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Dilemma in Individual Collaboration for Invention: Should We be Similar or Diverse in Knowledge?

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Abstract

This study integrates theories relevant to collaborative knowledge creation and provides evidence to discover effects of knowledge diversity on collaborative knowledge creation. The analysis uses a sample comprising 38,500 granted U.S. utility patents involving two collaborating inventors, from application year 1991 to 2005. Interindividual knowledge diversity is thought to affect collaborative knowledge creation in three dimensions: increasing probability of excellent ideas, increasing probability of disagreements, and lowering knowledge assimilation. Furthermore, these impacts are conditional on two proposed moderators: technology scope and affiliation scope. Empirical evidence supports the positive effect of knowledge diversity weakening as the scope of technology broadens. The effect also differs depending upon whether the collaboration occurs between organizations, within one organization, or outside any organization.

Keywords: invention, collaboration, knowledge diversity, knowledge quality, technology scope, affiliation scope

Introduction

> It is indisputably evident that a great part of every man's life must be employed in collecting materials for the exercise of genius. Invention, strictly speaking, is little more than a new combination of those images which have been previously gathered and deposited in the memory: nothing can come of nothing.
>
> \- Sir Joshua Reynolds, 1769

As stated above by Sir Joshua Reynolds, knowledge is the outcome of "collecting materials." It is undoubtedly the foundation of all human intellectual activity. Whenever an invention process is launched, prior knowledge (Kneser & Ploetzner, 2001) functions as input while newly created knowledge is output. Both tacit and explicit knowledge (Polyani, 1966) are either the source or outcome of inventions in a socialization, externalization, combination, and internalization (SECI) process, as explained by organizational knowledge creation theory (Nonaka, 1994; Nonaka & Takeuchi, 1995; Nonaka & Von Krogh, 2009).

Inevitably, such a process of knowledge creation involves collaboration among individuals. Evidence has demonstrated that collaborations, at both organizational and individual levels, are increasing in R&D (Morris & Hergert, 1987; Mowery, 1989; Singh & Fleming, 2010; Wuchty, Jones, & Uzzi, 2007). The rationale for this phenomenon is that more specialized types of expertise are emphasized and the complexity of knowledge has been growing rapidly as science and technology evolve (Hara, Solomon, Kim, & Sonnenwald, 2003).

Given these phenomena and explanations, many scholars have sought the fundamental mechanism of knowledge creation from the perspective of individual collaboration. One stream of research stems primarily from psychological and cognitive studies where an evolutionary search process across a combinatorial space is proposed to explain creative activities (Campbell, 1960; Simonton, 1999a, b). It comprises three subprocesses: variation, selection, and retention. Many scholars have applied such theory to empirical studies in order to explain the relationships on which they focused. For example, by investigating the effect of an inventor's affiliation on inventive outcome, Singh and Fleming (2010) demonstrated that partners within a team or organization would more rigorously reject bad ideas during the selection phase than would a lone inventor; thus, it is unlikely for them to invent very bad quality patents, and their likelihood of inventing breakthroughs is also higher because of the benefits of variation. Fleming's prior study also addressed the relevant question of how an invention's usefulness and inventive uncertainty could be affected by familiarity with technology (Fleming, 2001). The specific efficiency and effectiveness of brainstorming in an organizational context were also discussed in previous literature, where idea generation efficiency and effectiveness was analyzed in detail (Sutton & Hargadon, 1996). Another stream of research has emphasized the downsides of collaboration, such as communication difficulties that lead to productivity loss. This opposite viewpoint argues that a collaborating group is generally less productive than a group of non-interacting participants, and the productivity loss results from three effects of collaboration: interruption, free-riding, and self-interested laziness (Diehl & Stroebe, 1987; Mullen, Johnson, & Salas, 1991).

Despite these efforts, relevant research has to date produced no consensus. Therefore, we attempt to integrate these seemingly contradictory views and thereby describe the possible mechanisms of knowledge creation in the inventive collaboration process. We focus particularly on knowledge diversity (or dissimilarity) accompanying partnership in collaboration. Such partner-specific or relational diversity may reflect cognitive or informational differences between collaborating individuals with respect to their knowledge background. We propose that the effect of knowledge diversity on the quality of newly created knowledge is inconsistent and in fact varies on specific conditions. One condition on which prior studies have neglected is technology scope, which reflects the breadth of technologies involved in collaborative knowledge creation. Our analysis provides evidence to reveal the importance of this characteristic of the knowledge domain, while also responding to a research query in the literature (Jackson, 1992). Another condition on which we focus is affiliation scope in collaboration. Our investigation on this condition somewhat supplements the aforementioned research of Singh and Fleming (2010) by providing more detailed evidence of how knowledge creation differs in correlation with individual inventors' affiliations.

Conceptual Background and Hypotheses

Collaborative Knowledge Creation and Knowledge Diversity

Individuals' limited time and energy makes it difficult to specialize in a wide range of disciplines. Specialization has thus produced demands for interdisciplinary collaboration among scientists and engineers to integrate their knowledge, skills, and abilities (Stevens & Campion, 1994). Ever increasing technological complexities require increasing knowledge, skill, and ability, making it difficult for a single person to be a "lone superhero." When an individual fails to solve a problem alone, he or she would probably seek the missing complementary knowledge that is essential to a solution (Kneser & Ploetzner, 2001; Sakakibara, 1997; Shenkar & Li, 1999). A direct and effective method for reducing the cost of acquiring such necessary knowledge is collaboration with others who possess it, a particularly important strategy when the cost is infinitely large because of obstacles to acquiring the necessary knowledge.

Despite having different forms, collaboration has two important purposes: working together on a task to achieve a common goal, and sharing knowledge with collaborators (Hara et al., 2003; Kneser & Ploetzner, 2001). The common goal in collaborative invention is to create a new valuable invention from which the collaborating inventors may benefit. Eventually, "swarm creativity," analogous to unconsciously generated collective intelligence (Millonas, 1994), emerges from knowledge sharing among collaborators as they pursue the common goal (Gloor, 2006).

Before collaborators start to share knowledge, they should have prior knowledge and skills (Kneser & Ploetzner, 2001), which serve as the source of invention from which the inventor derives new knowledge. Some inventions may seem not to stem from specific prior knowledge, and we are often obsessed with exaggerating their novelty by using terms such as "revolutionary" and “destructive.” Indeed, even if they are considered novel, we affirm that they are based on or originated from prior knowledge (Basalla, 1988; Cohen & Levinthal, 1990). More importantly, prior knowledge has been also acknowledged to enhance learning capability and problem-solving skills for individuals in numerous theories and case studies by cognitive and psychological scientists (Anderson, Farrell, & Sauers, 1984; Bower & Hilgard, 1981; Glaser, 1984; Pirolli & Anderson, 1985).

An invention can be considered an outcome of new knowledge from knowledge creation. It is based on an inventor’s prior knowledge in a variety of tangible and intangible forms such as ideas, patents, and technical articles. In collaborative invention, prior knowledge should originate from all collaborating inventors, and the outcome should be jointly owned, newly created, collective knowledge. Therefore, in the process of collaborative knowledge creation, prior knowledge from collaborating inventors merges and, after a series of collaborating activities by all inventors in the group, new collective knowledge emerges. At least two basic subprocesses occur in this activity: idea generation and idea development. These two subprocesses are spirally interconnected. After combinatorial ideas are generated and agreed upon by collaborating inventors through variation, selection, and retention, they become further developed. Then, new ideas may again be generated from the updated prior knowledge including the recently developed ideas. Such spiral processes continue until satisfactory new knowledge is successfully created.

