The Jack of All Technologies: Knowledge Recombination across Technological Boundaries

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Abstract

Research on learning and innovation suggests that the ability to engage in distant technological search is of particular importance for sustaining the firm's competitiveness. While the extant literature primarily focuses on organizational-level mechanisms as a means to facilitate distant searches (e.g., interfirm alliances or acquisitions), the present study focuses on the micro-level by examining technological knowledge recombination in invention processes. In particular, we argue that there are significant differences across the human capital endowments of inventors, their knowledge sourcing practices and the composition of inventor teams, and that those differences are associated with differential ability to recombine knowledge either within or across technological domains.
Our findings highlight that a theory of organizational search and knowledge recombination needs to account for the abilities of the focal agent engaging in a search of the technological landscape. To date, however, many of the studies on technological search model the firm as the focal agent, and thus implicitly assume homogeneity in individual abilities to recombine knowledge across boundaries. Furthermore, our results complement recent research on star scientists. Notably, the 'Jacks of All Technologies' identified in this paper have a superior track record in knowledge recombination across technological domains, yet they would go unnoticed when applying established output-based approaches for identifying star scientists. We base our empirical analysis on a comprehensive data set covering 35,764 EP patents that was matched with an original survey data set obtained from 2,216 inventors.

Keywords: Inventors, Exploration, Recombinant Search, Patents, Patent Classes, Innovation.

1. Introduction

A large body of work suggests that firm-level differences in managing knowledge and learning have an important influence on firm competitiveness and value creation (cf. von Krogh 1998; Kogut and Zander 1992). The common theme in these studies is that firms have to balance exploration and exploitation in their R&D efforts in order to sustain their competiveness over time (March 1991; Levinthal 1995). In particular, studies indicate that firm-level R&D is typically a path-dependent process, constrained by local search activities in which a limited set of options is considered according to tightly held beliefs and to the knowledge at hand (Stuart and Podolny 1996; Greve and Taylor 2006). Yet, scholars also point out that a broader search involving more distant knowledge domains results in a larger variety of ideas to draw from, and can enable firms to identify new knowledge components that challenge current beliefs, stimulate innovative behavior and create the potential for breakthrough inventions (Miller, Fern and Cardinal 2006). For example, Hargadon (1998, p. 210) suggests the importance of 'technological fusion', that is "the combination of existing technologies from several industries, and the powerful market effects these combinations can create (…)."

In industries in which innovation and learning form an important basis for competition, managers may be particularly concerned about the effects of local search in their R&D efforts. Rosenkopf and Nerkar (2001) thus suggest that firms have to establish 'second-order competence', that is, the ability to create new knowledge across technological boundaries, and Kogut and Zander (1992) argue that firms need to build 'combinative capability' to be able to synthesize existing and newly acquired knowledge.

As the ability to engage in distant technological search is of particular importance for sustaining the firm's competitiveness, it is hardly surprising that scholars have shown strong interest in examining mechanisms which would allow firms to tap into distant knowledge domains and recombine their knowledge with far-flung knowledge elements. Such mechanisms include, for example, interfirm alliances and acquisitions (e.g., Capron, Dussauge and Mitchell 1998) and inventor mobility (e.g., Almeida and Kogut 1999). Yet, whereas prior research provides a number of key insights into the question how firms can tap into distant knowledge domains, it is intriguing that – except for the notion that external inventors can bring valuable new knowledge inside the firm – current studies largely neglect the role of the individual inventor in technological recombination. Arguably, this emphasis has been encouraged by the common framing of distant search and knowledge recombination as an organizational-level problem. However, prominent examples like Thomas A. Edison and the countless recombinant inventions he has produced throughout his career (Hargadon, forthcoming) remind us of the fact that the agents of technological recombination are people, and that it is through their human capital and their work practices that local and distant technological knowledge components get recombined and create potentially path-breaking inventions. While there has been some interest among researchers in individual-level knowledge and information acquisition (e.g., Gray and Meister 2004), the linkages between firm-level and individual acquisition of distant knowledge still need further analysis. We seek to contribute to this area with our study.

Following the core notion that the skills and routines required to recombine knowledge from different technological areas differ considerably from those required to recombine knowledge from within the same technological domain (March 1991), the purpose of the present paper is to shed light on the role of inventors in knowledge recombination across technological boundaries. Specifically, we argue that there are significant differences across the human capital endowments of inventors, their knowledge sourcing practices and their inventive teams, and that those differences are associated with differential ability to recombine knowledge either within or across technological domains. We base our analysis on a comprehensive data set covering 35,764 EP patents that was matched with an original survey data set obtained from 2,216 inventors. The combination of these two data sources enables us to uncover largely novel patterns of inventor performance and characteristics.

We proceed with a discussion of the theoretical background of our study, and develop our hypotheses in Section 3. We describe our data in Section 4 and present the empirical results in Section 5. Section 6 concludes the paper.

2. Recombinant Search and Technological Innovation

Analysts of innovation and technological progress have long argued that the process of innovation is one that critically relies on the recombination of existing ideas and artifacts (Fleming 2001). The argument is a classical one by now: in his ground-breaking work, Schumpeter (1934) defined innovation as the carrying out of new combinations. Likewise, Nelson and Winter (1982) suggested that “the creation of any sort of novelty in art, science, or practical life – consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence." (p. 130).[1]

This perspective on innovation rests on an implicit notion of boundaries between different technological domains, that is, certain components or technologies are seen as belonging together in a particular domain, as they address a particular real-world problem, share some underlying pattern of socially constructed meaning, or draw on a distinct theory, method, language, code, etc. (von Tunzelmann 1998; Hargadon 2002). While there are no restrictions on the scope of recombination among components from one domain with those of another, scientists have to possess at least some working knowledge of the involved technological domains in order to sensibly recombine different components (Cohen and Levinthal 1990; Fleming 2001).

As recombination within a particular technological domain and recombination across domains can both lead to technological innovation, yet entail fairly different challenges, studies frequently draw on the notion of a technological search space to distinguish between local and distant types of search and recombination (March 1991; Levinthal 1997). By indulging in local search, a firm recombines a narrow set of knowledge elements and generates deeper expertise in a given technology, which typically leads to incremental innovation. Although local search is associated with a number of advantages (notably, it conserves cognitive effort and resources, and also leads to more predictable outcomes), firms relying solely on local solutions run the risk of losing their ability to compete effectively (Kim and Kogut 1996; Nerkar and Roberts 2004). By pursuing local searches and following a path of local recombination, firms may gradually exhaust the possible combinations in their limited knowledge space (Fleming 2001), fall into competency traps (Levitt and March 1988) or develop core rigidities (Leonard-Barton 1995). The literature thus argues that firms also need to explore more distant technological domains so that they can combine their local knowledge with far-flung knowledge elements and identify radically different, potentially path-breaking solutions (March 1991; Rosenkopf and Nerkar 2001). Although distant search is often arduous and costly and may often not lead to viable outcomes, empirical evidence supports the notion that recombinations involving distant knowledge elements allow firms to reinvigorate their

[1] In a similar vein, Weick (1979, p. 252) defined creativity as "putting new things in old combinations and old things in new combinations".

knowledge base and produce highly valuable technological and scientific advances (Stuart and Podolny 1996; Fleming and Sorenson 2004; Nerkar and Roberts 2004; Taylor and Greve 2006).

Because distant technological domains may offer ideas that can be extremely useful to innovation through knowledge recombination, scholars have increasingly become interested in exploring the mechanisms which firms might employ to reach beyond their existing knowledge contexts and manage the difficulties of distant search. Specifically, the literature proposes two general sets of mechanisms that may enhance the firm's ability to execute distant combinations. The first set rests on the idea that firms can bring distant knowledge inside by engaging with external organizations or individuals that possess the desired knowledge. Specifically, extant studies suggest that interfirm alliances (Stuart and Podolny 1996; Rosenkopf and Almeida 2003), acquisitions (Capron, Dussauge and Mitchell 1998), or the hiring of inventors with distant knowledge (Almeida and Kogut 1999; Song, Almeida and Wu 2003) helps to overcome the constraints of localized research and development. In contrast, the second set of mechanisms takes an inward focus and suggests that the knowledge required for distant combinations can be generated through in-house initiatives. In particular, to build distant knowledge firms may launch corporate venturing activities (Wadhwa and Kotha 2006; Keil, McGrath and Tukiainen 2008), or – in case distant knowledge already resides in some secluded part of the organization – may engage in interdivisional collaboration to exploit that knowledge (Miller, Fern and Cardinal 2007).

