataset on 89 large corporations active in this industry and use data on their patenting activities to operationalize our measures. We find statistical support for our hypothesis confirming our arguments regarding the positive impact of internal distant search on generation of high impact inventions and the contingent role of organizational knowledge structures on this relationship.

This study attempts to contribute to several streams of literature. First, from perspective of organizational learning we suggest technological characteristics of built-upon knowledge and knowledge network structures that may improve experiential learning and allow organizations to better leverage their distributed experience. We further contribute to literature on local search by showing conditions under which inward-looking search can yield to higher payoffs than is generally assumed in the literature (Sorenson and Stuart, 2000; Rosenkopf and Nerkar, 2001; Miller et al., 2007). Finally, we hope to contribute to technology strategy literature and to practitioners in the field by suggesting internal technological search strategies and knowledge structures for effective technology portfolio management.

THEORETICAL BACKGROUND

Experiential learning, search and knowledge networks

Organization’s knowledge evolves as they respond to experience by altering their stocks of codified and tacit knowledge to incorporate lessons extracted from experience (Levitt and March, 1988). Learning from experience is, therefore, one of the main mechanisms through which organizations learn (March, 2010). Experiential learning ultimately improves organizational performance expressed in observable performance indicators, providing, hence, a potential source of competitive advantage (Levinthal and March, 1993; Argote, 1999).

At the same time, learning from experience poses significant challenges to organizations. Those difficulties stem from the cognitive and inferential limitations of organizations and their members, various organizational factors (e.g., disciplinary and departmental boundaries, knowledge structures; routines) as well as from the nature of the experience itself (March, 2010). In this regards, Levitt and March (1988) state three fundamental problems inherent in the nature of experiential. “Paucity” or “sample size problem” refers to the fact that organizations can have only a limited number of experiences relative to the plausible scenarios possible in the dynamic changing world. The problem of “redundancy” refers to the tendency of organizations to accumulate experience in the neighborhood of known solutions reducing the rate of experimentation and leading, hence, to ‘familiarity traps’ (Ahuja and Lampert, 2001). Finally, the problem of “complexity” refers to causal ambiguity inherent in experience’s interpretation due to interdependent processes of simultaneous learning that occur inside organizations. Thereby, in some instances experience can be rather a “bad” teacher and organizations may derive inappropriate inferences from it and make wrong generalizations (Tripsas and Gavetti, 2000; Ghosh et al., 2014); a phenomenon termed “superstitious learning” (Levitt and March, 1988).

To comprehend the processes through which exploitation of experience translates into improving (or diminishing) inventive outcomes we investigate organizations’ search behavior. Conceived either as a subprocess of learning or antecedent to learning (Knudsen and Levinthal, 2007; Argote and Miron-Spektor, 2011), search is one of the primary instruments through which organizations learn. Scholars in this tradition have emphasized organizational and technological boundaries that arise during knowledge sourcing activities (Rosenkopf and Nerkar, 2001) and distinguished between internal versus external, local versus distant search activities. These studies have further highlighted the positive outcomes from distant technological search, and, have focused primarily on external distant search as a mechanism to offset negative consequences of myopic learning (Ahuja and Lampert, 2001; Phene et al., 2012). However, less research has been committed towards identifying mechanism and organizational factors for overcoming the aforementioned complications involved in experiential learning. We emphasize, further, that the acquisition of external knowledge is not the only means to access technologically distant knowledge which would potentially improve experiential learning. Accordingly, we believe that a shortcoming of this literature is the implicit assumption that internal search is necessarily local search. Yet, for a firm that is technologically diversified enough, leveraging the expertise accumulated inside its boundaries through internal distant search may provide a viable means to access distant knowledge with lower cost (Miller et al., 2007). Thereby, we question in this paper, first, what internal search strategies – i.e., local vs distant knowledge sourcing – enhance inventive outcomes from experiential learning?

We seek to identify next organizational factors that facilitate such internal search. With this respect, organization's ability to retain and retrieve valuable experiential knowledge and extract appropriate lessons from it depends not only on the technological characteristics of sourced knowledge, but also on the way in which that knowledge is stored in its memory (Walsh and Ungson, 1991; Hargadon and Sutton, 1997; Yayavaram and Ahuja, 2008). Organization's technical knowledge resides in its knowledge networks (Carnabuci and Bruggeman, 2009) which are 'the linkages between kernels of scientific and technological knowledge' (Wang et al., 2014; p. 484). Moreover, Walsh and Ungson (1991) distinguished between 'memory's retention structure and the content of the decision information stored in it' (Walsh and Ungson, 1991; p. 73). More specifically, a structural attribute we investigate is the level of decomposability, which refers to the extent to which the knowledge constituents are coupled to each other or isolated from each other in separate knowledge clusters (Simon, 1962; Yayavaram and Ahuja, 2008). The structure of knowledge networks can vary from fully-decomposable to non-decomposable. (Yayavaram and Ahuja, 2008). Prior research highlights the advantages of nearly-decomposable structure as enhancing the usefulness of inventions and facilitating knowledge base adaptability (Simon, 1962; Yayavaram and Ahuja, 2008). Yet, existing research has not examined whether and how knowledge network structure affects inventive outcomes from experiential learning? We argue in this paper that decomposability attenuates cognitive and inferential limitations that organizational members face when learning from internal experiential knowledge.

Experiential and cognitive processes of learning

How precisely do organizations extract lessons from their past inventive tasks to solve technological problems in the focal inventive task? Research in organizational learning distinguishes between two search mechanisms driving organizational learning: experiential and cognitive (Levinthal and Gavetti, 2000; Starbuck et al., 2008). Experiential search, is based upon "online" evaluation of outcomes of implemented actions and leads to formation of routines derived from positive and negative feedbacks. Whereas cognitive search unfolds through "offline" evaluation of alternatives based upon actor's (i.e., individual, research subunit, organization) beliefs about cause-effect relationship between actions and outcomes (Simon, 1991). Such beliefs are based on its cognitive representation of the technological landscape and may be to a more or lesser extent consistent with the true underlying reality (Tripsas and Gavetti, 2000; Levinthal and Gavetti, 2000). Central to this argument is the premise that the two search mechanisms complement to each other, and that organizations that combine both logics of behavior manage to learn through "adaptive walks" without getting locked in local optima (March and Simon, 1958; Gavetti and Levinthal, 2000). Moreover, to identify mechanisms for overcoming complications in experiential learning one needs to examine these two processes, since those complications arise precisely along the interplay between these two search logics and from their pitfalls.