Knowledge diversity plays a crucial role in this process of collaborative knowledge creation. It reflects the differences in the collaborating inventors’ prior knowledge and resembles technological diversity (Sampson, 2007) that indicates relational and partner-specific differences in knowledge-related attributes. Scholars have addressed knowledge diversity characteristics that affect knowledge outcome in different ways. Here we summarize these characteristics and assert that knowledge diversity influences collaborative knowledge creation in three dimensions.

First, within a collaborating group, members bring combinations of individuals' prior knowledge. Campbell (1960) and Simonton (1999a, b) applied Darwin's evolutionary theory to creativity study and proposed a model to explain creative activities as a cognitive variation-selection-retention process. Weitzman (1998) developed a mathematical production function for new knowledge relying on new recombination of prior knowledge. In short, ideas generated from combinations of distinct perspectives and capabilities in prior knowledge drive production of inventions in knowledge-based activities (Campbell, 1960; Simonton, 1999a, b; Weitzman, 1998) and even facilitate entrepreneurship (Schumpeter, 1934). These new ideas form a potential "solution pool" for achieving the goal; furthermore, the larger the pool of ideas, the higher the probability of it containing workable solutions. A quotation from the great mathematician Henri Poincaré conveys the essence of knowledge creation in this dimension:

> *In fact, what is mathematical creation? … To create consists precisely in not making useless combinations and in making those which are useful and which are only a small minority. Invention is discernment, choice … Among chosen combinations the most fertile will often be those formed of elements drawn from domains which are far apart. Not that I mean as sufficing for invention the bringing together of objects as disparate as possible. Most combinations so formed would be entirely sterile. But certain among them, very rare, are the most fruitful of all … The sterile combinations do not even present themselves to the mind of the inventor. Never in the field of his consciousness do combinations appear that are not really useful, except some that he rejects but which have to some extent the characteristics of useful combinations … The true work of the inventor consists in choosing among these combinations so as to eliminate the useless ones or rather to avoid the trouble of making them, and the rules which must guide this choice are extremely fine and delicate* (Poincaré, 1956).

Empirical evidences further supports Poincaré's perspective. Powell, Koput, and Smith-Doerr (1996) stated that firms with access to a more diverse set of activities are more likely to be in information-rich positions, which in turn promote rapid subsequent growth. Keller (2001) found that diversity has a positive indirect effect through external communication on technical quality but has a negative indirect effect on group cohesiveness. In accordance with the knowledge-based view (KBV) of firms (Grant, 1996), Singh and Fleming (2010) argued that variation in a group's prior knowledge enables inventors to generate new ideas through combinatorial thought trials, which in turn helps collaborating inventors outperform a lone inventor. In addition, these authors also attributed the value of collaboration to its utility in trimming very poor outcomes and stimulating breakthroughs.

Despite its benefits, knowledge diversity also imposes costs on R&D collaboration. This dimension of influence suggests that greater the diversity in collaborating inventors' prior knowledge, higher the probability of conflicts and disagreements. These conflicts include but are not limited to task conflict, process conflict, emotional conflict, and relationship conflict. Jehn, Northcraft, and Neale (1999) found that informational diversity increases both task conflict and process conflict in workgroups. In addition, Pelled, Eisenhardt, and Xin (1999) reported two moderators—task routineness and group longevity—that affect the relationship between group performance and functional background diversity. These perspectives highlight the importance of conflicts and disagreements in collaboration. This dimension of influence is, predictably, inevitable in our understanding of collaboration.

Finally, because the learning occurs among individuals during collaborative knowledge creation rather than within a single brain, assimilated knowledge from external sources (i.e., partners) would be mitigated through interpersonal communication. The theory of absorptive capacity provides a plausible explanation: high diversity in a group would decrease the individual absorptive capacity critical for each member to assimilate external knowledge from others (Cohen & Levinthal, 1990; Zahra & George, 2002). The extent to which knowledge is mitigated depends on each individual's ability to perceive and express tacit and explicit knowledge from and to other members. Furthermore, this ability is determined by the common or mutual knowledge at the intersection of knowledge from all members in a collaborating group and comprises any relevant knowledge that may contribute to the collaborative invention. More importantly, common knowledge can necessitate knowledge integration in the group by encouraging members to share and integrate knowledge that is not common in the group (Clark & Wilkes-Gibbs, 1986; Clark & Marshall, 2002; Dixon, 2000; Grant, 1996).

Technology Scope and Affiliation Scope as Moderators

Knowledge quality implies the value of the newly created knowledge, which in turn reveals the effectiveness of collaborative knowledge creation for collaborating inventors. Furthermore, knowledge quality is shown to be influenced during the aforementioned two subprocesses—idea generation and idea development—of the collaborative knowledge creation process.

Insert Figure 1 about here

As we explained, there are three dimensions of the effect of knowledge diversity observable during the process of collaborative knowledge creation: increasing probability of excellent ideas, increasing probability of disagreements, and lowering knowledge assimilation. These effects on the quality of newly created knowledge occur individually in the two subprocesses. In the first dimension, the increased probability of excellent ideas through collaborative efforts plausibly suggests a potentially successful invention with considerable quality of knowledge. Subsequently, when generating and developing ideas, the group encounters a potential risk that explicit and implicit conflicts and disagreements may arise and impede their attainment of good quality knowledge because of the members' dissimilar knowledge backgrounds, which thus makes knowledge creation vulnerable. The third dimension effect of knowledge diversity—lowering knowledge assimilation—relates to group learning, and it usually causes inefficiency and ineffectiveness in understanding and learning from his/her partner because of the potential lack of prerequisite knowledge. This dimension also strongly affects both subprocesses of collaborative knowledge creation because an individual assimilates knowledge from external sources for the purposes of generating new ideas and developing the agreed-upon ideas.

Note that although a high-quality outcome is attributed to high-quality ideas, good ideas are not guaranteed to develop into good inventions. This uncertainty results from the cognitive, social, and technological uncertainties involved in the entire process from idea to invention (Fleming, 2001). For example, potentially valuable ideas may be abandoned and excluded from actual development attempts because of failures in judging their value and feasibility. In that case, we could attribute the uncertainty to the increased conflicts and decreased knowledge assimilation because they undermine idea generation by blunting individual judgment on the selected ideas' quality.

However, the effects of knowledge diversity in these three dimensions are inconsistent and subject to moderation by a number of factors. For example, Jackson (1992) posed the question, "Does the nature of the task moderate the impact of group composition?" to which Pelled et al. (1999) responded with an examination of task routineness. This factor proved to have a positive moderation effect on the influence of functional background diversity (Pelled et al., 1999).

Similarly, we propose another factor—technology scope—that may answer Jackson's question from another perspective. Technology scope indicates an invention's breadth across a variety of technologies. A broader technology scope may imply that the invention is designed for multiple purposes or involves multidisciplinary technologies. In contrast, a narrow scope invention indicates focus on a very specific technology field. In general, an invention with a broad technology scope is more likely to enable usage and application in correspondent areas within the scope where it is relevant. Thus, it appears attractive and suggests great importance and usefulness. However, developing the initial ideas to create new knowledge that spans a broad technology scope in a collaborative environment is relatively difficult compared to narrow scope knowledge. Specifically, a broad technology scope increases the difficulty of implementing knowledge exploitation, one of the four capabilities of absorptive capacity (Zahra & George, 2002). Examples of such difficulties include conflicts in design principles, insights, and other field-specific factors, which then reduce the benefits of a good quality idea originating from the inventors' dissimilar prior knowledge. Therefore, we hypothesize the moderation effect of technology scope as follows:

Hypothesis 1. The relationship between knowledge quality and knowledge diversity is moderated by the technology scope of a planned invention.

