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Value of Software Innovations: The Influence of Social Capital

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VALUE OF SOFTWARE INNOVATIONS: THE INFLUENCE OF SOCIAL CAPITAL

Valeur des Innovations Logicielles : L'influence du Capital Social

Completed Research Paper

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Abstract

Technology and innovation are key drivers of economic growth and global competitiveness. However, technological (computer-implemented) innovations are extremely heterogeneous in value. In this study, we investigate the impact of social capital accrued by inventors from collaboration networks in which they are embedded on value of software innovation. Based on empirical analysis on software patents data collected from United States Patent and Trademark Office, we find that the quality of a team's external direct contacts significantly influence the value of innovation while the quality of indirect contacts on the other hand has no significant impact. In addition, teams that have access to diverse knowledge across multiple regions are more likely to produce valuable innovations. Our results suggest the importance for firms to understand interpersonal collaboration network of inventors across traditional firm and regional boundaries to implement effective hiring, improve team productivity and create valuable innovations.

Keywords: software innovation, social capital, team productivity, regional diversity

Résumé

Dans cette étude, nous étudions l'impact du capital social sur la valeur de l'innovation logicielle. Nous constatons que la qualité des contacts directs externes d'une équipe influence significativement la valeur de l'innovation tandis que, d'autre part, la qualité des contacts indirects n'a pas d'impact significatif. En outre, les équipes ayant accès aux diverses connaissances réparties sur plusieurs régions sont plus susceptibles de produire des innovations utiles.

1. Introduction

There has been considerable growth and development in the software industry, "whether measured by revenues or profitability, number of firms or employees, or research expenditures" (Allison et al. 2007, p.1579). Software innovations have not only brought extraordinary rewards to their innovators (Graham and Mowrey 2003) but also moved beyond firm boundaries to create solutions for a much broader range of industries, including manufacturing (Allison et al. 2007).

The software industry is a knowledge intensive industry and is characterized by high intangible assets, which means that the ownership of intellectual property can influence the returns to innovators' investments (Graham and Mowrey 2003). This correspondingly provides firms with incentive to patent their innovations. Prior research on software patents revealed a significant increase in firms' inclination to patent software over the last two decades and argued that software patents are highly valued by the market (Bessen and Hunt 2007). Figure 1 demonstrates the steep rise in the number of patents applied for and granted over the past 22 years. During the 1990s, the number of granted software patents increased by a factor of five, which is incomparable to any other field (Schankerman et al. 2006).
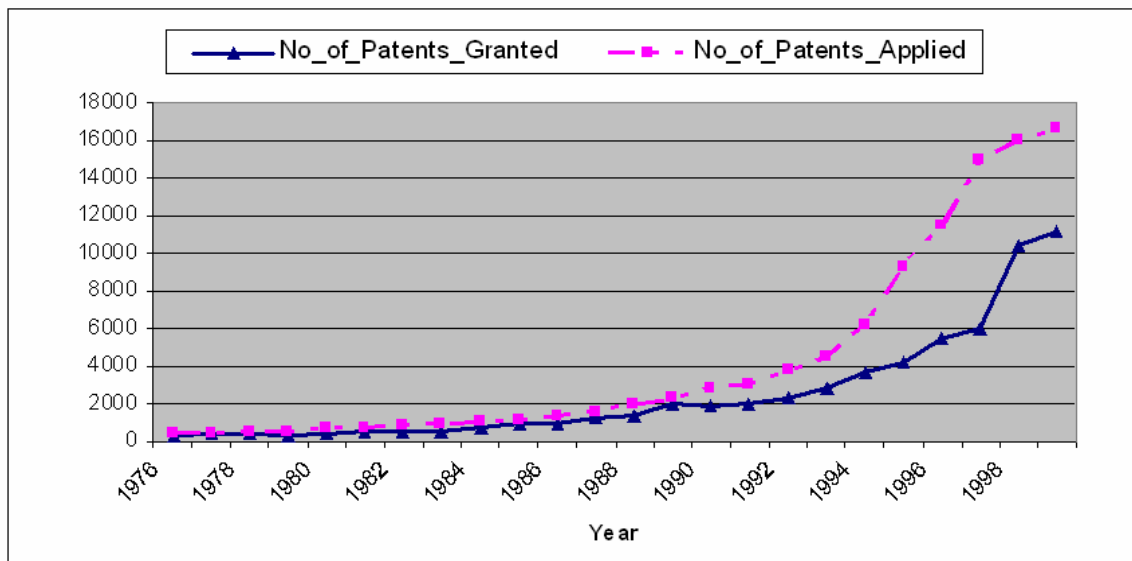

Figure 1. Trend in the Number of Software Patents Applied for and Granted Over Time

Software patents are more highly valued by the market than patents in other product categories, especially after 1990 (Hall and Macgarvie 2007). Stock of software patents was found to benefit software firms in cross-licensing negotiations (Mann and Thomas 2006), improve firm performance (Lerner and Zhu 2005), help internet companies survive the collapse of the dot-com bubble after 2001 (Cockburn and Wagner 2006), and correlate with indicators of market success (Merges 2006).