One manifestation of the interplay between these two behaviors is the analogical reasoning (Gick and Holyoak, 1987; Holyoak and Koh, 1987). Scholars in cognitive psychology claim that 'a person confronted by a novel problem can sometimes solve it by drawing analogy to a similar problem that has a known solution' (Holyoak and Koh, 1987, p. 332). Furthermore, research on knowledge brokerage (Hargadon and Sutton, 1997) claims that 'analogies play a critical role in organizational problem solving, because they allow problem solving groups to create innovative solutions by linking their inventory of past experiences to the current situations they face…and it does so in ways that differ from the mere aggregation of individual-level analogical reasoning' (Hargadon, 2002; p. 64).

Hence, the distinction between the two learning modes is made not to undermine one and recommend the other, but to recognize the merits and pitfalls involved in each (Starbuck et al., 2008; March, 2010). More specifically, experiential search that reinforces inefficient routines and constrains experimentation accentuates redundancy and paucity problems of experience and leads to competency traps. Whereas cognitive search that is based upon misperceived beliefs about causal structure of the world accentuates the causal ambiguity inherent in experiential knowledge and results in superstitious learning. Thereby, to enhance learning outcomes from experience organizations need to combine these two logics of search and manage the shortcomings accompanying each.

However, organizational practices often fail to allocate equivalent efforts to the two learning logics, resulting in inferior outcomes from experiential learning (Tripsas and Gavetti, 2000; Starbuck et al., 2008). Literature on cognitive psychology asserts that both mechanisms of learning incur substantial costs. Cognitive learning dominates whenever cognition is easier to modify than actions, whereas noncognitive learning dominates whenever actions are easier to modify than cognition (Festinger, 1962; Starbuck et al., 2008). The former is likely to lead to misfit between cognitive representations and real world since feedbacks from actual actions are not being evaluated. The latter is likely to lead to cognitive inertia (Tripsas and Gavetti, 2000) and 'competency traps' since past routines are being reinforced constraining experimentation and formation of new ones. To illustrate how these interplay manifests in practice we draw on the example of Polaroid, Inc. This giant of instant photography failed to leverage its expertise on a number of digital related areas because of cognitive inertia among its top executives. 'Polaroid is striking example of why it is important to adopt accurate representations. Although the cognitive representation underlying the razor/blade business model was appropriate for the traditional instant-imaging landscape, it was arguably a poor guide to managerial attention and choice in the digital-imaging domain' (Gavetti, 2005; p. 606).

Few studies on recombinant invention have examined the implications of cognitive and experiential search as jointly determining inventive outcomes from technological search. Exiting scarce work focuses mainly at inventor level of analysis (Fleming and Sorenson, 2004; Schilling and Green, 2011). Our study attempts to complement to this work by identifying internal search strategies and organizational factors that allow to effectively combine experiential and cognitive mechanisms and enhance, thereby, inventive outcomes of experiential learning Moreover, much literature examining internal search has overlooked the role of cognition and implicitly assumed that inventive search that builds upon internally developed knowledge is following local, routine-based logic and leads to learning traps. Instead, we emphasize that internal search may be driven also by mindful cognitive efforts which allow to upgrade organizational beliefs and routines and avoid superstitious leaning.

HYPOTHESIS

Internal search for technologically distant knowledge

In this section we suggest that building upon technologically distant knowledge residing inside organization's boundaries enables to enhance learning outcomes from technological experience. Absent the ability to directly observe processes of cognitive search in the process of experiential learning, we assume that the intensity by which individuals engage in cognitive search depends on the extent to which the sourced knowledge is technologically distant. More specifically, we argue that firm's ability to combine experiential and cognitive search and overcome their pitfalls is conditional on the extent to which internal search sources knowledge from a distant technological context.

When searching for solutions on territories far from the neighborhood of the current expertise, inventors have richer and more heterogeneous experience pool from which lessons may be drawn. 'Access to alternative perspectives regarding problems and solutions can help actors to apply solutions from one domain to problems in another; a process known as analogical transfer' (Schilling and Green, 2011; p. 1324). Such experiential search fosters experimentation and exploration of new opportunities, preventing organizational members from getting locked at local optima. Thus, experiential learning is less likely to suffer from redundancy and paucity problems inherent in the nature of experience.

Furthermore, internal distant search helps to avoid cognitive inertia (Tripsas and Gavetti, 2000) and misperceived cognitive maps attenuating, thereby, the ambiguity problem inherent in the nature of experience. Knowledge, especially tacit knowledge, is highly context-specific and is embedded within the technological and organizational boundaries (Nelson and Winter, 1982; Phene et al., 2006). As a results, inventors in different technological fields are likely to hold distinct cognitive representations of underlying technological landscape. Due to these differences knowledge drawn from a different technological context, even inside the same organization, may stimulate inventors to approach the focal task with a standpoint that is not biased by the dominant logic of the given field. During this process inventors are inclined to engage in mindful abstraction and controlled search for viable connections between otherwise distant elements of knowledge. Such 'mindful abstractions invoke a deliberate and concerted search for connections among past and present search efforts, rather than routinized decision making' (Ghosh et al., 2014; p. 577). Accordingly, organizational members that draw upon technologically distant knowledge would regularly upgrade their understanding about cause-effect relationship between actions and outcomes and critically access the appropriateness of their current cognitive frames. At the same time, the presence of common organizational context allows to attenuate hurdles associated with the utilization of distant knowledge; the sourcing inventors face less challenges in assimilating distant knowledge which is generated internally as opposed to distant knowledge which is integrated from external sources (Miller et al., 2007).

Few empirical research in the context of recombinant invention has examined the implications of internal distant search and has reported inconclusive findings. As such, Rosenkopf and Nerkar (2001) show that internal technological boundary spanning search has negative effect on the impact of inventions in their focal technological domains. Furthermore, Miller and colleagues (2007) find that internal search that spans technological boundaries is negatively related to the overall impact of an invention and to its impact on their focal domain, but positively related to the impact of the invention on other technological domains. We seek to complement to and reconcile these findings by employing a more fine-grained estimation of technological distance between different fields. More specifically, rather than categorizing the built upon knowledge into local and distant categories, we contend that technological distance is a matter of degree and expect that different levels of technological distance lead to divergent outcomes from experiential learning. We believe, thereby, that the contradicting findings with respect to internal distant search might be partially due to varying degrees of technological distance between the focal invention and its built upon knowledge. Accordingly, we hypothesize:

Hypothesis 1: The more distant the knowledge that is sourced through internal search, the higher the impact of inventions generated through such search.

Knowledge base structure and internal search for technologically distant knowledge

The use of technologically distant knowledge, however, acts as a double-edged sword: distant knowledge both enables the learners to avoid cognitive inertia, but it also heightens the ambiguity problem inherent in experiential learning. More specifically, cognitive search is more prone to dangers of superstitious learning when the built-upon knowledge comes from a distant technological domain (Levinthal and March, 1993; Phene et al., 2006). Moreover, experiential and cognitive search that build upon technologically distant knowledge are more fruitful when technological experience is sparsely distributed inside its boundaries without sufficient level of integration (Schilling and Green, 2011). We emphasize, therefore, the role of knowledge structures as conditioning the positive learning outcomes from internal distant search and question: under what knowledge structures internal distant search is more rewarding?