Yet, while prior research provides a number of valuable insights into the question how firms can tap into distant knowledge domains, it is intriguing that – except for the notion that external inventors can bring valuable new knowledge inside the firm – extant studies largely neglect the role of individuals in technological recombination in general, and of inventors in particular. Arguably, this perspective has been encouraged by the common framing of distant search and knowledge recombination as an organizational-level problem, and – from an empirical point of view – by treating patent data as firm-level information. Of course, we are not the first to point to this research question. The notion of search spaces and distant search is already implicit in early contributions to the classical engineering design literature (e.g., Marples 1961). Moreover, in various contributions authors such as Fleming and his colleagues have analyzed the contributions by inventors in detail. Our paper differs by making use of combined survey – patent data.

As inventive action ultimately takes place through the activities of inventors, the present paper seeks to address this critical void in the literature by arguing that there are significant differences across the human capital endowments of inventors, their knowledge sourcing practices and their inventive teams, and that those differences are associated with differential ability to recombine knowledge either within or across technological domains. Arriving at a better understanding of these micro-level factors associated with technological knowledge recombination is not only key for advancing research on innovation and learning, but also has important practical implications as it will allow R&D managers to be more effective in orchestrating organizational-level mechanisms of knowledge recombination with those on the individual and team levels.[2] In the following, we will thus develop three sets of hypotheses examining (a) the inventor's education and work experience, (b) the knowledge sources used in her research and invention activities, and (c) the size of her research team in technological knowledge recombination.

3. Hypotheses

3.1. The Inventor's Education and Work Experience

In order to establish distant technological combinations, inventors must first identify distant knowledge elements and then apply that knowledge together with other knowledge components to arrive at an inventive solution. Yet, because knowledge is contextual and, when acquired, often remains entangled in its original context and meaning, it is both difficult to comprehend knowledge residing in distant technological domains and to subsequently apply such knowledge in a recombinant process (Cohen and Levinthal 1990; Nonaka 1994).

Yet, while inventors face considerable difficulties when seeking to recombine knowledge across technological boundaries, we propose that some inventors have superior abilities in performing such recombinations. In particular, several arguments indicate that the level of formal scientific education that an inventor has attained influences his ability to recombine technological knowledge from different domains, with the basic notion being that the higher the educational level, the better his recombination abilities. In the case of inventors who have such superior abilities, we expect to see traces of distant search

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[2] The research that is closest to the spirit of our study was conducted by Hargadon and Sutton (1997) and Hargadon (1998, 2002) who investigated the role of individual actions and routines in firms that occupy knowledge brokering positions. Specifically, their field research shows how a design firm ('IDEO') has positioned itself in a way which allows gaining wide access to a variety of industries, enabling its designers to learn the diverse knowledge of many industries and to generate creative product designs by combining that knowledge (Hargadon and Sutton 1997). Furthermore, a related line of research investigates the roles of boundary-spanning individuals and gatekeepers in the innovation process (cf. Allen 1977; Roberts and Fusfeld 1981). For example, Allen (1977) suggested that focal nodes in the innovating firm's communication network bring external information into the internal communication network.

in the composition of the inventor's overall patent portfolio. In order to test our hypotheses we will therefore attempt to measure the technological breadth of the inventor's activities. We define technological breadth as the inverse of specialization. Inventors who are active in a relatively large number of technical fields display greater technological breadth than highly specialized inventors who focus narrowly on one or very few fields. In the following sections, we consider three main determinants of the inventor's technological breadth.

First, formal scientific education seems to be an important facilitator of knowledge recombination across technological boundaries because it allows researchers to gain an abstract understanding of the technological problem-solving process and – as they reflect on and hone their learning activities – to engage in meta-learning. As Gibbons and Johnston (1974, p. 239) explain: "It appears to be this second-order form of knowledge, the 'knowledge of knowledge', whereby the problem-solver with a university education (…) knows where and how to go about seeking the kinds of information he needs, which constitutes an important difference between the university graduate and the worker with a part-time practically-oriented education." Notably, this difference seems to be associated less with the specific knowledge or techniques learned while undergoing formal scientific education than with a more general ability to engage in a search to obtain new knowledge, to assess its adequacy and to recombine it with other knowledge components. In this regard, recent research by Fleming and Sorenson (2004) also indicates that the basic scientific knowledge acquired by inventors during formal scientific education provides them with some fundamental understanding of the underlying technological landscape. In particular, they suggest that basic science creates a map that facilitates technological search, as it helps inventors to avoid technological components that may be useless or may not lead to useful outcomes.

Second, it needs to be considered that inventors are boundedly rational individuals whose recombination activities are constrained by their cognitive abilities (March and Simon 1958). In particular, the limited information processing capacity of inventors will become increasingly strained when more information is collected, limiting the number of potential components and their combinations that can be taken into account simultaneously (Simon 1982; Fleming and Sorenson 2004). For example, research on cognitive abilities indicates that the most complex set of interrelationships an individual can process in working memory is a three-way interaction (Halford et al. 1994). Thus, beyond some number of potential components and their combinations, inventors may become overwhelmed by the complexity of the combination possibilities that a distant technological domain offers and may not arrive at useful outcomes. Still, some inventors may have better cognitive abilities in dealing with such complexity in technological innovation than others, as they have developed knowledge structures (schemata) to cope with the myriad of stimuli and uncertainties they encounter in their inventive activities. In particular, prior studies indicate that these structures can help individuals in processing new information and in unifying disparate sets of information, and also in arriving at qualitatively more sophisticated judgments (Gagné and Glaser 1987; Walsh 1995). As the attained level of formal education is reflective of an individual's cognitive ability and her knowledge structures (Pelled 1996), it thus appears that inventors with higher educational attainment should have superior abilities in dealing with the complexity of knowledge recombination across technological domains.

Third, as technological domains isolate and constrain the use of knowledge inventors require a certain level of openness, flexibility, curiosity and willingness to study other domains, to import the identified knowledge and to combine it in new ways. In this vein, prior research indicates that individuals who are more educated tend to be more receptive toward innovation, and are more likely to engage in boundary-spanning activities (Hambrick and Mason 1984; Hargadon 2004).

In sum, these arguments all suggest that inventors who have attained a higher level of scientific education should have better skills, abilities and a higher willingness to recombine knowledge across technological domains. We thus expect the following ceteris-paribus relationship between an inventor's education level and the breadth of her inventive output:

Hypothesis 1: There is a positive association between an inventor's attained education level and the technological breadth of her inventions.

The ability to recombine technological knowledge across domains is also shaped by the inventor's work experience. We focus our theorizing on a particular type of experience that inventors may acquire throughout their careers – research experience in different firms – while controlling for other work experience-related factors such as the temporal concentration of her inventive activities and the total number of years of work experience. Specifically, it seems that inventors who have engaged in inventive activity at more than one firm will have an advantage in bridging disparate technology domains, because they have been exposed to potentially different technologies and research processes (capabilities), have encountered different thought worlds and approaches, and have come into contact with ideas that may not be known in the hiring firm (Rosenkopf and Almeida 2003; Song, Almeida and Wu 2003). Also, the move to another firm often forces inventors to break out of their accustomed routines and frames of reference, providing them not just with the opportunity to transfer their knowledge, but also with the need to interpret this knowledge in a new context. Furthermore, the move to another firm might stimulate the creativity of inventors because they will be exposed to a new social network and also come in contact with new objects in their research activities (Hargadon 2004).

Support for this line of reasoning comes from empirical studies indicating that *inventor mobility* can enable firms to overcome the constraints of local search (Almeida and Kogut 1999; Rosenkopf and Almeida 2003; Song, Almeida and Wu 2003). The underlying notion that people are an important conduit of interfirm knowledge transfer has figured prominently in the innovation literature. Gilfillan (1935) and Arrow (1962) both suggested that labor mobility, especially among engineers, facilitates the flow of knowledge and potentially erodes the differential level of technological knowledge among firms. Notably, hiring inventors away from a competing firm is a way of acquiring knowledge that would otherwise be immobile. For instance, Almeida and Kogut (1999) show that after the hiring of a new inventor, there is a significantly greater tendency for the hiring firm to build on the prior patents of the new inventor than would otherwise be expected given its technological base. Thus, if interfirm mobility of inventors is indeed associated with inventions that break out of path-dependent R&D trajectories, it seems that the outcomes of the recombination process will not only to be reflected in the firm's overall patent portfolio (as current studies on organizational search indicate) but should also be visible in the technological breadth of the mobile inventor.

In sum, we believe that inventors who have gained experience in more than one firm can draw from a broader set of knowledge, research capabilities and experience when engaging in inventive activities, and thus have a greater ability to recombine knowledge across technological domains than inventors who worked at one firm only, all else equal. We hypothesize:

Hypothesis 2: There is a positive association between an inventor's interfirm mobility and the technological breadth of her inventions.