Although software innovations as a whole create value, not all innovations are equally valuable. Innovations exhibit an enormous variance in their "importance" or "value" (Trajtenberg 1990, Fleming 2007). While some innovations are radical innovations as they serve as basis for many subsequent technological developments, others are technological dead ends (Dosi 1988, Fleming 2001, Sahl 1985). Consistent with previous studies, our data suggest the same highly skewed distribution in the value of software innovations (see Figure 2) as measured by forward citations of patents (this measure is described in detail in Section 4.3).
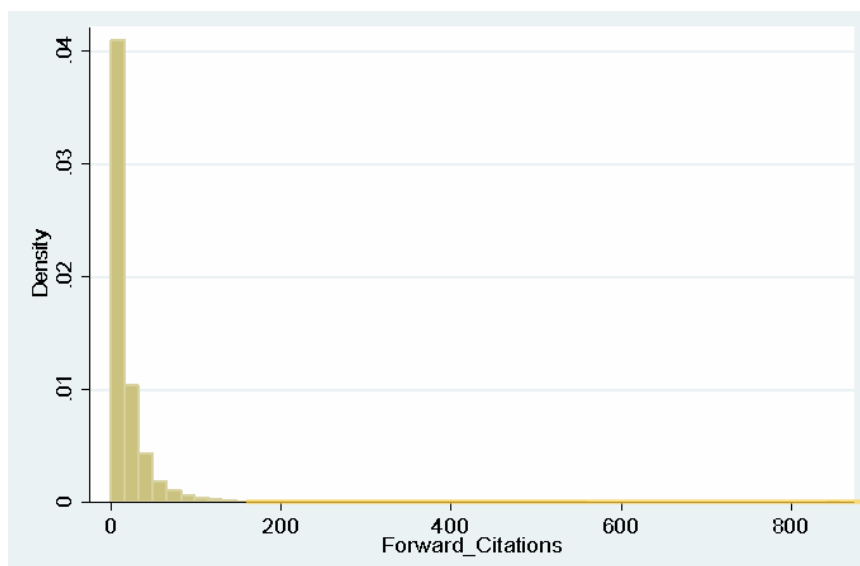
Figure 2: Highly Skewed Distribution in Value of Patents

While previous studies in software innovations have acknowledged the variance in value of software innovations (Hall and Macgarvie 2007), very little work has been done on what drives the variation. The research focus of these studies has been on explaining the increased propensity for firms to patent software (Graham and Mowery 2003, and Bessen and Hunt 2007), measuring the market value of software innovations (Hall and MacGarvie 2007), examining the effect of software patents on entry and exit (Allison et al. 2007), and studying the mobility of software inventors (Schankerman et al. 2006). Studies in the organization literature have attributed the creation of valuable innovations to firm characteristics, such as incumbent/entrant status (Cooper and Schende 1976, Foster 1986, and Ahuja et al. 2001) and alliance network among firms (Schilling and Phelps 2007, Ahuja 2000). However, the majority of these studies used simple patent counts as indicators of innovative output, which can not precisely capture the value of innovations given the extremely skewed distribution of innovation quality. In addition, none of these studies considered the direct influence of social capital accrued by inventors on value of innovations.

Innovation is typically a group effort (Fleming and Marx 2006). Inventors collaborate with one another to innovate, and many maintain contact with former collaborators after projects are finished. During this interpersonal relationship, knowledge can be transferred among collaborators (Singh 2005). Historically, innovators used to collaborate within a local cluster or within an organization. Correspondingly, this knowledge transfer was mostly delimited by regional or organizational boundaries. Recently, innovators have become increasingly mobile, moving from one firm or region to another. This increased mobility is particularly pronounced for software inventors compared to inventors in other product categories (Schankerman et al. 2006). As a result, small groups of inventors have begun to be linked into a larger mesh of networks through which information flows more freely across firms and regional boundaries. This interpersonal knowledge transfer through collaboration networks has received great attention in the sociology literature (Coleman et al. 1996, Granovetter 1973, Rogers 1995). Almeida and Kogut (1999) showed that the mobility of individuals can lead to knowledge diffusion across locations. Hansen (1999) further demonstrated that collaboration between inventors who have interpersonal ties across regions can improve knowledge flow within a firm. While this stream of research has stressed the importance of interpersonal collaboration networks to facilitate knowledge flow, it has not examined how this knowledge flow affects the quality of innovations.

Studies in social networks have examined the impact of interpersonal networks among inventors developed within an organization on team performance. Reagans and Zuckerman (2001) examined how a team's internal density and network heterogeneity (measured as the extent to which interaction on the team cuts across salient demographic categories) affects team productivity. Reagans et al. (2004) further found that teams with higher internal density and network range are more productive. None of these studies, however, have studied how the interpersonal collaboration network of inventors across firms influences the value of innovations. Given the increased mobility of software inventors across both regions and firms, across-firm interpersonal networks may have a greater impact on team performance. According to the organization learning literature, while internal knowledge (within an organization) helps an organization develop capabilities that are more likely to improve (short-term) performance

(Darr et al. 1995, Baum and Ingram 1998, Irwin and Klenow 1994), they may impede the organization's capability to produce innovations that hold the key to future performance (Levinthal and March 1993). To create valuable innovations, teams need to explore novel technologies (Ahuja et al. 2001) outside the firm boundaries. In this respect, an inter-firm collaboration network of innovators may provide a useful source of information for creating valuable innovations.