As noted by Afuah and Tucci (2012; p.360) 'because the focal agents expertise, routines, cognitive frames, and absorptive capacity underpin local rather than global search, it is likely to have difficulties interpreting alternatives, their consequences and, their possible impact on problem solving when conducting distant search'. Hence, the usage of distant knowledge accentuates the pitfall of cognitive search since it complicates the mindful retrieval and interpretation of relevant experiential knowledge. As a result, attempts to leverage past expertise into the current inventive task might yield to superstitious learning; a phenomenon termed "negative transfer" by research in transfer theory (Ellis, 1965; Gick and Holyoak, 1987). With this respect, scholars in this tradition have identified two mechanisms for reducing the risks of negative transfer: decomposition of task and concentrating the attention on a small set of tasks (Ghosh et al., 2014; Gick and Holyoak, 1987). In this paper we will examine how the decomposition of organization's knowledge networks as a whole effect on learning outcomes from distant search.

The extent to which the experiential knowledge reflected in inventions is accommodated within an integrated or clustered structure effects on the ability of inventors in distant technological communities to properly interpret it. As noted by Levinthal and March (1993; p. 98) '… tightly coupled systems are relatively good for system-wide error detection, but they are relatively poor for error diagnostics. Loosely coupled systems make diagnostics…'. Therefore, when knowledge elements are grouped in distinct clusters, it is easier later for the user of such knowledge to infer the cause-effect mechanism that is driving the relationships between actions and outcomes. In contrary, highly integrated knowledge structures are characterized by complex interdependences between knowledge elements and complicate the retrieval of relevant experiential wisdom from a distant field and its proper interpretation in a different context. Thereby, decomposability allows to avoid superstitious learning when sourcing for internal distant knowledge.

Moreover, cognitive and experiential search are more efficient under highly decomposable knowledge structures due to the following reasons. First, due to requisite variety maintained in highly decomposable knowledge networks (Simon, 1962), internal distant search would serve as a mechanism to upgrade cognitive maps and avoid cognitive inertia. Whereas, in highly integrated knowledge networks internal distant search is less likely to result in significant adaptation of cognitive representations because of homogeneous beliefs and shared mental models (Yayavaram and Ahuja, 2008). Second, the experiential search efforts are more efficient under highly decomposable knowledge networks, since such structures are less vulnerable to redundancy problem. Highly clustered knowledge structures are characterized by long path lengths which 'make it more difficult and time consuming for an individual to search their cognitive network, and may make the individual less likely to find a solution that is not in the immediate domain of the problem' (Schilling and Green, 2011; p. 1324). Hence, the benefits of distant search in terms of generation of high impact inventions are likely to be more significant under such structures because it allows to connect seemingly unrelated domains and exploit potentially fruitful recombinations. Accordingly, we expect the following:

Hypothesis 2: The interaction between the level of decomposability and the internal distant *search is positively related to the invention's impact generated through such search.*

METHODS

Empirical setting

Our objective in this paper is to investigate the mechanisms by which organizations learn from their prior technological experience which results in improved innovation performance, by examining the enactment of such processes in its inventions. To achieve this objective we will employ a longitudinal research design and use data on firms' patenting activities. The unit of analysis is the patent and the information associated with it, and the level of analysis is the firm.

The empirical setting is the global Photographic Equipment and Supplies industry from 1975-2008. Several reasons motivated the choice of imaging industry for this analysis. First, this period includes the transition from analog to digital technology putting under strong pressure the firms in this industry to innovate in order to survive. The traditional analog technology used silver halide film to capture and save the picture. Products manufactured in this period were generally classified into two main categories - equipment and sensitized materials – requiring largely different technologies for their production. Industry dynamics was largely changed with the emergence of digital technology starting from 1980s (Benner and Tripsas, 2012; Benner and Tushman, 2002; Tripsas and Gavetti, 2000). 'Digital camera technology utilizes semiconductor chips such as CCDs (charge-coupled devices) to capture and convert light images to binary data, replacing the role of silver halide film in analog cameras' (Benner and Tripsas, 2012; p. 282). Incumbent firms in the industry (e.g., Kodak, Agfa, Polaroid, Tamron) were challenged by competition from diversified entrants from consumer electronics (e.g., Sony, Panasonic, Advanced display Technologies) and computing (e.g., Micron Technology), as well as from graphic arts and printing industries (e.g., Xerox). Second, R&D activities of firms in this transformation era were broad in their scope combining traditional chemistry based photographic technologies with optics, semiconductor and electronics, computing technologies (Ghosh et al., 2014). Hence, organizations had expertise in diverse technological fields and their inventive search built upon technologies of different degree of distance.

Data and sample

We draw upon prior work in this discipline and use patents to capture technological knowledge residing inside firm and patent citations to capture the efforts to learn from knowledge codified in those patents (Henderson and Cockburn, 1994; Sorenson et al., 2006). More specifically, we adopt Sorenson and colleagues' (2006) conceptualization of patents as an embodiment of knowledge and of patented inventions as 'combinations of pre-exiting technological components' (p. 1000). The indication of each prior art citation in a patent document implies that the inventors engaged in the inventive search have learned from the knowledge encoded in that prior art cited patent. 'When a citation to prior art emerges on a new patent it suggests that the inventor has both successfully received and built upon the knowledge underlying the earlier patent' (Sorenson et al., 2006; p. 1000).

We intended to collect information on every organization active in the selected industry anywhere in the world from 1975 through 2008. To identify the leading players we first searched in COMPUSTAT Historical Segment database for all firms that had a segment with either primary, secondary or historical SIC code being 3861. This resulted in 201 firms. We complemented this list by running a similar search in COMPUSTAT Global database to obtain list of firms outside US. This resulted in 70 firms. After merging and eliminating firms that were present in both sources (4 firms) we obtained the final comprehensive list of 267 global public firms who had one of their business segments (primary or secondary) in Photography Equipment and Supplies industry[1].

We next searched at United States Patent and Trademark Office (USPTO) all patents filed by those firms during 1975-2008 period. Only 131 firms had applied for at least one patent during our study period. Following prior studies that employed similar methodology (Rosenkopf and Nerkar, 2001), we kept only those firm-year observations on which firm had applied for at least one patent (to allow calculation of independent variables) leading to an unbalanced panel structure. Finally, the econometric model required for at least 2 observation per panel (two firm-year), out of which one at least should have a nonzero value for the dependent variable. Hence, the final sample used for testing hypothesis consists of 89 firms covering 1208 firm-year observations. Those firms issued total 241,861 patents during the study window. The choice of firm-year as the unit of analysis is consistent with other studies in this literature answering similar research questions (Rosenkopf and Nerkar, 2001; Yayavaram and Ahuja, 2008).