Hypothesis 1a. Broad technology scope correlates positively with achieving high knowledge quality.

Hypothesis 1b. The influence of knowledge diversity on knowledge quality weakens as technology scope broadens.

Another factor that may cause an ineffective outcome or even failure relates to organizational boundaries. Numerous studies have explored why firms or organizations exist. The leading theory of transaction cost well explains that organizations have higher internal efficiency than the market because the transaction cost in the market is generally higher (Coase, 1937;

Williamson, 1973). From perspectives of transaction cost economics (TCE) and the resource-based view (RBV), an organization can facilitate knowledge integration, sharing, and transfer of information and the know-how of individual members within the organization (Kogut & Zander, 1992). Further, knowledge created by inventors who work for organizations usually exhibit more profound influence—and thus earn greater importance—than that created by freelance inventors. The reputation of the organizations with which the employed inventors are affiliated generally enhances their competitive advantage (Oliver, 1997) and increases return to actual quality (Benjamin & Podolny, 1999; Rhee & Haunschild, 2006). Moreover, the extended social network provided by affiliation to organizations also leverages the invention because it enlarges the pool of potential accessible resources for the inventors (Singh & Fleming, 2010). Therefore, affiliation with organizations should be beneficial to knowledge creation for both intra- and interorganizational collaboration.

When compared to collaborating freelancer inventors, affiliation to an organization might be superior merely for reputation and network rather than knowledge integration and sharing because freelancers do not exchange knowledge in the market but only within an invisible boundary, such as the small workgroup where they collaborate. Therefore, the impact of knowledge diversity in the dimensions of conflicts and knowledge assimilation for freelancer inventors and employed inventors should be roughly equivalent. However, when individual inventors work within an organization, the variation of knowledge becomes less important because the organization has routines for knowledge creation. Such routines, on one hand, help employed inventors curtail poor ideas (Singh & Fleming, 2010) but may, on the other hand, also curtail potential excellent but "off-track" ideas that do not quite align with the organization's R&D strategy. At times, prominent groups affiliated with organizations may overcome the disadvantages of existing organizational routines and benefit from knowledge variation, which should eventually produce a markedly high-quality invention.

The situation in interorganizational collaboration is rather complicated. The boundary between organizations introduces additional transaction cost that would encumber the integration, sharing, and transfer of knowledge in interorganizational collaboration. That is, dissent at the organizational level might discourage collaborative knowledge creation. This view is partially supported by empirical evidence suggesting that joint venture alliances outperform bilateral contracts because the former reduces the boundary between the alliance partners (Sampson, 2007). Therefore, greater the difference in knowledge between inventors from different organizations, greater the impediments they face in collaboration. We identify the relevant hypotheses on the assumed moderator—affiliation scope—as follows:

Hypothesis 2. The relationship between knowledge quality and knowledge diversity is moderated by the collaborating inventors' affiliation scope.

Hypothesis 2a. Affiliation with organizations correlates positively with collaborating inventors achieving high knowledge quality.

Hypothesis 2b. Knowledge diversity correlates positively with knowledge quality when collaboration occurs among freelance inventors who have no affiliation.

Hypothesis 2c. Knowledge diversity correlates positively with knowledge quality when collaboration occurs within one organization; however, the positive relationship is weaker than that for freelance inventors.

Hypothesis 2d. Knowledge diversity correlates negatively with knowledge quality when collaboration occurs between organizations.

Methods

Samples and Data Collection

We use data from the U.S. Patent and Trademark Office (USPTO) to empirically examine the hypotheses. Patents are the outcome of inventive activities, and patent data have been considered a convincing source of information by which to evaluate collaboration on technological advances. The dataset was sourced from the National Bureau of Economic Research (NBER) containing information on all granted utility patent records involving only two inventors and that were applied for between 1991 and 2005 at the USTPO. We chose to perform our analysis on cases in which only two inventors collaborated on an invention because it is the basic collaboration scenario. These observations accounts for nearly half of the non-single-inventor records from the NBER dataset during the 1991–2005 period, as indicated by Figure 2 (listing the share of patents by number of inventors that are within 10 inventors).

Insert Figure 2 about here

Because the inventor in this context refers to an individual person, we must identify those inventors with universal unique identifiers. We retrieve the well-established data processed through the algorithm developed by Torvik, Weeber, Swanson, and Smalheiser (2005) from the Institute for Quantitative Social Science (IQSS) at Harvard University. All inventor names have been disambiguated in the data. The name disambiguation was not accomplished with 100% accuracy through the algorithm, but IQSS is the best available source for our analysis to the best of our knowledge.

Measurements and Statistical Method

Dependent variables. *Knowledge quality* is measured by forward citations received from other patents during the five years after the observed patent was filed in the USPTO. This variable correlates positively and strongly with the economic value of a patent (Trajtenberg, 1990). Previous studies have acknowledged the validity of the correlation between the importance of an invention and its forward citations (Albert, Avery, Narin, & McAllister, 1991; Hagedoorn & Cloodt, 2003; Harhoff, Narin, Scherer, & Vopel, 1999; Jaffe, Trajtenberg, & Henderson, 1993; Trajtenberg, 1990). Although it is more of a method for measuring explicit knowledge than tacit knowledge generated from a collaborating group, it is believed to reflect the quality of tacit knowledge beyond what the patent document reveals (Mowery, Oxley, & Silverman, 1996; Patel & Pavitt, 1997).

Independent variable. *Knowledge diversity* is the primary focus of this study. Our purpose is to measure knowledge difference between individual inventors; therefore, a type of beta diversity (Whittaker, 1956), similar to "technological diversity" used by Sampson (2007), serves the purpose. As a result, we define knowledge diversity, based on a revised version of cosine index, as follows:

$$d = 1 - \frac{k_{\mathrm{A}} \cdot k_{\mathrm{B}}}{(|k_{\mathrm{A}}|^2 + |k_{\mathrm{B}}|^2)/2}$$

where k_{A} and k_{B} are prior knowledge vectors for inventor A and inventor B, respectively. Note that $\cdot$ refers to dot product and $|\quad|$ is the magnitude of the vector. The prior knowledge, including all granted patents in the five years before the inventor applies for the observed patent, are the materials from which we evaluate his/her knowledge stock.

The denominator in Sampson's (2007) technological diversity is the geometric mean of $|k_{\mathrm{A}}|^2$ and $|k_{\mathrm{B}}|^2$. However, we use the arithmetic mean instead. The benefit of this approach is that it produced varying meaningful diversity values for collaborator dyads that were equivalently treated because of the same categorical structure and proportional numbers of patents in those categories. For example, if inventor A and inventor B have both been granted patents that cover technology fields IPC1, IPC2, and IPC3, numbers of patents in each technology field are shown as follows:

Technology fields	k_{A}	k_B
IPC1	1	3
IPC2	2	6
IPC3	3	9

Apparently, both inventors have the same knowledge structure, but knowledge depth may differ for the numbers of granted patents they have contributed. In this case, it is difficult to determine whether they are equal in prior knowledge. However, the technological diversity calculated from the geometric mean is zero, which is suspicious, as explained. Therefore, we replace the geometric mean with the arithmetic mean, and the resulting value is generally a little larger but more meaningful.