This study examines the relationship between the social capital and value of software innovation. While there are differences in definition of social capital, in this study we follow the structural definition of social capital defined by Portes (1998, p. 6) as "social capital stands for the ability of actors to secure benefits by virtue of membership in social networks or other social structures". We examine the impact of social capital accrued by a team of inventors from (both intra-firm and inter-firm) collaboration networks in which they are embedded on value of software innovations. We follow the literature to use historical collaboration data among individuals to infer interpersonal relationships (Fleming et al. 2007a, Singh 2005). Specifically, we use collaboration information for software patents registered with the United States Patent and Trademark Office (USPTO) to construct interpersonal collaboration networks. Our results suggest that the quality of a team's external direct contacts significantly influences the value of innovation, while the quality of indirect contacts, on the other hand, has no significant impact. In addition, teams that have access to diverse knowledge across multiple regions are more likely to produce valuable innovations. Our results highlight the importance for firms to understand interpersonal collaboration networks of inventors across traditional firm and regional boundaries to implement effective hiring practices, improve team productivity and create valuable innovations.

Our findings offer important contributions to the three aforementioned literature fields. First, our results contribute to the software innovations literature by examining the social capital components accrued by inventors to explain the massive variation behind the value of innovations. Second, our results contribute to the sociology literature by linking knowledge transfer facilitated through interpersonal collaboration networks with quantifiable measures on the value of innovation. Third, our results contribute to the social network literature by incorporating the impact of inter-firm collaboration networks of inventors on team performance. Recent studies in open source have investigated the effects of centrality (Grewal et al. 2006) and community-level network structure (Singh 2007b) on project success. Our study contributes to this stream of research in three ways. First, open source software development is based on the philosophy of sharing in that developers voluntarily share their knowledge and expertise (Singh et al. 2007), which is different from patented software innovation. Correspondingly, it is not clear whether the results on the impact of social networks found in these open source studies hold for proprietary software innovation. Knowledge sharing in the creation of patented software innovation depends largely on mobility of the inventors across regions and firms. Thus, the dynamics of knowledge sharing are also very different in open source software development versus in patented software innovation. Second, in this study, when we infer knowledge sharing through direct or indirect collaborations, we take into account the quality of the collaborators in addition to a simple count of the number of collaborators (which is used in most previous studies as a measure of direct and indirect ties). Third, these studies analyze the short term performance of open source projects, including CVS commits and project downloads, while innovations usually lead to long-term benefits, which may not be available to firms immediately.

2. Software Inventor Collaboration Network

Patents are non-obvious and important innovations by definition. Co-inventors of a patent work together as a team over an extended period of time and keep contacts with co-inventors even years after filing the patent (Singh 2005). Singh (2005) reported that there is significant information flow among patent co-authors, as suggested by the large number of citations among patents invented by former collaborators. Fleming et al. (2007a) found evidence from field interviews that patent collaborations capture personal and professional ties between inventors and that interactions continue even when they no longer work in the same organization. Schankerman et al. (2006) found that working as part of a large team of inventors expands the professional network of software inventors. Hence, we can infer that an inventor has ties with many inventors working on different patents. Thus a relationship exists between two software inventors if they have co-authored a patent. These relationships result in an affiliation network in which all the actors (here inventors) participating in the same event (like patents) form a fully linked clique, and the fully linked cliques are connected to each other when actors participate in multiple events (Wasserman and Faust 1994). Figure 3 illustrates the bipartite network of inventors and its unipartite projection.
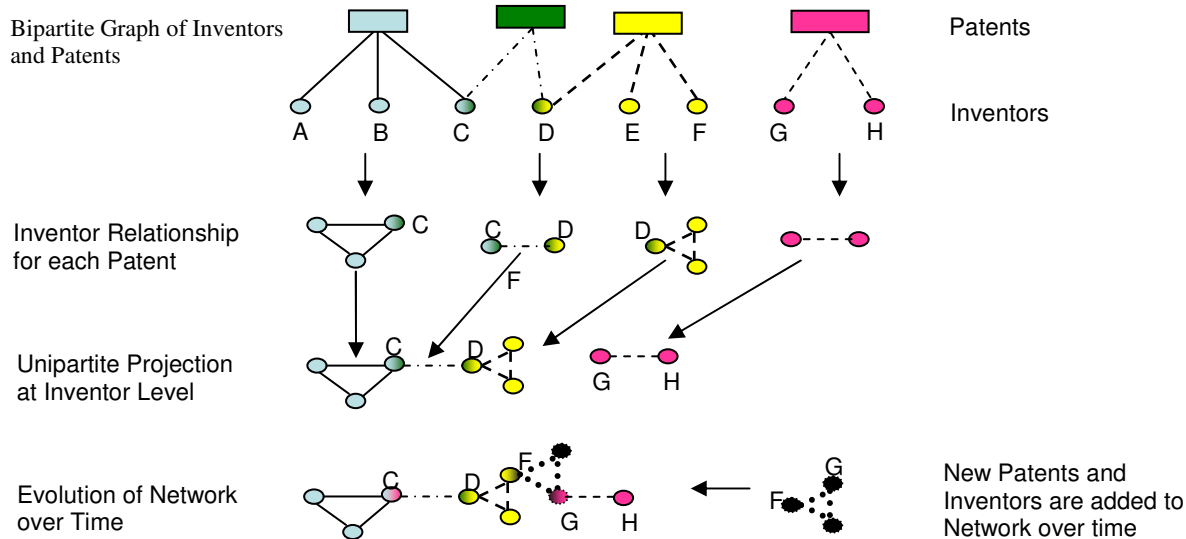
Figure 3. Software Inventor Collaboration Network