We next identified all the patents in USPTO that were cited by the sample patents showing the range of inventions that have served as an input for accomplishing the focal inventive task: 2,239,499 citations. Out of those citations we identified the patents that were issued by the focal citing firm (self-citation): 551,387. They accounted, thus, for 25% of total citations and allowed us to capture firm's efforts to learn from its experience. Finally, we collected also the number of future citations that the sample patents received from the entire population of USPTO patents.

Variable construction

[1] This list was checked and validated by extensive search over trade journals, industry reports and books.

Dependent Variable: Following studies in innovation literature we used patent citations as a proxy for an invention's technological impact or usefulness for future knowledge creation and its economic value (Hall and Trajtenberg, 2000; Fleming, 2001). We further followed the approach adopted by Fleming (2001) and Ghosh and colleagues (2014) by not excluding self-citations from the dependent variable. Furthermore, prior research asserts that patents receive majority of forward citations in the 5 years following their application date (Fleming, 2001). Accordingly, our measure of inventions impact for firm i on year t counts the number of citations that its patents received by future patents during subsequent 5 years.

Independent Variables: To create our main independent variables we examined the class assignments of each citing patent and that of its cited patents that were filed by the same firm (self-citations). The variable technological distance was constructed by using the technological distance measure proposed by Trajtenberg et al., (1997). The measure relies upon hierarchical classification of technological classes in USPTO system which assigns each patent to a class category composed of one to three digit numbers. The measure estimates the technological distance between the primary class of the focal citing patent from that of each of the prior art self-citation it made. The average distance of patent i from its prior art citations is computed based on the following formula:

$$Technological\ distance_i = \sum_{j=1}^{No\ of\ backward\ citations\ of\ i} \frac{tech\ distance_{ij}}{No\ of\ backward\ citations\ of\ i} \qquad (1)$$

where $technological\ distance_{ij}$= 0 if citing and cited patent are assigned to the same three-digit class; 0.33 if they are in same two-digit class; 0.66 if they are in the same 1-digit class; and 1 if they are in different 1-digit classes (Trajtenberg et al., 1997). The measure varies between 0 and 1 and, the higher is its value, the more distant is the built upon knowledge from the focal invention's technological domain. Next, the variable average technological distance internal for firm f on year t was estimated by averaging the technological distances of patents filed by firm f on year t that did at least one self-citation (self-citing patents):

$$Avg\ Technological\ distance\ Internal_{firm-year} =$$

$$\sum_{i}^{No\ of\ self-citing\ patents} \frac{\text{Technological distance}_i}{No\ of\ self-citing\ patents} \quad (2)$$

We computed next variables aggregated total technological distance, which is measured with respect to all the backward citations firm i's patents made on year t using the formula 2, and average technological distance external, which is measured with respect to all external citations firm i's patents made on year t using the same formula.

Level of Decomposability: To construct the measure of level of decomposability of knowledge networks we followed methodology employed by Yayavaram and Ahuja (2008). First, the coupling coefficient, a measure from literature on cluster analysis (Everitt, 1993), was computed between any two knowledge elements inside firm's knowledge base (Yayavaram and Ahuja, 2008). Second, the weighted clustering coefficient, a measure from literature on complex networks (Barrat et al., 2003), was estimated using the coupling coefficients to account for the strength of ties linking any two elements.

Firm's knowledge base is assumed to comprehend accumulated number of patents it had issued during last 3 years (Ahuja and Katila, 2002). This approach assumes that technology classes listed in a patent represent elements in organization's knowledge base (Fleming and Sorenson, 2001). A coupling between technology classes is inferred whenever any two classes are cross-classified in a patent document. The coupling coefficient is computed using the ratio known as Jaccard's coefficient which estimates for firm f on year t the coupling between technology classes j and k based on the following formula:

$$L_{f,\ j-k,\ t-3\ to\ t-1} = a/(a+b+c) \qquad (3)$$

where a counts the patents that are assigned to both classes j and k; b counts the patents that are assigned to class j, but not to class k, and c count the patents that are assigned to class k but not to class j. The structure of firm's knowledge networks is reflected, accordingly, in the coupling matrix that includes $L_{f,\ j-k,\ t-3\ to\ t-1}$ coefficient for all the technology class pairs in firm f's knowledge base on year t.

In Figure 1 and 2 we illustrate the knowledge network of one of the firms in our sample – Kodak – in 1980 and 1986 respectively. As one can notice the structure of its knowledge has undergone some changes during those 6 years. Moreover, the coupling matrixes of different firms incorporating same technological elements are different.

Insert Figure 1 about here.

Insert Figure 2 about here.

In the second stage we computed the weighted clustering coefficient of knowledge network, which gives as our measure of Level of decomposability. To take into account the strength of linkage (weights) between each coupled technology class we adopted the algorithm by Barrat and colleagues (2003): (4)

$$C_i^w = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{(w_{ij\,+}\ w_{ih)}}{2}\ a_{ij}\, a_{ih} a_{jh}$$

where w_{ij} is the Jacquard's coefficient between any two technology classes obtained above, and, $s_i(k_i - 1)$ is the normalization factor that multiplies the actual weight of each edge with the maximum number of triangles it could participate in. Thus, C_i^w 'is counting for each triple formed in the neighborhood of the vertex i the weight of the two participating edges of the vertex i. This coefficient varies between 0 and 1 and the higher is its value, the more clustered (decomposable) the knowledge network structure is[2].

Interaction terms: To test Hypothesis 2 we created three interaction terms between decomposability and search distance variables: avg technological distance internal X level of decomposability; avg technological distance internal X level of decomposability squared; avg technological distance total X level of decomposability.

Control Variables: We controlled, first, for the number of patents filed by firm on the focal year. Next, research highlights that the diversity or the scope of technologies in which firm has expertise is likely to impact its innovation performance (Miller et al., 2007; Yayavaram and Chen, 2015). Accordingly, we controlled for Technological Diversity using a Herfindahl index:

$$Technological\ diversification_{i,t} = 1 - \sum s_{itk}^{2} \quad (5)$$

where s_{itk} is the share of firm i's patents assigned to technology class k during t-3 to t-1 period.

To account for the intensity by which firm's exploit internally generated knowledge we computed a variable intensity of internal search which is the share of self-citations over the total number of backward citations made by firm i on year t.