3.2. Knowledge Sources Used in Research

To identify knowledge elements that can be used in technological innovation, inventors often need to turn to external knowledge sources to obtain new ideas, insights and expertise. For example, to seek out new knowledge, inventors may search the scientific literature, browse patents or get in contact with university laboratories. The Yale and PACE surveys on innovation have documented the wide range of knowledge sources frequently used in innovation in the US and in Europe (Arundel, Van de Paal and Soete 1995; Klevorick, Levin, Nelson and Winter 1995).

To be of value to the inventor, the knowledge obtained from a particular source must differ at least to some extent from that obtained from another source. If this would not be the case, inventors could substitute different knowledge sources with one another, without deriving any benefit of sourcing complementary knowledge from multiple sources (Leiponen and Helfat 2003). Thus, when inventors make use of a diverse set of knowledge sources, this means they are exposed to heterogeneous or even divergent perspectives, ideas and knowledge bases. Importantly, the availability of such divergent insights can stimulate novel insights and may cause inventors to pursue previously unexplored directions (Perry-Smith 2006). The exposure to divergent insights also means that inventors have to devote some time to reflection in order to come to conclusions that are consistent with the diversity of knowledge inputs they have obtained, and to connect the dots between seemingly unrelated knowledge components.

Whereas the use of diverse knowledge sources elicits the sort of learning and problem solving that in general tends to yield innovative outcomes (March and Simon 1958; Kogut and Zander 1995), it appears that the more diverse the set of knowledge sources an inventor utilizes in research, the greater his ability and tendency to recombine knowledge across technological boundaries. We thus expect the following relationship:

> *Hypothesis 3: There is a positive association between the diversity of knowledge sources used by an inventor and the technological breadth of her inventions.*

Although accessing a diverse set of knowledge sources may be associated with broader patents, it also has to be considered that an extensive search for external knowledge has its cost and may thus be impractical. To this end, it is important to understand which types of knowledge sources are of particular value with respect to knowledge recombination across technological boundaries. In the following, we examine the potential contributions of five types of knowledge sources that inventors frequently use to inform their research, that is, university laboratories, scientific publications, existing patents, users and competitors.

One potentially important source of new knowledge inputs are *university laboratories*, as they are often at the forefront of scientific knowledge creation and tend to engage in basic research. As Nelson (1959, p. 302) pointed out, such basic research is often “of greatest value as a key input of other research projects which, in turn, may yield results of practical and patentable value”. Hence, the use of university laboratories as sources of new knowledge should thus be associated with broader technological inventions.

Another source of new knowledge for inventors is the *scientific literature.* Analogues to our discussion of formal scientific education, it appears that a search of the scientific literature can provide inventors with more basic insights of technological landscapes, and as Fleming (2001) has suggested, helps them to create a mental map that facilitates technological search. Following the reasoning laid out in detail above, we thus expect a positive association between an inventor’s use of the scientific literature as a knowledge source in research and the breadth of his or her technological inventions.

Inventors can also source new knowledge from *existing patents.* The general notion that patents can offer important insights for research activities is not new, as existing patents provide inventors with relevant insights into the prior art during the development process. However, a search of existing patents may also stimulate the creativity of inventors and lead to new solutions. For example, based on research on 250,000 inventions in engineering disciplines, Altschuler (1986) explicitly suggests that existing inventions can provide new insights by way of analogies and also can point to possible applications to new contexts. It thus appears that there is a positive association between an inventor’s use of existing patents as a source of new knowledge and the breadth of his or her technological inventions.

Inventors may also turn to *users* to obtain new knowledge inputs for their research. Von Hippel (1988) has shown in various studies the importance of close relationships with users for innovation. Yet, given that user induced innovations are typically following along the same development trajectories as the initial innovation they build upon, the sourcing of knowledge from users may yield, on average, more constrained, domain-specific insights.

Finally, *competing firms* can serve as a source of new knowledge for inventors. Similar to knowledge sourced from users, sourcing knowledge from competing firms is likely to lead to constrained, domain-specific insights, because competing firms typically follow similar assumptions about their technological core and the products that can be derived from it (Prahalad 2004).

Against this backdrop we hypothesize the following relationships:

Hypotheses 4a-c: There is a positive association between knowledge sourced from (a) university laboratories, (b) scientific literature and (c) existing patents and the technological breadth of an inventor's inventions.

Hypothesis 4d-e: There is a negative association between knowledge sourced from (d) users and (e) competing firms and the technological breadth of an inventor's inventions.

3.3. The Inventor's Team

Another element influencing the outcome of the inventive process, suggested by an entire body of literature, is the size and composition of the inventor team. Our examination will focus on the size of the team, which is measured as the number of inventors who contributed to a particular invention and are named on the patent application.

Earlier studies provide considerable evidence that team size is an important driver of creativity and innovation (Williams and O'Reilly 1998), yet have not explored whether there is a relation between team size and the breadth of technological inventions. A number of arguments suggest, however, that such a relation exists. Specifically, knowledge recombination across technological boundaries may be facilitated in larger teams, as they have a greater knowledge base to draw from in their research and also have access to a greater number networks ties that can enrich the existing knowledge base (Rodan and Galunic 2004; Taylor and Greve 2006). In addition, prior studies suggest that a higher number of team members will increase the likelihood that different problem-solving approaches will be utilized which can help teams in identifying and using new knowledge components (Hargadon 2004). Moreover, the team not only brings individuals together in ways that allow them to build on each other's ideas, but also to challenge well-worn ideas, to elicit relevant though often non-obvious knowledge from individuals and to turn seemingly unrelated suggestions into potentially ground-breaking insights. The interactions in a group can thus lead to a creative cross-fertilization of ideas and can stimulate novel combinations of knowledge (Williams and O'Reilly 1998; Hargadon 1999).

While many benefits are associated with team work, the literature also points out that beyond a certain team size, teams may become dysfunctional and thus arrive at inferior outcomes (Cohen and

Bailey 1997). In particular, it is argued that the larger the number of people in a team, the more effort has to be spent on unifying the broader set of inputs, and the more costly communication, coordination and control tasks will become (Brooks 1975). Furthermore, there is the latent risk that teams may suffer from groupthink, and thus fail to question existing strategies and routines. Overall, this discussion suggests that – like in several studies on the effects of team size (cf. Cohen and Bailey 1997) – there is an inverted U-shaped relation between team size and the breadth of technological inventions. We hypothesize:

Hypothesis 5: There is an inverse U-shaped association between inventor team size and the technological breadth of an inventor's inventions.

4. Research Design

4.1. Data

To examine the research questions outlined previously, we require data on the human capital of inventors, their knowledge sourcing practices, their inventions, and a number of other factors that potentially impact the outcomes of inventive processes. As no public data set offers all of the information required for this study, we collected this information through a large, self-administered survey of inventors and complemented the survey information with data from patent databases which provide detailed information on the underlying inventions, and about the inventors' activities across time (Harhoff et al. 1999; Foray 2004). Patent data has been found useful to trace the recombination of technological knowledge components in a number of previous studies (Fleming 2001; Fleming and Sorenson 2004; Agrawal et al. 2006). We describe the combined data collection efforts in turn.

Survey data. We collected data by employing a standardized, self-administered survey of inventors.[3] After conducting an extensive pilot study (including interviews with 10 inventors), we developed the survey instrument and pretested it with 60 inventors. The survey instrument was sent out together with a free-franked return envelope to our sample of inventors of 10.500 EP patents. Based on a list of all granted EP patents with priority dates between 1993 and 1997 (total of 15.595 EP patents), 10.500 EP patents listing inventors residing in Germany were chosen by stratified random sampling (a

[3] We thank the European Commission, Contract N. HPV2-CT-2001-00013, for supporting the creation of the dataset.

stratified random sample was used in order to oversample potentially important patents[4]). The survey instrument was sent to the first inventor listed on the patent document. Overall, answers were received from 3,049 inventors, resulting in a response rate of 32%.