The top row represents four patents and seven inventors (A, B, C, D, E, F, G, and H). Co-authors of the same patent are members of fully linked cliques (e.g. ABC, CD, DEF and GH). Fully linked cliques are connected through inventors C and D, who work on multiple patents. The bottom row shows how these networks evolve over time as new patents are started.

3. Theories and Hypotheses

3.1. *Software Innovation*

Software innovation is an inherently uncertain creative problem-solving process, and solutions to these problems are found through search (Dossi 1988, Fleming 2001, Nuvolari 2005). Search processes that lead to the creation of new innovations are the result of recognizing, combining and recombining existing elements of knowledge (Fleming 2001, Henderson and Clark 1990). Every new innovation augments the existing set of knowledge elements that can be recombined in various ways to create further innovations (Fleming 2001). This is particularly true for software innovations, which are largely incremental (Cohen and Lemley 2001, Basili and Caldiera 1995, Boh et al. 2007). Most of the time, software innovations involve combining new coding with existing modules and subroutines rather than doing everything from scratch (Cohen and Lemley 2001). Thus, a significant amount of new software is developed through design improvements and use of existing knowledge in a new way. However, potential recombination of a given set of knowledge elements is limited (Ahuja et al. 2001, Fleming 2001). Hence, access to diverse recombinatory resources is critical for creating valuable software innovations. Thus, teams that have access to diverse knowledge will have a diverse pool to choose from and will be able to incorporate features from familiar but diverse material for creating valuable innovations (Dossi 1988, Fleming 2001). Creation of valuable innovations requires familiarity with a variety of knowledge elements, understanding of successful and failed approaches to novel problems and recognition of irrelevant knowledge (Hargadon and Faneli 2002). Inventors should also have awareness of where to search for complimentary expertise (Cohen and Laventhal 1990, Borgatti and Cross 2003). Interpersonal collaboration networks in which inventors are embedded are ideal sources for this kind of informal information (Singh 2007a). Inventors depend more on social sources than non-social sources for access to novel information. However, inventors are careful about seeking information from others, as asking for information or help from others can be costly (Borgatti and Cross 2003). Fleming et al. (2007a) found evidence from field interviews that patent co-authors are prime candidates for information. Thus, existing collaborative relationships among inventors become important, as they acquaint an inventor with the available resources and establish the boundary for the search.

3.2. Social Capital

"Social capital stands for the ability of actors to secure benefits by virtue of membership in social networks or other social structures," (Portes 1998, p. 6). Co-inventors of a patent work together as a team over an extended period of time and may have contacts with each other even years after filing the patent (Singh 2005). The inventors' past collaborators also share the knowledge and experience gained from working on other patents which do not involve inventors from the focal team (Gulati and Gargiulo 1999). As a result, inventors get linked into a larger mesh of direct and indirect relationships. These relationships thus provide inventors with access to technical know-how and information of inventors with whom they are connected directly or indirectly in the network (Singh 2005, Fleming et al. 2007a). Collaborative relationships among inventors facilitate knowledge spillovers and serve as conduits through which inventors learn about successful and/or failed approaches to novel problems and new insights into the solutions of existing problems. The structures of the direct and indirect ties influence the dynamics of information diffusion within the network and establish the amount and content of information that each inventor has access to and thus determine the social capital of inventors. Since innovation is a re-combination process that is inherently uncertain (Fleming 2001), the structural properties of networks that improve performance are the ones that will increase the access to diverse external resources and familiarity with a variety of knowledge elements.

3.3. External Resources

Previous collaboration relationships with inventors outside the focal team provide inventors with access to external resources. Direct and indirect relationships are two important sources of external resources.