Other than the definition of knowledge diversity, the way we count the number of patents in each technology field is also adjusted. A problem might arise if we simply count the number of occurrences of IPCs in an inventor's prior granted patents. For example, we assume that inventor A has three patents and each patent covers only one distinct field (IPC1, IPC2, and IPC3, respectively), and inventor B has only one patent that covers the same three fields as inventor A's patents. In this case, the two inventors have exactly the same prior knowledge vectors $k_{\mathrm{A}} = k_{\mathrm{B}} = (1, 1, 1)$. The number in the prior knowledge vector would be inevitably exaggerated if the patents cover many technology fields; that is, the effect of prior knowledge is overestimated in cases of patents with more technology fields. We solve this problem by normalizing the patent knowledge vector v for each patent. Patent knowledge vector v is similarly defined to represent knowledge in a patent in which each element is mapped to one IPC and each value equals $\frac{1}{|v|}$ ($|v|$ is the magnitude of the patent knowledge vector). This approach implies that every patent knowledge vector has the same magnitude, which equals one unit of knowledge. Then we add all patent knowledge vectors for each inventor to obtain his/her prior knowledge vector k. In foregoing example, the prior knowledge vector for inventor B is adjusted to $k_{\mathrm{B}} = \frac{1}{\sqrt{3}}(1, 1, 1)$, whereas $k_{\mathrm{A}} = (1, 1, 1)$ as it was.[1]

Tech scope. We count number of full-digit IPC codes recorded in the patent document specification by patent examiners as an objective measure. The more IPC codes into which the USPTO assigns the patent, the broader technology scope the patent covers, and the broader scope of knowledge the invention is assumed to represent. The validity and feasibility of this measure of proxy technology scope was discussed in study by Lerner (1994), which found a positive correlation with the value of firms in the biotechnology industry.

Intra collaboration and *inter collaboration*. These two dummy variables indicate affiliation scope and whether the collaboration is within one organization or between two organizations (i.e., intraorganizational and interorganizational collaborations). Of course, when these variables both equal to zero, the collaborators are freelance inventors with no affiliations to any organization. Prior findings suggest a beneficial influence of individual inventors' affiliation with an organization for achieving R&D breakthroughs (Singh & Fleming, 2010).

[1] We also re-estimated all models in Table 2, which reports the result of estimates from regressions, by using the non-normalized vectors. In addition, the aforementioned geometric mean version of the knowledge diversity proxy with both normalized and non-normalized vectors was also re-estimated. The results are similar to that in Table 2.

Control variables. *Number of claims.* Claims is a very important element in patent specification, representing exclusive property rights that the patent claims to protect the invention (Lanjouw & Schankerman, 2004). The number of claims indicates the “width” or “scope” of the invention’s protection (Jaffe, Trajtenberg, & Romer, 2005). Tong and Frame (1994) revealed its positive correlation with patent quality in an empirical analysis.

Number of references refers to the number of backward citations to “prior art,” which indicates how many external knowledge sources were obtained and applied to develop the invention. It is sometimes used to proxy the absorptive capacity, which reflects the ability to value, assimilate, and apply new knowledge in a collaborating group (Rothaermel & Thursby, 2005). We use this variable to control for direct prior knowledge sources that contribute to the invention.

Total current year patents reflects the collaborating group’s potential to invent by measuring the total number of patents applied for (and later successfully granted) during the same year when the group applied for the observed patent. It may proxy the team’s R&D productivity.

Total prior patents. We count the total number of patents applied in the past five years for all collaborating inventors in a team, and this variable reflects their R&D capability as suggested in Silverman (1999).

Total experience years measures the sum of experience years of all collaborating inventors in a group, starting from the year an inventor applied for his/her first patent through the present year, when the group applied for the observed patent. By including this variable, we determine whether the group’s long-term work experience in R&D facilitates or hinders the outcome of their collaboration.

Prior collaboration is a dummy variable indicating whether the inventors in a team had collaborated in the past five years. Such collaboration experience with same partners is thought to possibly reduce patent quality because repeat collaboration is believed to suppress idea generation (Skilton & Dooley, 2010).

Year dummies and industry dummies. To control for fixed effects introduced by time and technology classification (Judge, 1985), the analysis includes 15 year dummies (1991–2005) and 37 technology dummies.[2] The year factor may incur differences in knowledge complexity, and previous research has also suggested that systematic differences occur across technologies or industries (Hagedoorn, 1993; Jaffe et al., 2005; Rumelt, 1991; Schmalensee, 1985). For example, patents from traditional technology categories like mechanics receive fewer citations than those from emerging technology categories like telecommunication (Hall et al., 2001).

The dependent variable *knowledge quality*, measured by forward citation of the observed patent, comprises non-negative integer counts. With additional consideration of its over-dispersion (sample mean 5.034 versus standard deviation 8.819), therefore, we apply negative binomial models to estimate and test the hypotheses. This method accounts for large portion of zero and small counts values, and thus well meets our requirements for analyses (Hausman, Hall, & Griliches, 1984).

When testing the moderation effects of technology scope and affiliation scope, interaction variables are also generated as the econometric method suggested (Aiken, West, & Reno, 1991; Baron & Kenny, 1986). *Diversity X tech scope* represents the interaction variable between *knowledge diversity* and *tech scope*; similarly, *diversity X intra collaboration* represents the

[2] The categorization of technology follows the HJT scheme proposed by Hall, Jaffe, and Trajtenberg (2001). One technology dummy variable corresponds to one HJT technological sub-category. The variable for sub-category 37 is omitted in regressions, as is the variable for the year 2005 among year dummies.

interaction variable between *knowledge diversity* and *intra collaboration*, and the term *diversity X inter collaboration* measures the interaction between *knowledge diversity* and *inter collaboration*.

Results

The sample contains 38,500 observations, each representing one patent. Nearly 5.9% of patents in the sample are without affiliation. Roughly 93.0% are assigned to a single organization, and the others are assigned to multiple organizations. Table 1 reports the descriptive statistics for all dependent, independent, and control variables.

Insert Table 1 about here

Note that the control variable *total prior patents* has relatively high correlation (0.386) with the independent variable *knowledge diversity*. This situation may result in a multicollinearity problem, even though this variable is believed to reflect the inventors' general R&D capacity, as illustrated previously. When we exclude this control variable and re-estimate all models, the new result produces similar estimates, as the following regressions demonstrate. Table 2 presents estimates from the negative binomial regressions for both main effect and moderation effects as hypothesized.

Insert Table 2 about here

Columns (2)–(7) indicate that only when the hypothesized moderators are included does the estimate of knowledge diversity become statistically significant. Although estimates of knowledge diversity in columns (2)–(4) are positive, their insignificance (the p-values of 0.065, 0.071, and 0.086 are not below the required significance level 0.05) implies a failure to obtain the required relationship. This suggests that other conditions might be inevitable when we investigate the relationship between knowledge diversity and knowledge quality.