Patent data. In the present study we use patent data obtained from the online EPOLINE and the PATSTAT databases (Worldwide Patent Statistical Database) made available by the EPO.[5] Each patent contains the names and the addresses of the inventors, as well as information about the company to which the patent is assigned, the type of invention and the technology class(es) that the patent is associated with. It is this latter information that is of focal interest to the present study. Generally, EP patents are classified according to the International Patent Classification (IPC), which is applied in 54 countries. The IPC is based on the Strasbourg Agreement of 1971[6] and has been in use since 1975. According to the IPC, technology is classified in sections, classes, subclasses, groups, and subgroups. Overall it contains about 70,000 entries represented by 7-digit alphanumeric classification symbols.[7] Each patent application is assigned by the patent office to one or more classification symbols corresponding to the invention. To ensure comparability between different patent offices, examiners have to follow precise guidelines on how to classify patent applications.[8]

The grant procedure at the EPO comprises three major stages: (1) formality examination (the office checks whether the application meets formal requirements), (2) preparation of the search report including relevant prior art, and (3) substantive examination (decision whether the application meets the requirements for patentability, i.e. novelty, inventive step and commercial applicability).[9] For EP patents,

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[4] The sample includes all opposed patents (1,048) and patents which were not opposed and whose citation rates were in the top decile (5,333). A random sample of 4,119 patents was then drawn from the remaining 9,212 patents. When we apply population sampling weights to our multivariate analysis below, the results do not change in terms of coefficient signs or significance.

[5] The EPOLINE database contains information on all published EP patent applications as well as all published PCT applications since the founding of the EPO in 1978. PATSTAT includes patent data from 73 offices world-wide and post-grant patent data from about 40 offices. We used the EPOLINE data as of March 1st, 2003 and the PATSTAT data as of September 2007.

[6] The Strasbourg Agreement was signed in Strasbourg (FR), on March 24, 1971 and entered into force on October 7, 1975. It establishes a common classification system for patents, the "International Patent Classification" (IPC). See http://www.wipo.int/treaties/en/classification/strasbourg/trtdocs_wo026.html (accessed August 22, 2008).

[7] For instance, fuel cells for cars are classified as H01M 8/08 (H – Electricity; H01 – Basic electric elements; H01M – Processes or means, e.g., batteries, for the direct conversation of chemical energy into electrical energy; H01M8/00 Fuel cells, manufacture thereof; H01M8/08 Fuel cells with aqueous electrolytes). For a list of all IPC classes see http://www.wipo.int/classifications/ipc/en/ (accessed August 22, 2008).

[8] See http://www.wipo.int/export/sites/www/classifications/ipc/en/guide/guide_ipc8.pdf (accessed August 22, 2008).

[9] See http://www.epo.org/patents/Grant-procedure/Filing-an-application/European-applications.html (accessed August 22, 2008).

the classification is undertaken during formality examination by a formality examiner. As the IPC serves as the basis for assigning the patent application to the examiners, the office has a strong incentive to classify patents carefully. In case a patent has been assigned erroneously to a particular technological class, it will be reclassified during the search or examination stages. We employ the corrected classifications in this case.

Technological classifications employing the IPC system are typically based on the information contained in the description of the technological invention as well as the examples, drawings, and claims provided in the application document.[10] This is a key difference between the IPC system and the US classification system (United States Patent Office Classification, USPOC). Whereas the USPOC classifies patents according to the claims stated within the application document (i.e., the scope of protection), the IPC system considers the complete technological information contained in the application document and thus classifies patents with respect to the technologies associated with the invention (OECD 1994). For a study interested in the recombination of technological knowledge components across technological areas, the IPC thus provides a more suitable classification system than the USPOC. Also note that the EPO is an independent classification authority, so that the assigned technology classes are determined objectively by the examiner, and not by the inventors themselves.

Several proposals exist that convert the over 70,000 symbols into a technical nomenclature suitable for statistical analyses. In this study, we use a nomenclature proposed by the German Fraunhofer Institute for Systems and Innovation Research (FhG-ISI) and the French Intellectual Property Institute (INPI) to form largely homogeneous technology groups. This classification aggregates the IPC classes to 30 technological classes (OECD 1994) such as "telecommunications", "optics", and "biotechnology".[11] Depending on the type of invention, patents can fall either within or across these 30 classes. Our analysis

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[10] See http://www.epo.org/patents/patent-information/ipc-reform/consequences.html (accessed August 22, 2008).

[11] The 30 technological areas comprise: Electrical devices / electrical engineering, audiovisual technology, telecommunications, information technology, semiconductors, optics, analysis / measurement / control, medical engineering, organic fine chemistry, macromolecular chemistry / polymers, pharmaceuticals / cosmetics, biotechnology, materials / metallurgy, agriculture / food, general technological processes, surfaces / coating, material processing, thermal processes and apparatus, chemical industry and petrol industry / basic materials chemistry, environment / pollution, machine tools, engines / pumps / turbines, mechanical elements, handling / printing, agricultural and food machinery and apparatus, transport, nuclear engineering, space technology / weapons, consumer goods and equipment, civil engineering / building / mining. For a list of the technological areas as well as the assignment of the IPC classes to these areas see Table A1 in the Appendix.

will make use of these 30 technological classes, which represent an extremely broad form of technological recombination and thus allow for a conservative empirical test of our hypotheses.[12]

.**Matching of Survey and Patent Data.** The survey data was merged with bibliographic and procedural information on the respective patents obtained from the EPOLINE and PATSTAT databases. We carefully identified, screened and assembled the complete patenting history of the surveyed inventors. To trace the patent applications of each inventor over time, the EPOLINE database was used to search for all patent applications belonging to the 3.049 inventors with priority dates between 1977 and 2003. The search procedure resulted in a total of 39.410 EP patent applications. Because we can assume that the technological breadth of the inventors' patents increases with her patenting output, we excluded inventors from the sample who are listed on less than three patent applications between 1977 and 2003.

4.2. Definition and Measurement of Variables

Dependent Variable

Technological Concentration*:* To develop our measure of technological concentration (breadth), we follow earlier studies which utilized the Herfindahl index to capture technological concentration (e.g., von Tunzelmann 1998). Specifically, given our focal interest in the inventor's technological concentration (breadth), we calculate the Herfindahl index on the patents generated by a particular inventor. For each inventor, the share of patent *j* in the technological area *i* is summarized over all patents per inventor and divided by the total number of technology areas per inventor. The Herfindahl index (HI) employed in our study is thus defined as:

$$HI = \sum_{i=1}^{30} \left(\frac{\sum_{j} share\ tech\ area_{ij}}{no.\ of\ \ tech\ areas_{total}} \right)^2$$

with $i = 1, \ldots, 30$ technological areas and $j = 1, \ldots, J$ patents, per inventor.

To get a more intuitive understanding of this index, Table 1 shows the calculation of index values for four types of inventors. We see that the smaller the index value, the higher the level of recombination

[12] In studying technological recombination with patent data, we follow earlier research and proxy technological component (areas) with patent classes (cf. Fleming 2001). Yet, like Fleming (2001) we do not want to suggest that inventors combine patent subclasses directly, only that these technological (sub-) classes can be used for an indirect observation of the process of recombinant search and learning.

across technological boundaries.

[[Please insert Table 1 about here]]

Other studies have used alternative measures of patent breadth (or scope), yet only as explanatory variables. Lerner (1994) proposed to use the number of different four-digit IPC classes listed on U.S. patent applications as a meausure of patent scope. Trajtenberg, Henderson and Jaffe (1997) proposed two measures for patent breadth relying on patent citations, that is, the Generality Index and the Originality Index. Yet, for a number of reasons these measures are not as well suited for the present study. First, compared to the four-digit count measure proposed by Lerner (1994), our measure is able to distinguish between patents that were classified into a number of IPC classes belonging to different technological areas and patents with IPC classes belonging to the same technological area. Our measure explicitly takes the technological concentration into account by employing the Herfindahl index. Second, both indexes proposed by Trajtenberg et al. (1997) are problematic in the context of European patent data, as, for instance, the Generality Index can only be calculated for patents with at least one citation (otherwise the index values are assumed to be zero). Yet, as EP patents receive fewer citations than U.S. patents[13], with a large proportion of EP patents receiving no citation at all, the index values would have to be set to zero for a large share of patents in our sample (48%).[14]

Independent Variables

Level of Education. We measure the inventor's level of education based on reported formal educational attainment (in terms of degrees received in the German schooling system). Dummy variables capture the highest educational degree received by the inventor: (1) secondary school, high school diploma, or vocational training, (2) university studies or vocational academy ("Berufsakademie"), and (3) doctoral or

[13] Average number of citations EP: 4.37; US: 12.96, cf. Michel and Bettels (2001).

[14] Both indices may work well for US patent data, since the applicant at the USPTO is required to submit a complete list of the existing state of the art. Not meeting this legal requirement can lead to a revocation of the patent application (Michel, Bettels 2001). At the EPO, on the contrary, examiners prepare the search report according to the "Guidelines for Examination in the European Patent Office" (see http://www.epo.org/patents/law/legal-texts/guidelines.html - accessed August 24, 2008). Examiners are required to select the most relevant documents to be included in the search report. The examiner should not cite more documents than necessary to avoid increasing costs (Part B, IV.3.1). We therefore prefer to operationalize our measure of technological breadth in terms of IPC classifications rather than citations.

postdoctoral studies.