3.3.1. External Direct Ties

External direct ties of an inventor are formed when the inventor has worked with inventors other than his current team members in the past. Previous research has argued that knowledge resides within and is created by individuals (Nonaka 1994). The know-how and information that individuals accumulate over time form their knowledge stocks. Inventors maintain close interpersonal contacts with collaborators even years after filing the patent (Singh 2005). Knowledge accumulated in the knowledge stocks of all the past collaborators of an inventor is also accessible to her. Increasing the number of direct ties in a network increases the amount of information, ideas and resources in it. The number of direct ties provides inventors with access not only to new knowledge but also to new experiences. The availability of more resources increases the probability of obtaining a specific resource needed for a particular innovation. In addition, individuals with richer knowledge stocks should have higher ability and be able to create more valuable innovations. Therefore, inventors will benefit more if they are connected to individuals with higher ability.

HYPOTHESIS 1: The number of high-ability direct contacts of a team of inventors has a positive impact on the value of software innovation invented by the team.

3.3.2. Indirect Ties

Inventors maintain relationships and interact with those with whom they have worked before. The inventors' past collaborators also share the knowledge and experience gained from working on patents which does not involve inventors from focal team (Gulati and Gargiulo 1999). Hence, an inventor's relationship with another inventor provides her with access to not just the knowledge stock of her own past collaborators but to the knowledge stock of her collaborator's collaborators (Ahuja 2000, Gulati and Gargiulo 1999). Indirect relationships are weaker than direct ties and hence are more conducive to knowledge spillovers than resource pooling (Ahuja 2000). Nevertheless, these distant and infrequent relationships (i.e., weak ties or indirect ties) bridge otherwise disconnected groups and individuals (Granoveter 1973) and thus may serve as conduits that channel the flow of information among inventors embedded in the network. Indirect ties serve as information gathering devices that provide information on the successes and failures of many innovative efforts, relevant developments in different technologies and promising technological trajectories as well as technological dead ends (Ahuja 2000). Knowledge acquisition depends on knowing who knows what, and inventors with a large number of indirect ties are more likely to have this information (Borgatti and Cross 2003).

HYPOTHESIS 2: The number of high-ability indirect ties of a team of inventors has a positive impact on the value of software innovation invented by the team.

3.4. Network Diversity

Innovations often result from combining or recombining existing sets of knowledge elements (Schilling and Phelps 2007, Fleming 2001). However, there are only a limited number of ways in which a set of knowledge elements can be combined (Ahuja et al. 2001). Kim and Kogut (1996) argue that "The repeated application of a particular set of technologies or organizing principles eventually exhausts the set of potential combinations". Hence, teams that have access to diverse knowledge will have a more diverse pool to choose from, allowing a richer possibility of novel combinations. Different regions develop local expertise that is often quite distinct and complimentary (Porter 1990, Nelson 1993, Cantwell and Janne 1999, Clark et al. 2000, Mahmood and Singh 2003), and exploration of knowledge across regions will result in access to diverse knowledge. Different firms develop expertise in different technical areas (Dosi 1988), and to make novel innovations, firms need to combine ideas not only from their areas of expertise but also from ideas outside (March 1991, Fleming 2001). However, knowledge tends to remain localized within firms and regions (Szulanski 1996, Jaffe et al.. 1993) and is extremely hard to transfer. The extant literature in sociology has emphasized the information flow through interpersonal collaboration networks (Singh 2005, Fleming et al. 2007a, Coleman et al. 1996, Granovetter 1973, Rogers 1995). Hansen (1999) and Frost and Zhou (2005) demonstrate that cross regional interpersonal ties are important sources of knowledge flow. Almeida and Kogut (1999) have shown that mobility of individuals leads to knowledge diffusion across firms. The interpersonal ties are crucial for transfer of ideas between inventors working in different technical domains, firms and regions, without which knowledge across local boundaries could not have been combined. The teams that have ties that spread across regions will have access to diverse knowledge, allowing for a richer possibility of knowledge combinations and hence creation of valuable innovation.

Hypothesis 3: Teams that have ties across regional boundaries will produce more valuable innovations.

4. Methods and Data

4.1 Data Description

Our data are collected from the United States Patent and Trademark Office (USPTO) homepage and consist of all U.S. software patents[1] applied for from 1988 through 1991 and granted by 2004. Each patent record contains the patent number, the application date, the grant date, names of inventors, addresses of inventors, technology classes and subclasses, and the owner firm. For each patent, our dataset also contains the list of all other patents cited by the patent (backward citations) and all the future patents that cite the patent (forward citations) until November 2007 (the end of our data collection).

The original patent data do not provide unique identifiers for inventors and do not distinguish between parent and subsidiary firms as patent owners. We then follow the name-matching algorithm developed by Singh 2005 to identify unique inventors and use Compustat identifiers from the NBER 2005 dataset to identify the corresponding parent firm as the owner of each patent in our dataset.