To account for effects of firm size on its innovation performance we included also a variable log sales for firm i on year t. Because organization's innovativeness varies along its lifecycle (Sorenson and Stuart, 2000; Ghosh et al., 2014) we controlled also for firm age. Additionally, given

[2] Since variables search distance and level of decomposability are ratio ranging from 0 to 1, we standardized them before running the regressions to facilitate the interpretation of estimated regression coefficients.

the differences across countries in patenting tendencies and research productivity (Yayavaram and Ahuja, 2008), we included a dummy variable non-American firm which was equal to 1 if the firm's country of origin was outside United States. Finally, we included also dummies for years from 1975 to 2008 with 1975 as the reference year to control for possible unobserved effects that vary over time but are invariant across sample firms (e.g., patenting trends; technological discontinuity). And second, we included firm-fixed effects to capture any effect that is invariant over time within each panel.

Statistical approach

The dependent variable in both Hypothesis 1 and Hypothesis 2 is a count variable which exhibits overdispersion – the variance is significantly higher than the mean. Accordingly, negative binomial regression analysis was preferred over Poisson model. Furthermore, since the dependent counts are not independent within the firm we accounted for unobserved heterogeneity by estimating fixed-effects negative binomial models (Hausman et al., 1984) using XTNBREG routine in STATA. Finally, we estimate all models with standard errors based on observed information matrix.

Descriptive Statistics

Table 1 reports the descriptive statistics and correlation table between main variables.

Insert Table 1 about here

None of the independent variables showed significant correlation between them. Among control variables average technological distance external is positively and significantly correlated with total technological distance, indicating a tendency for sourcing distant knowledge when searching outside firm's boundaries. However, in regression models we do not include these two variables together. Also, as one may expect, the number of patents issued and the total number of citations made by those patents is positively and significantly correlated with the dependent variable. Further analysis of variance inflation factors of our main explanatory variables were below 10 which has been traditionally considered as cutoff point by prior studies and the conditional number was less than 30. Consistent with prior findings firm age is positively and significantly correlated (.46) with intensity of internal search indicating that elder firms tend to rely more on their internally generated knowledge (Stuart and Sorenson, 2000). The main independent variable – average technological distance internal - is positively and significantly correlated with the number of forward citations (.19) consistent with Hypothesis 1.

Results

Table 2 report the results of negative binomial regression models. sAcross Models 1 to 7 we start by including first only control variables and then introducing independent variables and their interactions. The Model that fits the best is the 6. Both Hypothesis 1 and 2 receive significant statistical support.

Insert Table 2 about here

Across all models the variable intensity of internal search shows positive impact on firm's inventive outcomes in terms of citation counts. This is in line with our arguments that building upon internally generated knowledge does not necessarily lead to negative learning outcomes. As expected, variables firm age, number of patents and log sales are positively associated with invention impact across all models.

Model 2 adds the variable total technological distance which exhibits negative and statistically significant effect on dependent variable ($p < 0.05$). Model 3 decomposes the aggregated technological distance measure between technological distance of internal and external knowledge. Log-likelihood ratio test shows that the distinction between internal and external search distance significantly improves the model fit (χ^2= 4.9, $p < 0.026$). The coefficient for avg technological distance internal is positive and statistically significant ($p < 0.05$) confirming Hypothesis 1. By exponentiating the parameter estimates (exp (0.0674) =1.07) we obtained the incidence rate ratios (IRR) which can be interpreted as follows: patents are expected to receive 7% more citations for every one standard deviation increase in technological distance internal, with the remaining predictor values held constant. Furthermore, the coefficient of avg technological distance external is negative and statistically significant ($p < 0.05$).

Models 4-5 include also the moderating variable: level of decomposability. Consistent with prior studies (Yayavaram and Ahuja, 2008), decomposability of firm's knowledge network has an inverted U-shape relationship with invention's impact. Estimated coefficients indicate that the turning point or the maximum value is obtained at 0.468 (non standardized raw value), which falls within the observed range of the variable. Incidence rate ratios imply that for a one standard deviation increase in the level of decomposability the number of citations patent receives is expected to increase by 93%, holding other predictors in the model constant, and it is expected decrease by 46% for a one standard deviation increase in the level of decomposability squared.

Models 5 to 7 include interaction terms. We first test in Model 5 whether or not the (negative) effect of total technological distance is contingent on the structure of knowledge networks. Results show that the interaction term total technological distance X level of decomposability is not statistically significant. We, next proceeded to Model 6 where we interacted the decomposability with internal distant search. The positive and significant ($p < 0.01$) coefficient for interaction term avg technological distance internal X level of decomposability confirms Hypothesis 2. This implies that more decomposable the knowledge network the higher the benefits from searching internal distant knowledge. Moreover, when adding also the avg tech distance internal X level of decomposability squared at Model 7, both of the interaction terms become insignificant. Likelihood ratio test confirms that the model without quadratic interaction term fits better fit (χ^2= 0.07, p < 0.794). This implies that there are no decreasing returns from sourcing for internal distant knowledge under increasing levels of decomposability.

Figure 2 illustrates this moderation effect by plotting predictive margins at three levels of decomposability – variable's 25th (0.3), 50th (0.47) and 75th quartile (0.54) values. The three slopes show that the effect of distant search internal on the expected number of future citations varies across observations at three levels of decomposability. Moreover, for a given value of technological distance internal predicted margins for citation counts are the highest for observations with higher value of level of decomposability.

Insert Figure 3 about here

To further explore the interaction effect in our non-linear model we followed methodology by Hilbe (2011) to derive the precise slopes and incidence rate ratios for values (non standardized) of decomposability and technological distance internal at three quartiles (25th, 50th and 75th). Based upon estimates from Table 2, Model 6 we computed the following formula since we have continuous-continuous interaction:

$$IRR_{tec\ dist\ int\ X\ decomp} = \exp\left[\beta_{tec\ dist\ int} + \beta_{tech\ dist\ int\ X\ decomp} * (decomp\ \mathrm{quartile})\right] \quad (6.1)$$

$$IRR_{decomp\ X\ tec\ dist\ int} = \exp\left[\beta_{decomp} + \beta_{\mathrm{tec\ dist\ int\ X\ decomp}} * (tec\ \mathrm{dist\ int\ quartile})\right] \quad (6.2)$$

Insert Table 3 about here

Table 3 reports the values of decomposability and technological distance internal at three quartiles, and their incidence ratios. They show that citation counts increase by 1.05 times (or 5%) for every one standard deviation increase in the technological distance internal for observations with level of decomposability equal to 0.3 and by 1.14 times (or 14%) for observations with level of decomposability equal to 0.54. Furthermore, citation counts increase by 1.84 times (or 84%) for every one standard deviation increase in the level of decomposability for observations with technological distance internal equal to 0 and by 2.07 or (or 107%) for observations with technological distance internal equal to 0.165. Overall these results provide statistical support for our arguments concerning the positive effect of internal distant search on inventive outcomes and the positive moderating effect of knowledge network decomposability on this relation.