Inventor Mobility. Following prior research on inventor mobility (e.g., Hoisl 2007), we created a dummy variable indicating whether an inventor had moved ("1"), or not ("0"). A move is defined as a change of the employer. The classification of "move" (the inventor changed the employer) and "no move" (the inventor did not change the employer) was done manually on the basis of the applicants listed on the EP documents.[15]

Knowledge Sources. Inventors can utilize a variety of knowledge sources in R&D (Arundel et al. 1995; Klevorick et al. 1995). As discussed, our study focuses on five frequently used sources of knowledge in inventive activities, that is, university laboratories, the scientific literature, existing patents, users, and competitors. Following earlier studies (e.g., Leiponen and Helfat 2003), a five-point Likert-type scale was employed to measure the importance of different sources of knowledge for the development of an invention ("absolutely not important" to "very important"). A dummy variable was created for each source of knowledge, combining categories 1 (absolutely not important) to 3 (partly important) as well as categories 4 (important) and 5 (very important), with the latter implying the use of the respective knowledge source by the inventor.[16]

Concentration of Knowledge Sources. A Herfindahl index indicates whether the use of knowledge sources by an inventor is concentrated to a small number of sources, or is rather diversified. For each inventor, we first calculated the number of used knowledge sources divided by the total number of knowledge sources. We then calculated the Herfindahl index, which corresponds to the sum of squared shares of knowledge sources. For example, if an inventor uses only one source of knowledge (e.g., other patents) the concentration of knowledge sources is at its maximum and equals 1.

Inventor Team Size. The size of the inventor team, i.e., it contains the number of inventors listed in the patent application (Gambardella et al. 2006).

[15] Research on inventor mobility frequently assumes that the applicant is also the employer (e.g., Rosenkopf and Almeida 2003) In our survey, we asked inventors whether the applicant listed on the patent document was also their employer. Results of this survey question showed that 92% of all respondents were employed with the applicant of the respective patent. Thus, the assumption that the applicant is also the employer should not lead to any significant bias in our analysis.

[16] Results are robust for different specifications of this variable. For example, we also created a dummy variable that combined answers '2' to '5' in one category. Results remained robust, with one additional variable (users as a knowledge source) showing a significant effect in the hypothesized direction (negative association).

Controls.

Years of Work Experience. This variable captures the number of years of the inventor's work experience in 1999. As the start of inventive productivity typically varies with the level of the education (i.e., inventors with a higher level of education start inventing at later age (Jones 2007)), the years of work experience equals the age of the inventor in 1999 minus the number of years τ spent on education, where τ is 20 in case the inventor attained a high school diploma (or less), $\tau = 25$ in case of university studies, and $\tau = 30$ in case of doctoral / postdoctoral studies. Information on the inventor's age was obtained from the questionnaire.

Temporal Concentration: This variable controls for temporal effects, i.e., it captures whether an inventor kept on inventing constantly during his inventive life or whether he carried out his inventions within a short period of time. We employ an index that was calculated as follows:

$$TEMP_{CON} = \frac{number\ of\ applications_{t\,(\max)}}{number\ of\ applications}$$

where t(max) is the application year, in which the inventor holds the maximum number of applications. In case the inventor's applications are all applied for in the same priority year, the index is at its maximum, and equals 1.

Number of Patents per Inventor. This variable includes the total number of patent applications per inventor.

Classification Authority: We also control for artifacts of the patent system in which the patent was classified into subclasses. These variables were received from the PATSTAT database of the European Patent Office and indicate which classification authority classified the invention. We created three dummy variables to distinguish between patents classified by the EPO, the JPO, or any other classification authority. Before 1988, the JPO required patent applications to be limited to a single claim resulting in an inflation of narrow patent applications. Since 1988, the JPO has allowed multiple claim applications in order to reduce the workload of the examiners. Nevertheless, Japanese patent officers still favor narrow patent applications containing only a small number of claims (Kotabe 1992; Rutchik 1995). Patent applications classified at the JPO could thus be characterized by a higher technical concentration.

Average Number of Claims: Patent claims define the scope of an invention for which patent protection is requested. This variable measures the average number of claims an inventor is requesting for his patents.

Average Number of Citations (5 years): The variable contains the average number of citations a patent application of an inventor received within 5 years following the publication of the search report. This variable was obtained from the citation database established within the Patent Citation Project 2007 (Harhoff 2007).

Share of References: This variable includes the number of X, Y or A type references[17] each divided by the total number of references listed in the search report. The share of patent references provides information about the novelty and the inventive step of the invention for which a patent was filed (Harhoff/Reitzig 2004).

PCT Application: A dummy variable is factored into the value regression, which takes the value 1 in case a PCT application has been filed for the patent. A PCT application is assumed to be positively related with the value of a patent.

Average Technological Concentration Employer. Some firms operate using a broader range of knowledge than other firms, i.e. firms differ in their technological diversity (cf. Pavitt, Robson, and Townshend 1989). To calculate a concentration index for each employer, we searched for the patent portfolio of each applicant (again assuming that the applicant of the patent is also the current employer of the inventor). Then we again calculated Herfindahl indices for each applicant patent portfolio. The entropy index per inventor was defined as the sum of the applicant Herfindahl indices over the total number of patents per inventor divided by the total number of patents per inventor. Thus, the index also takes into account that the inventors changed their employers.

Firm Size. Research frequently indicates systematic differences in research conducted by small and by large firms (e.g., Nelson 1959). To parcel out this type of variation in our data, we followed prior studies (e.g., Rosenkopf and Almeida 2003) and controlled for the size of the employer. Information on firm size – operationalized as the number of employees – was obtained from the survey instrument and utilized in the form of eight dummy variables (from "< 50 employees" to "> 50,000 employees").

Technological Areas: Because the underlying state of technology in part determines the potential for

[17] References listed in the search report at the EPO are classified as to their contribution to the search process. A type references, e.g., refer to documents defining the general state of the art, X-type references are particularly relevant documents when taken alone (a claimed invention cannot be considered novel or cannot be considered to involve an inventive step), and Y type references are particularly relevant if combined with another document of the same category (Harhoff et al. 2008).

technological innovation (Klevorick et al. 1995) and because different technological areas show different propensities to patent inventions, we control for this variation in our data by assigning each inventor the technological area to which most of his applications belong. In case an inventor shows equal activity in more than one technological area within the time period under consideration, one of the areas was selected at random.

4.3. Methods

To test our hypotheses, we use an OLS regression model (1) to estimate the determinants of the technical concentration of the inventors. The model will be estimated at the inventor level and the estimator employs heteroskedasticity-robust standard errors. In particular, the technical concentration of an inventor is modeled as a function of the following explanatory variables:

$$\begin{aligned} HI\_techcon &= \chi_0 + \sum_k \chi_{1k} \cdot d\_educ_k + \chi_2 \cdot d\_mobility + \sum_q \chi_{3q} \cdot d\_knowsource_q + \chi_4 \cdot teamsize \\ &+ \sum_h \chi_{5h} \cdot controls_h + \omega \end{aligned} \tag{1}$$

The control variables included in model (1) comprise the work experience of the inventors, the temporal concentration of their patents, the number of patents per inventor, the classification authority, the average number of claims per inventor, the average number of citations (5 years), the technical concentration of the employer, the size of the employer as well as dummies for the technical areas in which the inventors are active.

5. Results

5.1. Descriptive Statistics

The descriptive statistics and the correlation matrix are reported in Table 2. Correlations are relatively low, indicating that collinearity should not be a concern. To give some more intuition on the Herfindahl measure of an inventor's technological breadth, Table 3 lists the top 15 inventors in our sample, their respective Herfindahl indexes, and some additional information. This table already offers some interesting insights into the characteristics of inventors who recombine knowledge across technological boundaries. In particular, we see that technical breadth is not necessarily related to the quantitative output of inventors, as some inventors with a high technological breadth have relatively few patents. Moreover, it seems that the inventors' educational attainment plays a critical role in technological recombination, as 10 out of 15 inventors have attained a post-doctoral degree, whereas their age seems to be secondary. Finally, these inventors are spread out over a variety of different technological classes and industries.

[[Please insert Tables 2 and 3 about here]]

5.2. Multivariate Results

To test our hypotheses, we have estimated a set of OLS regression models predicting inventor technological concentration (Table 4). In a hierarchical analysis, Model 1 estimates a baseline model of controls only, Model 2 adds the educational level variables, Model 3 adds the variable capturing inventor mobility, and Models 4a and 4b investigate the effect of the inventor's knowledge sources. Finally, Model 5a and 5b add the linear and squared terms of inventor team size.