For inventors with U.S. addresses, we use the metropolitan area to define "region" (Jaffe et al. 1993, Thompson 2006, Singh 2007). We have used metropolitan areas for analysis as metropolitan areas are created based on actual economic activity in a region, whereas state boundaries might have been drawn for administrative reasons (Singh 2007). We used the mapping developed by Thompson (2006) to identify U.S. cities in USPTO data to metropolitan areas. We used the approach of defining a "phantom area" per state for U.S. cities that cannot be associated with any metropolitan areas (Singh 2007a, Thompson 2006). For non-U.S. inventors, we use country as a representation of "region" (consistent with Singh 2007a).

4.2. Network Construction

Social network studies use either "whole-network" or "egocentric" approaches to build interpersonal networks. In the egocentric approach, one randomly selects a starting inventor, adds all inventors who have collaborated with the focal inventor in the past to the network, and then repeats this process for each newly-added inventor until no new

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[1] We follow the searching algorithm developed by Hall and MacGarvie (2007) to identify software patents from the set of all patents.

inventors are identified or the network size reaches an upper limit. There are two potential limitations of this approach in our context. First, inventors who are not connected (isolates) cannot be reached by this approach. Second, the final network is very sensitive to the choice of starting inventor. We may miss large subsets of inventors who are connected among themselves but not to the starting inventor. We follow the whole network approach, which is the predominant approach used in situations where an appropriate network boundary can be established. Examples include inter-firm alliance networks (Ahuja 2000, Schillings and Phelps 2007), regional innovation networks (Fleming et al. 2007a), Broadway artist collaboration networks (Uzzi and Spiro 2005) and open source projects (Singh 2007b). We follow this approach and include all inventors of software patents in our network. Choice of industry as network boundary has also been used in previous studies (e.g. Schilling and Phelps 2007).

Previous research has suggested that inventors are productive for a period of three to five years (Rappa and Graud 1992). Accordingly, we created affiliation networks of software inventors using three-year windows. Similar approaches have been adopted in the literature with windows ranging from one to five years (e.g. Fleming et al. 2007a, Gulati and Garguilo 1999, Stuart 2000, McFadyen and Cannella 2004, Schilling and Phelps 2007). Because patents usually correspond to activities preceding the patent application year (Ahuja 2000), we study the effect of collaborating activities in the three-year period from 1988 to 1990 on the value of patents applied for in 1991. Affiliation network was used to create a unipartite projection for the inventor network (similar to Figure 3). From unipartite projection, an undirected binary adjacency matrix[2] was developed, which represents the relationships between any two inventors in the network. We then used UCINET 6 to obtain measures on these networks as described below (Borgatti et al. 2002).

4.3. Measures

4.3.1. Dependent Variable

We measure the value of an innovation (patent) using the number of citations that it receives from subsequent patents. Forward citations are indicative of the technological significance and economic value of innovations (Trajtenberg 1990, Singh 2007) and have been used as a measure of innovation quality in several studies (Ahuja and Lampert 2001, Rosenkopf and Almeida 2003, Argyres and Silverman 2004, Nerkar and Parchuri 2005, Singh 2007).

Patent citations have a legal dimension, as they limit the scope of the property rights established by a patent's claims (Trajtenberg 1990). Investments made by profit-seeking organizations in costly R&D to further develop an innovation disclosed in previous patents also signify the economic value of cited innovations (Trajtenberg 1990, Hall et al. 2005). Previous research has established the correlation between the number of citations that a patent receives and several direct measures of patent value, including consumer surplus generated (Trajtenberg, 1990), expert evaluation of economic value of patents (Albert et al., 1991), patent renewal rates (Harhoff et al., 1999), firm's market value (Hall and MacGarvie 2007) and royalties received by the inventors/firms.

4.3.2. Independent Variables

For each patent, we calculate the following measures for the team of inventors who collaborate on the patent. We call this team the focal patent team.

Direct Ties. For each inventor, we count the number of inventors she has collaborated with in the past three years outside of the focal patent team. In addition, each linked external collaborator is assigned a weight based on her ability, which can be measured by the value of the patents on which the collaborator has worked. Accordingly, the weight for the linked external collaborator i is constructed as:

$$W_i = \frac{\sum_{j=1}^{T} f_j}{T} \quad ,$$

where f_j is the number of forward citations received by patent j that external collaborator i has worked on, and T is the total number of patents on which external collaborator i has worked during the last three years. Because direct

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[2] In the matrix, row and column headings represent inventors. A value of one indicates the presence of a relationship between the two corresponding inventors, and a value of zero indicates the absence of such a relationship. The adjacency matrix is undirected, as the relationship between two inventors is mutual.

ties measure the level of knowledge that each inventor accesses through her network of collaborators outside the focal patent team, we exclude the patents on which the focal team members have worked when we calculate the weights. Then we take an average of the weighted number of direct ties for all team members as the measure of direct ties for the focal team. Compared to simply counting the number of linked external collaborators, which is used as a measure of direct ties in most previous studies, our measure captures additionally the quality of the collaboration network.