The significant estimates of *tech scope* in columns (3), (5), and (7) reveal that patents with a wide technology scope receive more citations than those with a narrow scope, while holding knowledge diversity and control variables constant. On average, if the observed patent is assigned into one more IPC, the expected log count of forward citations increases by roughly 0.05. As we explained, a patent's broader technology scope enables more subsequent inventions in those technology fields to build upon it, and thus it potentially causes more citations from those fields. The variable *diversity X tech scope* indicates the interaction between knowledge diversity and technology scope. The estimated coefficient of the interaction term *diversity X tech scope* is statistically significant at the 0.001 level, and it indicates the change of slope introduced by a one-unit rise of technology scope. For example, in model (7), the positive influence of knowledge diversity would vanish accompanying a decrease in slope by 0.031 as one more IPC code is assigned to the observed patent. That is, when the technology scope increases to about 16 IPC codes, the benefit of diverse knowledge vanishes, and high diversity becomes an impediment to producing a high-quality patent as well as knowledge. To demonstrate this phenomenon more clearly, we plot Figure 3 to illustrate to what extent knowledge diversity affects knowledge quality under broad, medium, and narrow levels of technology scope. We define these levels as, (1) mean plus five times the standard deviation (23.213), (2) mean (4.703), and (3) mean minus the standard deviation (1.000) of the sample. The estimated coefficients of knowledge diversity are −0.230, 0.336, and 0.449, respectively, for the three levels of technology scope.[3] However, the predicted curve for broad scope remains above that for medium scope and narrow scope because the absolute value of the estimate of *tech scope* is greater than that of *diversity X tech scope*.

[3] We use the re-centering method to generate three new variables by subtracting the mean+5*SD, mean, and mean–SD from *tech scope*, and then re-estimate the three models with the three new variables. Figure 2 is then plotted from the new estimates.

Insert Figure 3 about here

The moderation effect of affiliation scope, reported in models (6) and (7), exhibit the hypothesized result. First, patents invented by either intraorganizational collaborators or interorganizational collaborators receive more forward citations than those invented by freelance inventors not employed by any organization, and the increment in log count of forward citations are 0.229 and 0.501 as reported in model (7). This finding is to some extent consistent with the empirical evidence that inventors affiliated with organizations are more likely to achieve breakthroughs and less likely to invent particularly poor outcomes (Singh & Fleming, 2010). Second, the positive effect of diverse knowledge weakens in intraorganizational collaboration compared to that for freelance inventors (the slope is 0.160 versus 0.479), and it becomes negative (−0.417) when collaboration occurs among inventors from different organizations, as the significant negative interaction terms *diversity X intra collaboration* (significant at the 0.01 level) and *diversity X intra collaboration* (significant at the 0.001 level) suggest in model (7). Similarly, we plot Figure 4 to demonstrate the predicted curves in the three conditions. We observe that when similar inventors (with a low level of knowledge diversity, below 0.46) work together, the quality of the outcome by interorganizational collaboration is higher than that by intraorganizational and freelance collaborations. Surprisingly, when collaborating inventors have relative high knowledge diversity (greater than 0.72), the quality of inventions by freelance inventors is higher than those by intraorganizational and interorganizational inventors. This finding might imply the importance of freelance inventors as a small but nontrivial force in the innovation system despite R&D by organizations representing the main stream.

The estimates of the control variables also provide interesting results. The potential for creating more inventions (i.e., *total current year patents*) positively correlates with knowledge quality, which might imply that productive inventors also create better quality knowledge in general. The results of *number of claims*, *number of references*, *total experience years*, and *prior collaboration* are all statistically significant. *Number of claims* and *number of references*, which respectively imply the patent's protection scope (potential legal profitability) and to what extent it uses prior knowledge resources (technological sources), have positive effects on knowledge quality. These factors are sometimes applied as underlying indicators of patent quality in prior research (e.g., Lanjouw & Schankerman, 2004). *Prior collaboration* correlates negatively with patent quality, possibly because repeat collaboration suppresses idea generation as Skilton and Dooley (2010) suggest. Surprisingly we find that *total experience years* negatively affects knowledge quality, probably because long-term work experience discourages idea generation and creativity development. The following quotation could well explain the negative effect of experience:

> *"… Some say that the advantage of experience is in knowing what works. But the great disadvantage of experience is the loss of the grand stupidity and absurd bravery that comes with not knowing what works. Because when you don't know what works, you'll try anything … you'll discover all the new things that work …"* (Calloway, 2007).

Discussion and Conclusion

Numerous studies have analyzed collaboration with support by the KBV that highlights the importance of knowledge as an essential resource (Grant, 1996). Knowledge, in either tacit or explicit form, strongly affects innovative R&D activities, and its structure and composition greatly influences collaboration outcomes. The influence, however, is uncertain. Proponents of diverse groups largely emphasized the theory that new ideas arise from a combination of different ideas by dissimilar individuals. Opponents of that theory have argued that diversity reduces effectiveness and efficiency in assimilating external knowledge from collaborating partners. Research findings have supported both viewpoints.

In the present study, we integrate these contradictory viewpoints and propose that the effect of knowledge diversity on quality of newly created knowledge differs with the changing conditions of technology scope and affiliation scope.

The results of the hypothesis tests support the arguments as predicted. First, we found a negative moderation effect of technology scope on the relationship between knowledge diversity and knowledge quality by incorporating interaction between technology scope and knowledge diversity. Although a broad technology scope is more likely to attract potential subsequent utilization, it also imposes communication difficulties such as increased probability of disagreements and reduced knowledge assimilation resulting from the difference between collaborating inventors' prior knowledge.

Second, the status of affiliation with organizations also moderates the relationship between knowledge quality and knowledge diversity. On one hand, organizations can encourage knowledge integration, sharing, and transfer within their scope, and the reputation of organizations and their extended social network can further enhance the usefulness of output inventions. On the other hand, organization routines limit free idea generation by, for example, restricting selection of generated ideas to accord with the organization's strategy, thus reducing the benefits of having dissimilar knowledge. Moreover, when collaborating inventors come from different organizations, knowledge diversity may even hinder them from creating high-quality knowledge because such organization boundaries add transaction costs that would encumber knowledge integration, sharing, and transfer in interorganizational collaboration. This boundary harms collaborative knowledge creation especially because of the proportionally rising probability of disagreements and lowered knowledge assimilation resulting from the difference between collaborating inventors' knowledge.

These moderation effects are consistent to findings in previous research. Pelled et al. (1999) argued that people who perform non-routine tasks, which are usually complex, are more likely to be anxious and thus rely more heavily on cognitive mechanisms to simplify information processing (Staw, Sandelands, & Dutton, 1981). Therefore, emotional conflicts are more likely to arise in a highly diverse group. This complexity effect also occur in multidisciplinary knowledge with a broad technology scope; therefore, it is straightforward to infer that broad technology scope also results in emotional conflicts and thus moderates the effect of knowledge diversity. Findings from Jehn et al. (1999) partially support the moderation effect of affiliation scope. They hypothesized and proved that informational diversity is more likely to increase group performance when value diversity and social category diversity in the group are low because of potential conflicts otherwise. Similarly, interorganizational collaboration introduces potential social category diversity and particularly value diversity because those collaborating organizations may differ in task, goal, target, or mission as well as standardized routines.