[[Please insert Table 4 about here]]

Hypothesis 1 proposed a positive association between an inventor's education level and the technological breadth of her inventions. Even with a number of strong control variables in place and utilizing a fairly conservative (because broad) definition of technology classes, the dummy variable 'doctoral/postdoctoral studies' indicates a negative and significant effect on an inventor's technological concentration, whereas we find no effect for university studies (Model 2). We thus claim support for H1.

Hypothesis 2 argued that inventor mobility has a positive association with the breadth of an inventor's technological inventions. In keeping with this hypothesis, the coefficient in Model 3 of Table 4 is statistically significant and negative.

Models 4a and 4b of Table 4 investigate the role of knowledge sources used in research. In this vein, Hypothesis 3 suggested a positive association between the diversity of knowledge sources used and technological breadth of the inventions. As Model 4a indicates a negative and significant coefficient of the variable 'Concentration of Knowledge Sources" we claim support for H3. Model 4b substitutes this more general measure of knowledge sourcing with five specific variables capturing the knowledge sourced from university laboratories, the scientific literature, existing patents, users and competing firms. As the coefficient estimates of the respective variables indicate, we find support for three hypotheses, namely knowledge sourced from university laboratories (H4a) and the scientific literature (H4b) significantly increasing the technological breadth of an inventor, and knowledge sourced from competing firms (H4e) significantly decreasing the technological breadth of an inventor.

Finally, Hypothesis 5 argued that there is an inverse U-shaped association between inventor team size and the technological breadth of an inventor's inventions (Models 5a and 5b). We find support for this hypothesis in Model 5a as both the linear and the quadratic term of team size are significant; yet, once we substitute the more general measure capturing the concentration of knowledge sources with the five specific variables capturing different types of knowledge sources (Model 5b), the quadratic term is insignificant. Overall, we thus only find weak support for an inverse-U shaped association (H5).

Looking at the controls, we note that the temporal concentration of inventive activity has a significant association with an inventor's technological breadth. As one might expect, the average technological concentration of the employer also has a significant effect, and a relatively large effect size. Coupled with the observation that the breadth of inventor's technological is significantly associated with firm size (i.e., the larger the firm as measured by the number of employees, the less technologically concentrated an inventor), this indicates that a firm's scope and scale are both significantly associated with the breadth of the inventor's technological inventions. We conclude that large firms offer a *less* advantageous environment for distant search than smaller corporations. The invention environment in a large firm appears to favor concentration, possibly at the expense of losing valuable activities of distant search at the individual level. Large firms may be able to set up a large number of highly focused and concentrated search processes. But without distant search activities generating high technological breadth at the level of individual invention processes, the overall outcome may be one of excessive specialization.

6. Discussion

We began this paper by noting the importance of distant searches and knowledge recombination for achieving a sustainable competitive advantage (March 1991, Levinthal 1995). While most prior research has investigated organizational-level mechanisms facilitating knowledge recombination across technological boundaries, the present research sought to take a micro-level perspective by examining whether differences across the human capital endowments of inventors, their knowledge sourcing routines, and their teams, are associated with differential ability to recombine knowledge either within or across technological domains. Drawing from two complementary data sources (patent data matched with survey data) our analysis has produced several interesting results. First, and most generally, we find that – even with numerous control variables in place to account for factors that might affect the breadth of an inventor's technological innovations and with a highly conservative (because broad) dependent measure – the individual human capital endowments of inventors, their knowledge sourcing practices, and their inventive team have a significant association with knowledge recombination across technological boundaries. Second, our results show that particular human capital endowments of inventors (educational level and mobility) are significantly related to knowledge recombination, and so are their knowledge sourcing practices. It is also important to realize that some knowledge sources tend to constrain inventive behavior, while others provide inspiration and insights that facilitate knowledge recombination across boundaries. Third, we find that the size of the inventive team has an inverse-U shaped relationship with technological breadth, albeit this hypothesis was only weakly supported by our data. Thus, although one would like to think that more human capital (i.e., more team members) is better for inventive activities, there are some limits to this notion as "less is more" in technological recombination when team size becomes too large.

Developing an improved understanding of these micro-level factors associated with technological knowledge recombination is not only key for advancing the literature on innovation and learning, but also provides several novel insights for research on inventors and their abilities.

6.1. Implications

Most generally, our analysis indicates that we need to look beyond the organizational-level mechanisms investigated in the existing literature in order to arrive at a more complete understanding of technological recombination as a means to achieve sustainable competitive advantage. While extent research on inventor mobility provides initial evidence suggesting that human capital matters in technological recombination, a more detailed analysis of inventors has been lacking so far. As we identify systematic differences between inventors who recombine knowledge across technological boundaries and those who recombine knowledge in a more constrained manner, our findings indicate that a theory of organizational search and knowledge recombination needs to account for the abilities of the focal agent engaging in a search of the technological landscape. To date, however, many of the studies on technological search model the firm as the focal agent, and thus implicitly assume homogeneity in the ability of the inventors to recombine knowledge across technological boundaries.

Our results also contribute to research on inventors and, in particular, advance our understanding of the influential sub-group of 'star scientists'. Back in 1926, Lotka analyzed the distribution of productivity among scientists by examining the number of name entries appearing in the decennial index of Chemical Abstracts between 1907 and 1916, and the names appearing in the index of Auerbach's "Geschichtstafeln der Physik" (Lotka 1926, p. 317). Several authors have applied Lotka's insights to the study of patents. For example, Narin and Breitzman (1995) examined inventors in four semiconductor firms, and Zucker and Darby (1996) investigated star scientists in the biotechnology industry. Notably, all of these studies aim at identifying "productive" researchers (scientists or engineers) by using quantitative output measures (patent or publication counts). More recently, a few studies have used citation-weighted patent counts to control for the quality of the output (e.g., Ernst et al. 2000). Nevertheless, the findings presented in this paper reveal that inventors characterized by technological breadth are neither the inventors (a) holding the largest number of patents nor (b) the highest number of citations. On the contrary, patent counts as well as average citation counts do not even show a significant effect in our multivariate analysis (Table 4); in other words, our " Jacks of all Technologies" would have gone unnoticed, despite their impressive track record in knowledge recombination across technological boundaries. Thus, another important contribution of this paper is to point out that there may be different kinds of outstanding inventors, and that researchers need to develop a more nuanced understanding of what constitutes a star inventor as this notion is highly dependent on what a firm tries to achieve with its R&D efforts.

6.2. Limitations

In interpreting the results of this study, certain limitations must be kept in mind. First, like a growing number of studies on learning and innovation, our study is based on patent data, which provides an incomplete coverage of innovative activity, as not all outcomes of R&D processes are patented or patentable (Cohen et al. 2000). Second, it has already been pointed out that the technological classification of the EPO provides a better measure of technological breadth than the technological classification of the US patent system, because the IPC classes listed on EP patents reflect the technology described in the complete patent document, whereas the US classification is based on information given in the patent claims only. Yet, employing IPC classes to measure the technological breadth of inventors still has some limitations. In particular, technological recombination may be easier with some patent classes than with others, as different pairs of IPC classes are usually not separated by the same technological distance; for instance, IPC classes in the fields of chemistry and biology are closer than those in chemistry and mechanics. We sought to limit this influence by deciding for a conservative measure of technological concentration at the level of 30 broad technological fields, and against finer grained levels such as the 7-digit level of the IPC. Additionally, we note that our results may be biased towards chemicals and pharmaceuticals, since IPC classes and sub-classes are most differentiated in these technological fields. Thus, although we control for the technological field(s) in which the inventors are mostly active, we cannot fully rule out that technological breadth is biased towards fields with higher patenting propensity.

6.3. Conclusion and Outlook on Future Research

This study has produced a number of new insights on inventors, inventive activities and knowledge recombination across technological domains. Several interesting opportunities for future research are suggested by our findings. In particular, we encourage researchers to delve deeper into the knowledge recombination process by exploring how technological recombination across boundaries is actually accomplished by inventors (e.g, using ethnography). While our results point to some knowledge sourcing activities that facilitate such knowledge recombination, the inventive process is a multifaceted endeavor that can hardly be captured in all its nuances through large-scale empirical research. Furthermore, given that the inventor's educational attainment plays a key role in knowledge recombination, future research could look more closely at different types of study areas, and examine whether some areas or combinations of areas are particularly helpful in facilitating recombination across boundaries. Finally, future studies may also develop a better understanding of how the commercialization of patents that recombine knowledge across technological boundaries differs from the commercialization of narrower patents. In this regard, earlier studies on technology entrepreneurship and patenting behavior indicate that patent characteristics are an important determinant of start-up creation (Shane 2001).