Indirect Ties. Our measure for indirect ties is constructed based on a modification of the frequency decay measure proposed by Burt (1992). This decay function for an inventor i is given as:

$$d_{ij} = (1 - f_{ij} / (N_i + 1))$$

where f_{ij} is the number of inventors that i can reach within and including path length j, and N_i is the total number of inventors that i can reach in the network. Then d_{ij} is the decay weight associated with the information that is received from inventors at path length j. Similar to our argument for direct ties, the quality of information transferred from indirectly linked external collaborators should also depend on the ability of the linked collaborators. Therefore, in addition to the decay function, we also assign each indirect link a weight based on the ability of that linked external collaborator. The indirect ties measure for inventor i is then calculated as:

$$Indirect\ Ties = \sum_{j=2}^{N} d_{ij} w_{ij}$$

where N is the total number of inventors in the network, w_{ij} is the number of collaborators that lie at a path length of j from i weighted by the ability of these collaborators (using the same weight function as defined for direct ties). The number of valuable patents that these indirectly linked collaborators have worked on is also positively related to the quality of the knowledge that an inventor can access through these collaborators. For patents having more than one developer, we take an average of the indirect ties for the associated inventors.

Regional Diversity. The regional diversity measure takes into account the geographical dispersion of the direct and indirect ties of focal inventors. Formally, it is calculated as

$$D_R = 1 - \sum_{r=1}^{R} \left(\frac{n_r}{n} \right)^2 .$$

Here, n_r is the number of patents developed by the team members' past collaborators in a particular region, and R is the total number of regions in which these collaborators have filed patents in the past three years. This measure gauges the distribution of collaborators across regions – a team that has interpersonal ties with inventors having worked in a large number of regions with equal representation of each has high regional diversity.

4.3.3. Control Variables

1. **Team human capital and ability.** We include the number of inventors in a team (team size) to account for the number of people actively engaged in an innovation. To control for team ability, we follow the pre-sample approach by Blundell et al. (1995) and calculate the total number of forward citations received by all the previous patents of the inventors in the focal patent team during the three years prior to entry into sample (Schankerman et al 2006).

2. **Prior art age**. We include the average patent number of all the patents cited by the focal patent. Because patents are numbered sequentially, this variable correlates with the age of technology upon which inventors have built the patent. Newer technologies may provide more fertile opportunities for inventors and have been shown to correlate with value of innovation as measured by forward citations (Alcacer and Gittleman 2005)

3. **Total patent stock.** This is defined as the total number of patents filed by the focal patent's owner firm in the previous three years. A larger number of patents could either increase innovation quality through more recombination possibilities or greater perceived technological prowess (Podolny et al. 1996) or decrease innovation quality by making the firm inward looking and myopic in its search.

4. **Region Patent Stock.** We also control for characteristics of the region where the focal patent originates. Since patents from certain region may receive more citations because of localized knowledge flow, we create this variable by counting the number of patents for each region in the last three years.

5. **Time window for forward citations**. Although the patents used in our analysis were all applied in the same year (1991), they were granted in different years. Because a patent can get citations only after being granted, we control for how long a patent has been granted until November 2007 (the end of our data collection).

5. Model Specification

Our dependant variable, the number of forward citations received by a patent, is a count variable, takes only non-negative integer values and has a skewed distribution. Therefore, in our analysis, utilizing linear regression can result in inconsistent, biased and inefficient estimations. A common approach to modeling count data is to use Poisson regression (Hausman et al. 1984). However, this method makes the strong assumption of equal mean and variance. If over-dispersion is present, standard error of coefficients will be underestimated, leading to spuriously high levels of significance (Cameron and Trivedi 1986). Because our data demonstrate over-dispersion (rejection of Poisson model at $p<0.0001$), we utilize negative binomial regression for our analysis, which is a generalization of the Poisson model and allows for over-dispersion. We perform logarithmic transformation on the variables that are highly skewed, including team size, pre-sample forward citations by team members, firm total patent stock and region patent stock (Gelman and Hill 2007). We utilize Huber-White correction to control for potential correlation in error terms as a result of cross-sectional dependency across teams (Greene 2003). To address the concern of reverse causality (that is, the team's performance shapes the network, not vice versa), we construct the network measures at least one year before a patent is applied for. That is, we examine the impact of network measures constructed for 1988 to 1990 on patents applied for in 1991.

6. Results and Discussion

The results of negative binomial regression analysis are presented in Table 1. The analysis is done for both the complete sample of patents (column 1) and the sample excluding the patents with no direct contacts (column 2). Similar results are obtained for both samples. Hypothesis 1 and hypothesis 3 were supported. Consistent with our hypotheses, weighted direct ties and regional diversity have positive impacts on the value of innovation. However, we did not find support for our second hypothesis - the weighted indirect ties appear to have no significant impact on innovation. Although indirect links provide access to knowledge spillover, they may not be very useful for transferring complex knowledge (Hansen 1999). Software has become so complex that it has become very hard for a single person to understand the whole program (Schankerman et al. 2006). The limited capability of indirect ties to transfer the complex knowledge required for software innovation may explain the insignificant effect of indirect ties in our findings. In addition, patents are characterized by legal arrangements, and hence information is exchanged only through strong connections (direct ties); in this case, direct access to a variety of resources may provide better knowledge benefits than indirect ties. Indirect ties may be more beneficial for open source software development, which is based on principles of sharing (Singh et al. 2007), but not for development of proprietary software patents.