Moreover, we noted that certain prominent groups affiliated with organizations may overcome the disadvantages of existing organizational routines and benefit from knowledge variation, and finally produce markedly high-quality inventions. Therefore, we further examined the moderation effect of affiliation scope on the role of knowledge diversity for predicting the likelihood of producing an extreme high-quality patent. The result revealed no statistically significant moderation effect of affiliations scope. Thus, those employed inventors (those with affiliations) either within an organization or between organizations would probably overcome disadvantages resulting from organizational routines so that they could incubate excellent ideas. Further, when we examined whether the employed collaborating inventors are more likely to produce extremely low-quality knowledge, the estimates were also statistically insignificant.[4] These results might be inconsistent with findings by Singh and Fleming (2010) where employed inventors were hypothesized to be more likely to achieve breakthroughs and less likely to invent particularly poor outcomes. However, our study does not deny that affiliation can leverage the outcome. Instead, we provided a finer theoretical analysis and evidence to demonstrate the effect of knowledge diversity on outcomes under conditions of different affiliation scope. The purpose was to infer and prove the possible mechanisms underlying the supportive evidence of the beneficial impacts of affiliation. Thus, as Figure 4 depicts, the employed collaborating inventors somehow manifest their disadvantage when their prior knowledge exceeds a certain level of dissimilarity. This finding might be partially helpful to complement Singh and Fleming's (2010) research.[5]

[4] The results from the models demonstrated in this paragraph are provided in Appendix. We identify all patent observations whose forward citations during five years are among the top one percent of all observations. These patents received 63 forward citations on average. We then generated a new dependent variable *Q99*, with a value of either zero or one, to indicate which observations are of extreme high quality. Likewise, a new dependent variable *Q0* was also generated to indicate the extreme low-quality patents (with zero forward citations during the five years). We employed the logistic regression model to estimate.

[5] In contrast, the moderation effect of technology scope was found consistent in both cases, producing extreme high and low quality patents as our hypotheses *1*, *1a*, and *1b* suggested.

Including control variables produces additional findings. The numbers of claims and references positively influence knowledge quality. This result is consistent with findings in prior literature (Lanjouw & Schankerman, 2004; Tong & Frame, 1994). Experience, in years contributed to patenting inventions over the entire career, is surprisingly found to be slightly harmful to knowledge quality. We may infer that the long-term work experience, usually in a limited number of technological fields, inhibits new idea generation and creativity development. This issue remains ambiguous and open for dispute as in prior literature (Argote, McEvily, & Reagans, 2003; Ingram & Baum, 1997). The negative effect of prior collaboration experience with the same inventor could also be attributed to the inhibition of idea generation. Finally, a greater number of patents is, to some extent, positively correlated to patent quality, suggesting that productive inventors usually create good quality knowledge.

Despites these contributions, this study has two limitations. First, regarding the method for calculating knowledge diversity, we examine only patents involving two individual inventors; thus, the results may lack sufficient persuasiveness if we attempt to directly extend them to more complex collaborations. Sampson (2007) took the average value of every combinatorial pair of collaborators to solve this problem. However, we suspect that this solution may lose considerations on other factors; for example, in cases of three collaborators, diversity that captures all their attributes as a whole (i.e., the combined attributes three collaborators) is missing. Other methods that largely apply the Blau index or entropy index for calculation can avoid these considerations; however, they are not a partner-specific measure that reflects the relational characteristics among individuals in a group. Nevertheless, the present study's method remains plausible and helpful in revealing the proposed implications. Second, detailed evidence of certain effects in the three dimensions we explore—increasing probability of excellent ideas, increasing probability of disagreements, and lowering knowledge assimilation—remain absent. We had insufficient information on, for example, how many ideas are generated, how many conflicts are perceived, or to what extent an inventor learns external knowledge from a partner. A future study that incorporates field study and questionnaires among a small range of inventors might overcome this limitation.

Further studies could follow several paths to extend the research on inventive collaboration. Research could adopt finer granularity analysis of collaboration in the knowledge creation process. Furthermore, existing studies provide some initial insights; for example, Zahra and George (2002) reviewed literature on absorptive capacity and thus improved and developed a conceptual model, while Weitzman (1998) provided a mathematical method for building the knowledge production function upon combinatorial ideas. These two studies offered ways to decompose the knowledge creation process. Taking the degree of relatedness of various technology fields into account may further improve the measurement of knowledge diversity (Huo & Motohashi, 2014). Moreover, on the basis of prior research that explains the relationship between creativity and how inventors are connected (Perry-Smith & Shalley, 2003; Uzzi & Spiro, 2005), the social network could also be incorporated to extend the scope of research because creativity is believed to be spurred by diverse ideas flowing within a network of inventors, and the diversity of collaborators may be related to their networks' structure.

Although much more research on this issue is expected, the present study advances the understanding of how the difference between collaborating inventors' prior knowledge affects inventive outcomes. This study should benefit management and administration in inventive activities to achieve better development of knowledge-based capabilities and inventions with higher value.

Table 1 Descriptive Statistics

	VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Knowledge quality											
(2)	Knowledge diversity	0.026										
		(0.000)										
(3)	Tech scope	0.050	0.006									
		(0.000)	(0.000)									
(4)	Intra collaboration	0.036	0.061	0.028								
		(0.000)	(0.000)	(0.000)								
(5)	Inter collaboration	−0.012	−0.005	0.004	−0.396							
		(0.019)	(0.312)	(0.390)	(0.000)							
(6)	Number of claims	0.156	0.040	0.080	0.013	−0.001						
		(0.000)	(0.000)	(0.000)	(0.009)	(0.913)						
(7)	Number of references	0.144	0.023	0.074	0.014	−0.004	0.188					
		(0.000)	(0.000)	(0.000)	(0.006)	(0.383)	(0.000)					
(8)	Total current year patents	0.124	0.122	0.069	−0.019	−0.005	0.103	0.138				
		(0.000)	(0.000)	(0.000)	(0.000)	(0.362)	(0.000)	(0.000)				
(9)	Total prior patents	0.056	0.386	0.084	0.021	−0.010	0.094	0.115	0.346			
		(0.000)	(0.000)	(0.000)	(0.000)	(0.045)	(0.000)	(0.000)	(0.000)			
(10)	Total experience years	−0.010	0.194	0.035	−0.027	−0.017	0.053	0.064	0.250	0.272		
		(0.059)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)		
(11)	Prior collaboration	−0.046	−0.150	0.001	−0.053	0.000	−0.020	0.002	−0.030	−0.048	−0.006	
		(0.000)	(0.000)	(0.864)	(0.000)	(0.980)	(0.000)	(0.725)	(0.000)	(0.000)	(0.237)	
	Mean	5.034	0.668	4.703	0.930	0.012	16.566	13.676	2.262	21.444	22.261	0.798
	S.D.	8.819	0.267	3.704	0.256	0.108	14.211	25.771	4.061	31.289	10.631	0.401
	Min	0.000	0.003	1.000	0.000	0.000	1.000	0.000	1.000	2.000	2.000	0.000
	Max	185.000	1.000	115.000	1.000	1.000	424.000	614.000	62.000	471.000	65.000	1.000

n = 38,500. Significance levels appear below correlations.