Robustness checks

Comparison to prior research

Existing scarce empirical research on the relationship between internal distant search and invention impact has reported somewhat different findings. Hence, to further assure the validity of our results we compared our findings with studies by Rosenkopf and Nerkar (2001) and Miller and colleagues (2007) examining similar relationship. Rosenkopf and Nerkar (2001) operationalize four exploration strategies; *"local"* exploration builds upon similar technology, *"internal boundary spanning* exploration*"* builds upon different technologies which are inside firm's technological expertise, "external boundary s*panning"* builds upon similar technologies residing outside firm's boundaries and *"radical"* exploration builds upon different technologies which are unfamiliar to the firm as whole. They estimate the implications of each of those strategies on the number of future citations that inventions receive from patents in the focal technological field (i.e., optical disc) – *"domain impact*" - and from all other fields – *"overall* *impact"*. Miller and colleagues (2007) further added a third dependent variable -*"total* impact*"*- which is the summation of the impact of the invention in its focal domain and outside its domain. To identify technological boundaries, we followed Miller and colleague's (2007) methodology and relied upon aggregated subcategories developed by Hall and colleagues (2001). This aggregation classifies 400 USPTO classes into 36 broad technological domains. We run our analysis at patent level in order to control for idiosyncrasies in citation rates in different technological fields. On average, firms in our sample filed patents in 83 different USPTO technological classes and 9 broad subcategory. We run final models on 233,110 patents[3] filed by 89 firms using negative binomial regression with dummies for firm, year and subcategory including also the main control variables. Table 4 reports the estimates for three models with three dependent variables.

Insert Table 4 about here

Our findings were partially different from that reported by Rosenkopf and Nerkar (2001) and almost identical with those reported by Miller and colleagues (2007). For domain impact (Model 1), similar to prior studies, we find that self-citations beyond technological domain (internal distant search) have significant negative effect on invention impact. For non-domain (overall) impact (Model 2), consistent with Miller and colleagues (2007), we find significant positive effect of internal distant search as compared to non-significant effect reported by Rosenkopf and Nerkar (2001). Finally, for total impact (Model 3) we find that internal distant search has positive significant effect on invention impact as opposed to negative effect found by Miller and

[3] 8751 patents were omitted from this analysis since they were assigned to classes that were likely been added to USPTO after 2001 and, were not classified, thereby, under a subcategory developed by Hall and colleagues (2001).

colleagues (2007). This difference may be due to different samples used for analysis. Taken together, these results confirm the robustness of our results by using a different measurement of search distance; suggesting that the use of internal distant knowledge enhances the outcome from experiential learning.

We implemented additional robustness checks to further ensure the validity of our findings. In We run random effects model including a dummy variables for the SIC code to which firm belongs and technological subcategory in which firm filed patents during the period. Overall, results are consistent with main models reported in Table 2.

DISCUSSION AND CONCLUSION

This paper examined the fundamental challenges organizations face with respect to experiential learning and attempted to address them by showing internal search strategies and knowledge network structures that improve learning outcomes. In developing our reasoning we build upon a premise from behavioral theory of the firm which asserts that organizational search processes combine two logics of behavior; cognitive – based on cognitive representations - and experiential – based on routinized actions in response to feedback. And to enhance outcomes from experiential learning organizations need to allocate equivalent efforts to these two search mechanisms and sustain organizational environment that allows to overcome the pitfalls inherent in each. We hypothesized, in particular, that inventive search efforts that source for technologically distant knowledge from organization’s experience pool positively affect learning outcomes in terms of generation of high impact inventions. Furthermore, organizations that have highly decomposable knowledge networks benefit more from such internal distant search. Overall, our findings highlight internal search strategies – i.e., search for local vs distant knowledge - and knowledge structural attributes that allow organizations to effectively leverage their technological expertise and overcome learning traps. The empirical evidence from global photographic equipment and supplies industry provides statistical support for our arguments.

Limitations and Future Research: This study has yet a number of limitations which provide multiple directions for refining our findings. More specifically, following other studies in organizational learning literature we examined the outcomes of experiential learning in terms of observed performance indicators (i.e., invention impact), rather than observing directly the actual processes through which learning occurs (Kim et al., 2009; Ghosh et al., 2013). As such, we did not directly observe cognitive search processes organizational members engage in while combing technologically distant knowledge elements.

Overall, this study advances research on experiential learning by demonstrating how cognitive and experiential processes interactively influence learning outcomes in the context of recombinant invention and by identifying technological characteristics of experiential knowledge that improve these processes. In addition, we call attention to a firm's knowledge structure as an important contingency for enhancing learning outcomes from experience.

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Table 1. Descriptive statistics and Correlations

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1	**No of forward citations**	575.6	2862.9	0	43307	1											
2	**Total Technological Distance**	0.34	0.18	0	1	0.03	1										
3	**Avg Tech Distance Internal**	0.1	0.13	0	1	0.19	0.3	1									
4	**Avg Tech Distance external**	0.34	0.18	0	1	0.03	0.98	0.23	1								
5	**Intensity of Internal search**	0.13	0.15	0	1	0.15	-0.13	0.48	-0.16	1							
6	**Firm age**	19.97	9.67	2	34	0.12	-0.05	0.27	-0.06	0.46	1						
7	**No of patents (year t)**	190.3	561.54	0	5925	0.73	0.02	0.24	0.01	0.27	0.23	1					
8	**No of total backward citations**	1762	6372.9	0	62314	0.66	0.07	0.28	0.06	0.22	0.17	0.9	1				
9	**Technological Diversification**	0.86	0.18	0	1	0.1	-0.06	0.14	-0.08	0.22	0.37	0.18	0.13	1			
10	**Ln (sales)**	7.66	3.07	-4.02	14.83	0.15	-0.02	0.14	-0.04	0.16	0.32	0.26	0.2	0.26	1		
11	**Non US firm (dummy)**	0.37	0.48	0	1	0.12	-0.02	-0.12	-0.03	-0.15	-0.16	0.21	0.13	0.02	0.53	1	
12	**Level of Decomposability**	0.42	0.26	0	1	0.05	0.04	0.14	0.04	0.14	0.24	0.07	0.07	0.25	0.11	-0.08	1

N=1208 firm-years

Table 2. Negative Binomial Analysis for effects of Search distance and Knowledge Structure on Citation counts