The results presented in this paper can be viewed as an important step in uncovering the micro-foundations of technological knowledge recombination across boundaries. We hope that our findings provide future studies critical information on the trail to a multi-level theory of technological search.

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TABLES

Table 1 Examples: Inventors' patenting activity and corresponding Herfindahl Index values

<table>
<tr><th></th><th></th><th>Area 1</th><th>Area 2</th><th>Calculation of the Index</th></tr>
<tr><td rowspan="3">Inventor 1</td><td>Patent 1</td><td>●</td><td>●</td><td rowspan="3">$HI_{I1} = \left(\frac{0.5+1}{4}\right)^2 + \left(\frac{0.5+1}{4}\right)^2 = 0.28$</td></tr>
<tr><td>Patent 2</td><td>●</td><td></td></tr>
<tr><td>Patent 3</td><td></td><td>●</td></tr>
<tr><td rowspan="3">Inventor 2</td><td>Patent 1</td><td>●</td><td></td><td rowspan="3">$HI_{I2} = \left(\frac{1+1}{3}\right)^2 + \left(\frac{1}{3}\right)^2 = 0.55$</td></tr>
<tr><td>Patent 2</td><td>●</td><td></td></tr>
<tr><td>Patent 3</td><td></td><td>●</td></tr>
<tr><td rowspan="3">Inventor 3</td><td>Patent 1</td><td>●</td><td></td><td rowspan="3">$HI_{I3} = \left(\frac{3}{3}\right)^2 = 1$</td></tr>
<tr><td>Patent 2</td><td>●</td><td></td></tr>
<tr><td>Patent 3</td><td>●</td><td></td></tr>
<tr><td rowspan="3">Inventor 4</td><td>Patent 1</td><td>●</td><td>●</td><td rowspan="3">$HI_{I4} = \left(\frac{0.5*3}{6}\right)^2 + \left(\frac{0.5*3}{6}\right)^2 = 0.13$</td></tr>
<tr><td>Patent 2</td><td>●</td><td>●</td></tr>
<tr><td>Patent 3</td><td>●</td><td>●</td></tr>
</table>

Table 2 Descriptive statistics and correlation matrix

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	Technical Concentration	0.59	0.25	1																					
2	High School Diploma or less	0.11		0.09	1																				
3	University Studies	0.51		0.12	-0.35	1																			
4	(Post-) Doctoral Studies	0.39		-0.18	-0.28	-0.80	1																		
5	KnowSource - Universities	0.23		-0.11	-0.12	-0.11	0.18	1																	
6	KnowSource - Literature	0.64		-0.16	-0.16	-0.16	0.26	0.31	1																
7	KnowSource - Patents	0.68		-0.05	-0.14	-0.12	0.21	0.13	0.35	1															
8	KnowSource - Users	0.73		0.00	0.01	0.09	-0.10	0.04	0.05	0.18	1														
9	KnowSource - Competitors	0.58		0.04	-0.02	0.02	-0.01	0.09	0.14	0.36	0.31	1													
10	Concentration KnowSource	0.07	0.11	0.14	0.01	0.09	-0.10	0.15	0.16	0.14	0.19	0.19	1												
11	Inventor Mobility	0.37		-0.13	-0.05	-0.02	0.05	0.04	0.06	0.01	-0.01	0.004	-0.09	1											
12	Inventor Team Size	3.05	1.35	-0.16	-0.15	-0.25	0.35	0.11	0.21	0.17	-0.07	0.05	-0.07	-0.005	1										
13	Years of Work Experience	23.65	10.63	0.01	0.34	0.10	-0.32	-0.11	-0.11	-0.09	0.01	-0.06	-0.04	0.06	-0.23	1									
14	Temporal Concentration	0.33	0.16	0.20	0.05	0.07	-0.11	0.01	-0.06	-0.10	0.03	-0.02	0.44	-0.12	-0.04	-0.14	1								
15	No. of Patents per Inventor	16.16	21.86	-0.11	-0.08	-0.18	0.23	0.03	0.12	0.15	-0.05	0.06	-0.34	0.03	0.25	0.01	-0.39	1							
16	Class. Authority EPO	0.89	0.12	0.06	0.07	0.14	-0.19	-0.04	-0.09	-0.06	0.06	-0.03	-0.01	-0.04	-0.18	0.07	-0.04	-0.05	1						
17	Class. Authority JPO	0.07	0.11	-0.07	-0.08	-0.14	0.20	0.02	0.08	0.06	-0.07	0.01	-0.02	0.04	0.18	-0.10	0.04	0.06	-0.83	1					
18	Class. Authority OTHER	0.04	0.07	-0.01	0.00	-0.04	0.04	0.03	0.05	0.01	-0.01	0.03	0.05	0.004	0.05	0.03	0.02	0.01	-0.52	-0.05	1				
19	Av. No. of Claims	10.98	4.65	-0.04	-0.01	0.01	-0.01	0.06	0.02	0.01	0.05	0.02	0.01	0.07	0.03	-0.08	0.06	-0.04	0.05	-0.05	-0.01	1			
20	Av. No. of Citations (5yrs)	1.04	0.78	-0.08	-0.07	-0.18	0.23	0.02	0.11	0.11	-0.03	0.03	-0.10	0.04	0.30	-0.13	-0.08	0.16	-0.13	0.15	0.001	0.13	1		
21	Av. Tech. Concentration Employer	0.33	0.22	0.40	0.19	0.16	-0.29	-0.05	-0.16	-0.05	0.10	0.06	0.11	-0.02	-0.29	0.13	0.10	-0.13	0.16	-0.14	-0.07	0.13	-0.16	1	
22	Av. Size of the Employer	50926	93309	-0.02	-0.10	-0.05	0.12	0.05	0.05	-0.05	-0.07	0.01	-0.05	-0.04	0.09	-0.10	-0.0004	0.06	-0.05	0.04	0.02	-0.11	0.05	-0.38	1

Pearson correlation coefficients (for two continuous variables) / Point biserial coefficient (for one continuous variable and one dummy variable) / Phi coefficient (for two dummy variables) (N = 2,216)

Table 3 Examples of inventors and their technical concentration

Rank	Technological concen-tration	Age in 1999	# of applica-tions	Average # of citations received	Highest level of education	Field of university education	# of technological areas	Main technological areas (% of patents in the respective area)	First priority	Last priority
1	0.116	60	28	1.07	(Post-)doctoral studies	Electrical engineering	14	Optics (20%), Space Technology & Weapons (19%)	1982	2001
2	0.141	45	9	1.44	(Post-)doctoral studies	Mechanical Engineering	8	Agric. & Food Machinery (26%), Constr. Techn. (15%), Analysis, Measurement & Control Techn. (15%)	1992	1999
3	0.141	52	15	1.07	(Post-)doctoral studies	Physics	12	Surfaces, Coating (21%), Optics (18%)	1983	2002
4	0.142	56	20	0.95	University studies	Mechanical Engineering	14	Medical Engineering (18%), General Techn. Processes (27%)	1977	2002
5	0.146	46	10	1.20	(Post-)doctoral studies	Chemistry & Bio-chemistry	10	Agric. & Food (27%), Pharmaceuticals & Cosmetics (18%)	1990	1997
6	0.147	38	13	0.85	University studies	Physics	11	Electrical Engineering (24%), Semiconductors (20%)	1991	2001
7	0.148	42	4	1.50	(Post-)doctoral studies	Physics	8	Analysis, Measurement & Control Techn. (37%), Biotechnology (18%)	1988	1997
8	0.152	51	43	2.16	(Post-)doctoral studies	Chemistry	9	Organic Chem. (26%), Agric. & Food (17%)	1985	2002
9	0.156	40	40	0.78	University studies	Physics	11	Therm. Processes (32%), Optics (27%)	1990	2003
10	0.157	63	36	1.81	(Post-)doctoral studies	Physical Chemistry	10	Analysis, Measurement & Control Techn. (29%), Petrol & Materials Chem. (24%)	1979	2001
11	0.159	61	27	1.93	University studies	Electrical Engineering	12	Telecom (35%), Electrical Engineering (23%)	1978	1998
12	0.162	37	9	0.22	University studies	Physical Technology	9	Electrical Engineering (32%), Telecom (21%)	1993	2003
13	0.167	38	22	0.55	(Post-)doctoral studies	Chemistry	11	Organic Chem. (17%), Polymers (14%)	1994	2003
14	0.167	43	20	0.90	(Post-)doctoral studies	Physical Chemistry	8	Civil Engineering (30%), Materials (19%), Petrol & Materials Chem. (17%)	1989	1998
15	0.167	46	43	1.21	(Post-)doctoral studies	Chemistry	13	Audiovisual (27%), Petrol & Materials Chem. (25%)	1983	2002