Our findings have several important implications. The significant impact of external direct ties and regional diversity on a patent's forward citations emphasizes the importance of the interpersonal collaboration network on the value of innovation. This implies that it is important for firms to understand the participation of their employees in interpersonal collaboration networks that span regions and provide valuable sources of information. Firms should encourage their employees to participate in events such as technical conferences, which can help inventors to build and sustain relationships across regions and thus can help them to tap knowledge from different regions. The advancement in information technology has made it possible for organizations to gather and process large volumes of data, which was not possible earlier (e.g. patent data which is publically available), to understand the interpersonal collaboration network of inventors. Firms can utilize the knowledge of networks of inventors for hiring. For example, it may be more beneficial for a firm to hire inventors whose networks span across regions where employees of the firm have no ties. In addition, it is important for the firm to consider not only the ability of the person it is hiring but also the ability of his past collaborators. This is particularly true for the software industry, where mobility of inventors is very high. Reagans et al. (2004) demonstrate that social capital variables might be more useful to mangers than demographic variables to assemble teams within organizations. Our results suggest that assembling teams for creating valuable innovations requires mangers to understand the networks of inventors that

span across regions and firms and consider network variables while hiring inventors. The result that regional diversity helps create valuable innovations also has important implications for development of projects across regions and countries. The outsourcing of software jobs from developed countries to developing countries may not be welfare reducing, and migration of software inventors (brain drain) from developing countries should not be seen as erosion of the local knowledge base. These cross-region migrations may augur well for the development of the software industry and provide benefits to both developed and developing countries.

Table 1. Regression Results of Negative Binomial Regression

	All Patents	**Patents w/ Direct Links**
Dependent Variable	Forward Citations	Forward Citations
Weighted Direct Ties	0.0006113** (0.0002675)	.0002988* (.0002686)
Regional Diversity	0.4291581** (0.1935401)	.295371 * (.1887999)
Weighted Indirect Ties	-0.0000438 (0.0001092)	-.0000822 (.0001076)
ln(Team Size)	0.1857028*** (0.0346466)	.3335514*** (.0598398)
ln(Pre-sample Forward Citations)	0.030809*** (0.0075894)	.1308304*** (.0303225)
Prior Art Age	0.000000512*** (0.000000118)	9.17e-07*** (1.81e-07)
ln(Firm Total Patent Stock)	-0.0269885*** (0.0058578)	-.0353631 (.014153)
ln(Regional Patent Stock)	-0.0226209 (0.012044)**	-.0748681** (.0249558)
Time Window for Citation	0.0941285*** (0.016049)	.1681937*** (.0272763)
Individual Patent Dummy	0.2702331*** (0.0798572)	.4081499* (.247831)
No Backward Citation Dummy	2.561298*** (0.5814804)	4.523025*** (.8867926)
No External Tie Dummy	0.3322365*** (0.0713036)	
Number of Obs.	3083	743
LR chi2	204.33	830.45

Standard errors in parenthesis; ***p<0.01,**p<0.05,*p<0.1.

7. Conclusions and Future Research

This research offers several important contributions for understanding the influence of a team's social capital on the value of software innovation. First, while the importance of innovation in the software industry is well established and previous studies have acknowledged the large variance in value of software innovations (Hall and Macgarvie 2007) and influence of interpersonal networks on knowledge transfer, to the best of our knowledge, no study has attempted to study the effect of a team's social capital on the value of software innovation. Second, although the literature on team performance provides useful insights for team performance, inter-firm networks of inventors, which have become valuable resources for innovation performance, have not been studied. Recent studies in open source software (Singh et al. 2007, Singh 2007b, Grewal et al. 2005) have studied the impact of social networks on project performance. Nevertheless, it is not clear that social networks will impact the patented innovations in a

similar manner. As a matter of fact, our results suggest that the impact of social networks is different for patented software innovation and open source software development.

While our results suggest interesting implications for software innovations, there are several limitations of our current analysis which raise opportunities for future extensions. First, our results are based on a single type of interpersonal relationships, which may capture only a fraction of interpersonal ties. However, this makes our results more conservative. Future research can explore other types of interpersonal relationships in addition to patent collaboration ties. Second, our results are based on patent data from 1988 to 1991, where we examine the effect of networks formed in 1988 to 1990 on patents applied for in 1991. These results may be specific to this particular year. We are currently working on an expanded data set containing all software patents granted from 1976 to 1997, which can further help us to check the robustness of our results. Third, we have examined only the effects of direct ties, indirect ties and regional diversity. It will be interesting to examine the impact of other network variables, such as structural holes and team centrality, on innovation performance and the robustness of our results to the inclusion of these variables in our model. These issues will be further examined using the expanded dataset in our future study. Finally, it may also be interesting to explore the effect of macro-level network properties such as the small world property on the value of software innovation and the way networks evolve over time.

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