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Total Technological Distance		-0.363**					
		(0.184)					
Avg Tech Distance Internal[4]			0.0674**	0.0657*	0.0572	0.0958***	0.0975***
			(0.0334)	(0.0341)	(0.0350)	(0.0359)	(0.0366)
Avg Tech Distance external			-0.466**	-0.530***	-0.759***	-0.689***	-0.692***
			(0.182)	(0.187)	(0.281)	(0.193)	(0.194)
Level of Decomposability[a]				0.661***	0.594***	0.684***	0.688***
				(0.111)	(0.126)	(0.112)	(0.113)
Level of Decomposability squared[a]				-0.609***	-0.597***	-0.610***	-0.614***
				(0.108)	(0.108)	(0.108)	(0.109)
Avg Tech Distance Total X Level of Decomposability					0.646		
					(0.587)		
Avg Tech Distance Internal X Level of Decomposability						0.0927***	0.111
						(0.0282)	(0.0770)
Avg Tech Distance Internal X Level of Decomposability squared							-0.0200
							(0.0772)
Intensity of Internal search	1.379***	1.364***	1.125***	1.077***	1.090***	0.922***	0.918***
	(0.272)	(0.270)	(0.299)	(0.299)	(0.299)	(0.303)	(0.303)
Firm age	0.0405***	0.0418***	0.0414***	0.0322***	0.0328***	0.0331***	0.0329***
	(0.00765)	(0.00769)	(0.00772)	(0.00784)	(0.00786)	(0.00781)	(0.00783)
No of patents (year t)	0.000399***	0.000398***	0.000393***	0.000384***	0.000385***	0.000382***	0.000381***
	(3.88e-05)	(3.87e-05)	(3.86e-05)	(3.73e-05)	(3.73e-05)	(3.73e-05)	(3.75e-05)
Technological Diversification	0.595***	0.615***	0.667***	0.234	0.247	0.257	0.259
	(0.228)	(0.229)	(0.233)	(0.245)	(0.245)	(0.239)	(0.239)
Ln (sales)	0.0524**	0.0506**	0.0495**	0.0493**	0.0490**	0.0450**	0.0450**
	(0.0213)	(0.0212)	(0.0213)	(0.0213)	(0.0213)	(0.0213)	(0.0213)
Non US firm (dummy)	-0.407***	-0.400***	-0.404***	-0.390***	-0.394***	-0.363**	-0.361**
	(0.148)	(0.148)	(0.148)	(0.147)	(0.147)	(0.147)	(0.148)
Year dummies (1976-2008)	Included	Included	Included	Included	Included	Included	Included
Constant	-6.783***	-6.816***	-6.689***	-5.520***	-5.649***	-5.520***	-5.519***
	(1.043)	(1.043)	(1.047)	(1.064)	(1.070)	(1.063)	(1.063)
Observations	1,208	1,208	1,208	1,208	1,208	1,208	1,208
Number of firms	89	89	89	89	89	89	89

Standard errors in parentheses, based on observed information matrix
Firm fixed effects models; *** p<0.01, ** p<0.05, * p<0.1

[4] Standardized values by subtracting the variable mean and dividing by its standard deviation

Table 3. Interaction effect interpretation: Internal distant search and level of decomposability

Technological distance internal X Decomposability			
Decomp	Decomp standardized	Quartile (%)	IRR
0.54	0.462	75	1.149
0.47	0.192	50	1.120
0.3	-0.462	25	1.055

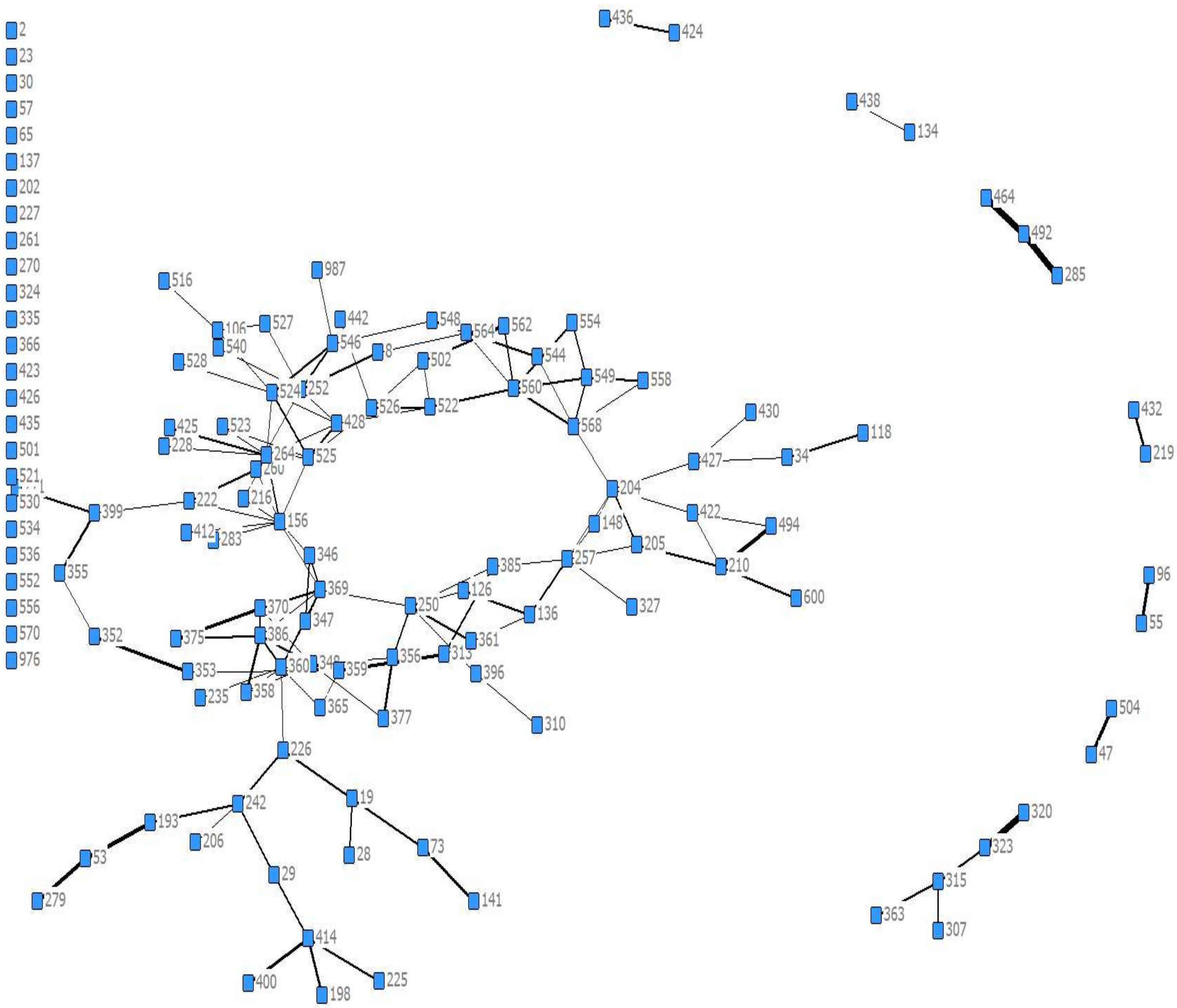
Decomposability X Technological distance internal			
Tec dist int	Tec dist int standardized	Quartile (%)	IRR
0.165	0.5	75	2.076
0.05	-0.385	50	1.913
0	-0.769	25	1.845