Table 4 Multivariate analysis of technological breadth

Variable	Model 1 Coeff. (S.E.)	Model 2 Coeff. (S.E.)	Model 3 Coeff. (S.E.)	Model 4a Coeff. (S.E.)	Model 4b Coeff. (S.E.)	Model 5a Coeff. (S.E.)	Model 5b Coeff. (S.E.)
Level of Education (reference group: high school diploma or less)							
University studies (0/1)	#	-0.008	-0.003	-0.005	0.005	-0.005	0.004
		(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Doctoral/postdoctoral studies (0/1)	#	-0.041**	-0.036*	-0.037**	-0.02	-0.035*	-0.019
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Inventor Mobility (0/1)	#	#	-0.041***	-0.040***	-0.040***	-0.040***	-0.039***
			(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Knowledge Sources							
Concentration of Knowledge Sources	#	#	#	0.094**	#	0.098**	#
				(0.048)		(0.048)	
University Laboratories (0/1)	#	#	#	#	-0.029**	#	-0.028**
					(0.011)		(0.011)
Scientific Literature (0/1)	#	#	#	#	-0.042***	#	-0.040***
					(0.011)		(0.011)
Existing Patents (0/1)	#	#	#	#	0.005	#	0.006
					(0.012)		(0.012)
Users (0/1)	#	#	#	#	-0.017	#	-0.017
					(0.011)		(0.011)
Competiting Firms (0/1)	#	#	#	#	0.022**	#	0.022**
					(0.010)		(0.010)
Inventor Team							
Average Team Size	#	#	#	#	#	-0.032***	-0.027**
						(0.012)	(0.012)
Average Team Size (squared)	#	#	#	#	#	0.003*	0.002
						(0.001)	(0.001)
Control Variables							
Years of Work Experience	-0.0001	-0.001	-0.0004	-0.0004	-0.0003	-0.001	-0.0005
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temporal Concentration	0.260***	0.256***	0.239***	0.217***	0.243***	0.218***	0.245***
	(0.032)	(0.032)	(0.032)	(0.035)	(0.032)	(0.035)	(0.032)
Number of Patents per Inventor	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	-0.0001	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Classification Authority EPO (share)	-0.055	-0.058	-0.055	-0.054	-0.064	-0.06	-0.069
	(0.070)	(0.070)	(0.071)	(0.070)	(0.071)	(0.071)	(0.071)
Classification Authority JPO (share)	-0.134	-0.131	-0.118	-0.118	-0.137	-0.117	-0.137
	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
Average Number of Claims	-0.004***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Number of Citations (5yrs)	-0.001	0.001	0.001	0.002	0.001	0.004	0.003
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Average Techn. Concentration Employer	0.511***	0.505***	0.502***	0.499***	0.496***	0.493***	0.491***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Average Firm Size (reference group: < 51 Employees)							
51 - 250 Employees	0.002	-0.002	-0.003	-0.005	-0.006	-0.004	-0.005
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
251 - 500 Employees	0.041	0.036	0.031	0.031	0.028	0.038	0.033
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
501 - 1,500 Employees	0.050*	0.045*	0.041	0.042	0.033	0.054*	0.043
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)
1,501 - 5,000 Employees	0.091***	0.085***	0.075***	0.077***	0.071***	0.088***	0.081***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
5,001 - 10,000 Employees	0.070**	0.068**	0.061**	0.063**	0.059**	0.076***	0.070**
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
10,001 - 50,000 Employees	0.088***	0.086***	0.076***	0.076***	0.072***	0.092***	0.085***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)
> 50,000 employees	0.110***	0.108***	0.098***	0.099***	0.094***	0.115***	0.107***
	(0.028)	(0.028)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)
30 Technological Area Dummies (Wald test)	Chi2(29)= 3.46 p=0.000	Chi2(29)= 3.41 p=0.000	Chi2(29)= 3.33 p=0.000	Chi2(29)= 3.54 p=0.000	Chi2(29)= 3.30 p=0.000	Chi2(29)= 3.51 p=0.000	Chi2(29)= 3.29 p=0.000
Constant	0.420***	0.462***	0.482***	0.479***	0.522***	0.544***	0.576***
	(0.085)	(0.087)	(0.088)	(0.088)	(0.089)	(0.090)	(0.090)
Observations	2,216	2,216	2,216	2,216	2,216	2,216	2,216
R-squared	0.254	0.257	0.262	0.264	0.274	0.268	0.277

OLS regression model with heteroskedasticity-robust standard errors
* significant at 10%; ** significant at 5%; *** significant at 1%; # = not included

APPENDIX

Table A1: OST/INPI/ISI Classificatin of Technology Areas and Subareas (updated October 11th 2000)

I.	**Electrical engineering**	**IPC Classification**
1.	Electrical machinery and apparatus, electrical energy	F21; G05F; H01B, C, F, G, H, J, K, M, R, T; H02; H05B,C,F,K
2.	Audio-visual technology	G09F,G; G11B; H03F,G,J; H04N-003,-005,-009,-013,-015, -017,R,S
3.	Telecommunications	G08C; H01P,Q; H03B,C,D,H,K,L,M; H04B,H,J,K,L,M, N-001-007,-0
4.	Information technology	G06; G11C; G10L
5.	Semiconductors	H01L, B81
II.	**Instruments**	
6.	Optics	G02; G03B,C,D,F,G,H; H01S
7.	Analysis, measurement, control technology	G01B,C,D,F,G,H,J,K,L,M,N, P,R,S,V, W; G04; G05B,D; G07; G08B,G; G09B,C,D; G12
8.	Medical technology	A61B,C,D,F,G,H,J,L,M,N
9.	Nuclear engineering	G01T; G21; H05G,H
III.	Chemistry, pharmaceuticals	
10.	Organic fine chemistry	C07C,D,F,H,J,K
11.	Macromolecular chemistry, polymers	C08B,F,G,H,K,L; C09D,J
12.	Pharmaceuticals, cosmetics	A61K, A61P
13.	Biotechnology	C07G; C12M,N,P,Q,R,S
14.	Agriculture, food chemistry	A01H; A21D; A23B,C,D,F,G,J,K, L; C12C,F,G,H,J; C13D,F,J,K
15.	Chemical and petrol industry, basic materials chemistry	A01N; C05; C07B; C08C; C09B,C,F, G,H,K; C10B, G,H,J,K,L,M; C11B,C,D C,F,
16.	Surface technology, coating	B05C,D; B32; C23; C25; C30
17.	Materials, metallurgy	C01; C03C; C04; C21; C22; B22, B82
IV	**Process engineering, special equipment**	
18.	Chemical engineering	B01B,D (without -046 to -053), F,J,L;B02C; B03; B04; B05B; B06; B07; B08; F25J; F26
19.	Materials processing, textiles, paper	B29; B31; C03B; C08J; C14; D01; D02; D03; D04B,C,G,H; D05; 06B,C,G,H,J,L,M,P,Q; D21
20.	Handling, printing	B25J; B41; B65B,C,D,F,G,H; B66; B67
21.	Agricultural and food processing, machinery and apparatus	A01B,C,D,F,G,J,K,L,M; A21B,C; A22; A23N,P; B02B; C12L; C13C,G,H
22.	Environmental technology	A62D; B01D-046 to -053; B09;C02; F01N; F23G,J
V.	**Mechanical engineering, machinery**	
23.	Machine tools	B21; B23; B24; B26D,F; B27; B30
24.	Engines, pumpes, turbines	F01B,C,D,K,L,M,P; F02; F03; F04; F23R
25.	Thermal processes and apparatus	F22; F23B,C,D,H,K,L,M,N,Q; F24; F25B,C; F27; F28
26.	Mechanical elements	F15; F16; F17; G05G
27.	Transport	B60; B61; B62; B63B,C,H,J; B64B,C,D,F
28.	Space technology, weapons	B63G; B64G; C06; F41; F42
VI.	**Consumption**	
29.	Consumer goods and equipment	A24; A41B,C,D,F,G; A42; A43B, C; A44; A45; A46B; A47; A62B,C; B25B,C,D,F,G,H; B26B; B42; B43; B44; B68; D04D; D06F,N; D07; l G10B,C,D,F,G,H,K
30.	Civil engineering, building, mining	E01;E02;E03;E04;E05;E06;E21