Table 2 Negative Binomial Regression Results

VARIABLES	(1) Controls only	(2) Main effect	(3) Tech scope	(4) Affiliation scope	(5) Tech scope & interaction	(6) Affiliation scope & interaction	(7) All interactions
Main effect							
Knowledge diversity		0.045	0.044	0.042	0.186***	0.352***	0.479***
		(0.031)	(0.031)	(0.031)	(0.050)	(0.098)	(0.105)
Tech scope effect							
Tech scope			0.045**		0.050***		0.049***
			(0.017)		(0.007)		(0.007)
Diversity X tech scope					−0.031***		−0.031***
					(0.009)		(0.009)
Affiliation scope effect							
Intra collaboration				0.049		0.238***	0.229***
				(0.030)		(0.062)	(0.062)
Inter collaboration				−0.058		0.465*	0.501*
				(0.085)		(0.196)	(0.199)
Diversity X intra collaboration						−0.329**	−0.319**
						(0.102)	(0.102)
Diversity X inter collaboration						−0.856**	−0.896***
						(0.263)	(0.267)
Control variables							
Number of claims	0.013***	0.013***	0.013***	0.013***	0.012***	0.013***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of references	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total current year patents	0.020***	0.021***	0.021***	0.021***	0.021***	0.020***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total prior patents	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total experience years	−0.002**	−0.003***	−0.003***	−0.003***	−0.003***	−0.002**	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prior collaboration	−0.069***	−0.065***	−0.066***	−0.064***	−0.068***	−0.066***	−0.069***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	−0.599***	−0.625***	−0.636***	−0.668***	−0.858***	−0.848***	−1.072***
	(0.162)	(0.162)	(0.163)	(0.167)	(0.166)	(0.173)	(0.176)
Year fixed effect	Included	Included	Included	Included	Included	Included	Included
Tech fixed effect	Included	Included	Included	Included	Included	Included	Included
Chi^2	5138	5147	5150	5168	5353	5197	5401
df	56	57	58	59	59	61	63

Robust standard errors in parentheses. *n* = 38,500.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