Table 4. Robustness check: Negative Binomial regression for impact of search on citations count

VARIABLES	Model 1 Domain Impact	Model 2 Non-domain Impact	Model 3 Total Impact	Model 4 Total Impact
Extraorganizational citations within technological domain	0.0258***	-0.0214***	0.00734*	0.00736*
	(0.00892)	(0.00283)	(0.00431)	(0.00430)
Exrtaorganizational citations beyond technological domain	-0.0168***	0.0546***	0.00695***	0.00695***
	(0.00614)	(0.0138)	(0.00241)	(0.00242)
Self-citations within technological domain	0.00730	-0.0486***	-0.0104**	-0.0104**
	(0.00670)	(0.00721)	(0.00510)	(0.00510)
Self-citations beyond technological domain	-0.0227**	0.0461***	0.00690*	0.00685*
	(0.0112)	(0.0115)	(0.00404)	(0.00405)
Level of Decomposability				0.456
				(0.529)
Level of Decomposability squared				-0.150
				(0.527)
Technological diversification	0.184	0.0649	0.0974	-0.0646
	(0.365)	(0.371)	(0.359)	(0.371)
No of patents (year t)	-3.18e-05	-4.68e-05*	-3.38e-05	-3.30e-05
	(2.15e-05)	(2.74e-05)	(2.56e-05)	(2.63e-05)
Tech categories (36)	Included	Included	Included	Included
Firm dummies (89 firms)	Included	Included	Included	Included
Year dummies (1976-2008)	Included	Included	Included	Included
Constant	0.00671	-1.759***	0.264	0.576
	(0.522)	(0.400)	(0.453)	(0.497)
Observations	232,957	232,957	232,957	232,957

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. Kodak knowledge network, 1980, cutoff =0.04, based on median coupling coefficient for firm i on year t[5]



[5] Figures are drawn using UCINET network analysis software

Figure 2: Kodak knowledge network, 1986, cutoff =0.05, based on median coupling coefficient for firm i on year t

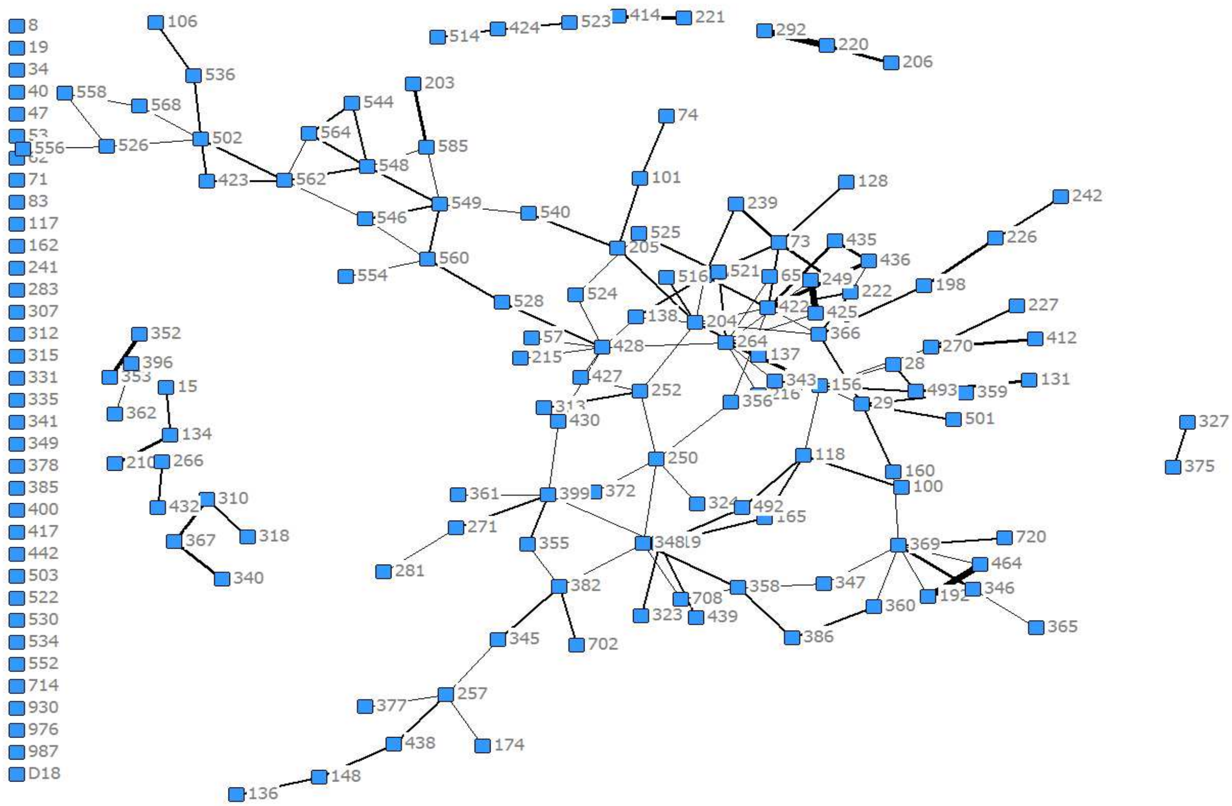
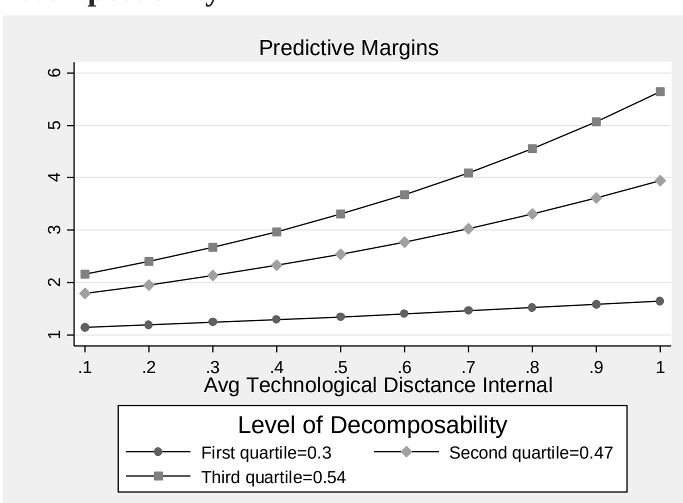


Figure 3. Interaction between Technological Distance Internal and Level of Decomposability



Note: Using first, second and third quartile values of level of decomposability with avg technological distance internal at x axis and expected number of citations at y axis.