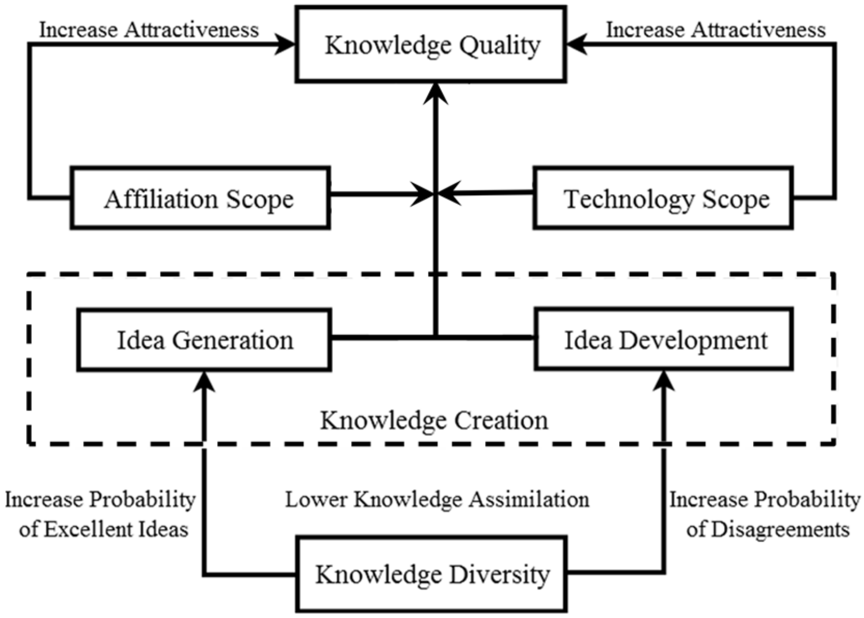

Figure 1 Effect of Knowledge Diversity on Knowledge Quality

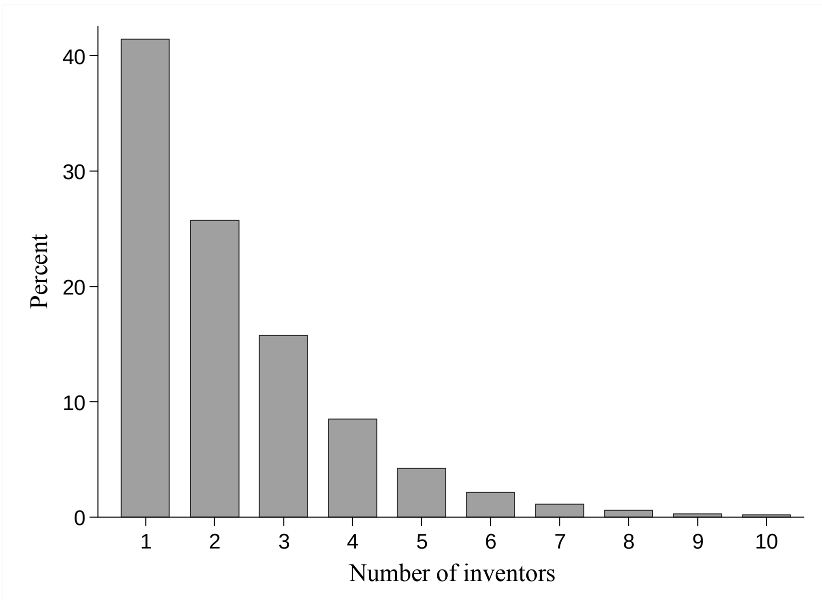

Figure 2 Share (%) of Granted Utility Patents by Number of Inventors

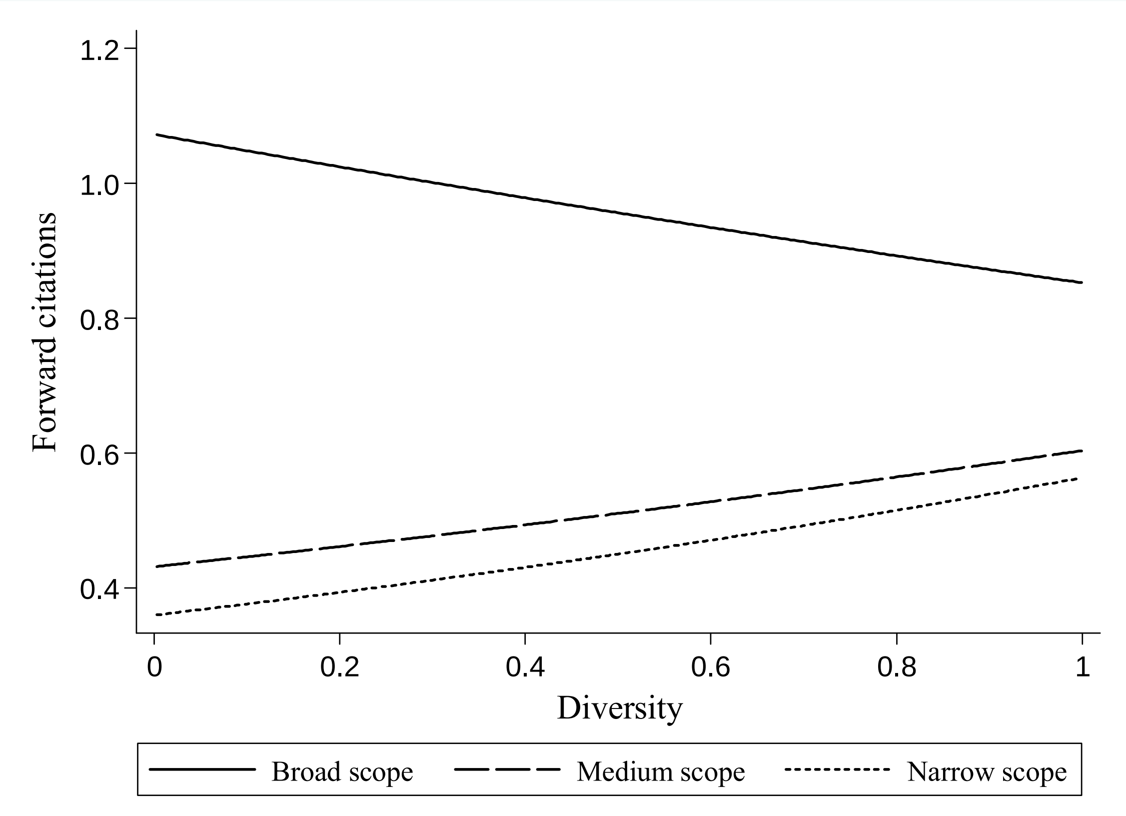

Figure 3 Moderation Effect of Technology Scope

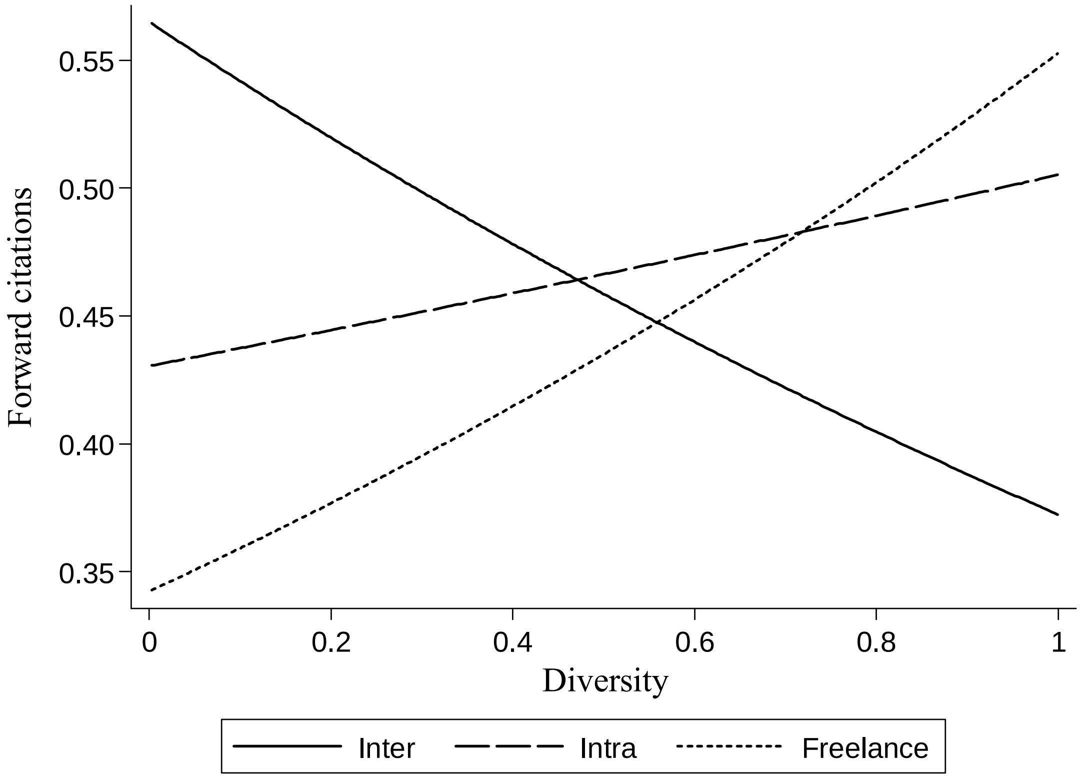

Figure 4 Moderation Effect of Affiliation Scope

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Appendix

Table A1 Logistic Regression Results of Extreme High-quality Outcomes

VARIABLES	(1) Controls only	(2) Main effect	(3) Tech scope	(4) Affiliation scope	(5) Tech scope & interaction	(6) Affiliation scope & interaction	(7) All interactions
Main effect							
Knowledge diversity		0.364	0.348	0.342	0.945**	2.349	2.989*
		(0.217)	(0.218)	(0.218)	(0.302)	(1.255)	(1.325)
Tech scope effect							
Tech scope			0.043***		0.138***		0.138***
			(0.010)		(0.035)		(0.034)
Diversity X tech scope					-0.126**		-0.125**
					(0.043)		(0.041)
Affiliation scope effect							
Intra collaboration				0.575		2.039*	2.122
				(0.297)		(1.033)	(1.098)
Inter collaboration				0.935		3.173*	3.397*
				(0.538)		(1.520)	(1.570)
Diversity X intra collaboration						-2.080	-2.143
						(1.265)	(1.327)
Diversity X inter collaboration						-3.266	-3.500
						(2.064)	(2.116)
Control variables							
Number of claims	0.017***	0.017***	0.016***	0.017***	0.016***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Number of references	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total current year patents	0.053***	0.054***	0.054***	0.053***	0.054***	0.053***	0.054***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Total prior patents	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total experience years	0.000	-0.001	-0.001	0.000	-0.001	0.000	0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Prior collaboration	-0.400***	-0.373***	-0.371***	-0.363**	-0.388***	-0.367**	-0.382***
	(0.110)	(0.112)	(0.112)	(0.111)	(0.112)	(0.112)	(0.112)
Constant	-7.419***	-7.641***	-7.931***	-8.219***	-8.433***	-9.640***	-10.521***
	(0.614)	(0.619)	(0.630)	(0.677)	(0.672)	(1.170)	(1.246)
Year fixed effect	Included	Included	Included	Included	Included	Included	Included
Tech fixed effect	Included	Included	Included	Included	Included	Included	Included
Chi^2	757.0	753.3	778.1	771.2	753.8	772.6	768.5
df	44	45	46	47	47	49	51

Robust standard errors in parentheses. *n* = 34,248.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2 Logistic Regression Results of Extreme Low-quality Outcomes

VARIABLES	(1) Controls only	(2) Main effect	(3) Tech scope	(4) Affiliation scope	(5) Tech scope & interaction	(6) Affiliation scope & interaction	(7) All interactions
Main effect							
Knowledge diversity		-0.072	-0.064	-0.069	-0.237**	0.124	-0.042
		(0.054)	(0.054)	(0.054)	(0.089)	(0.196)	(0.206)
Tech scope effect							
Tech scope			-0.020***		-0.048***		-0.049***
			(0.004)		(0.012)		(0.012)
Diversity X tech scope					0.039*		0.039*
					(0.016)		(0.016)
Affiliation scope effect							
Intra-collaboration				-0.033		0.088	0.087
				(0.058)		(0.130)	(0.130)
Inter-collaboration				-0.100		-0.132	-0.159
				(0.131)		(0.334)	(0.335)
Diversity X intra collaboration						-0.211	-0.213
						(0.202)	(0.202)
Diversity X inter collaboration						0.020	0.046
						(0.478)	(0.480)
Control variables							
Number of claims	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of references	-0.007***	-0.007***	-0.006***	-0.007***	-0.006***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total current year patents	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total prior patents	0.001**	0.002**	0.002***	0.002**	0.002**	0.002**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total experience years	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prior collaboration	0.091**	0.085*	0.085*	0.084*	0.086*	0.084*	0.085*
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Constant	0.752***	0.792***	0.894***	0.822***	1.018***	0.714**	0.943***
	(0.180)	(0.182)	(0.184)	(0.189)	(0.190)	(0.218)	(0.224)
Year fixed effect	Included	Included	Included	Included	Included	Included	Included
Tech fixed effect	Included	Included	Included	Included	Included	Included	Included
Chi^2	2752	2758	2797	2761	2804	2763	2809
df	56	57	58	59	59	61	63

Robust standard errors in parentheses. *n* = 38,500.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$