Research Policy 48 (2019) 1564–1572

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Team diversity as dissimilarity and variety in organizational innovation

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ARTICLE INFO

Keywords:
Team innovation
Team composition
Diversity
Dissimilarity
Variety
Knowledge availability
Knowledge utilization

ABSTRACT

How team composition exactly influences innovation outcomes remains a complex and unsolved puzzle in the literature on creativity and innovation. Our study differentiates two types of team technology-related diversity—technological dissimilarity and technological variety, and investigates their influences on the impact of an invention created by a team. Analyses of over half million U.S. utility patents in the 1991–2005 period invented by teams reveal that technological variety of team inventors has a positive effect on invention impact, and that technological dissimilarity between team inventors plays both positive and negative roles, eliciting an inverted U-shaped effect. In addition, we find that the positive effect of dissimilarity is significantly reduced after controlling for variety. Theoretical and practical implications of our findings are discussed.

1. Introduction

Workplace creativity and innovation are vital to organizational success (Hennessey and Amabile, 2010; Shalley and Gilson, 2004; Zhou and Hoever, 2014). Literature in this area suggests that teamwork enables team members to bring in diverse task-relevant knowledge that a lone creator does not have, empowering teams to enrich the recombinant opportunity in creative search (Singh and Fleming, 2010; Taylor and Greve, 2006; Walsh et al., 2016). As such, these teams inherently involve certain levels of task-relevant diversity, with respect to knowledge-based attributes such as expertise, experience, education, and function (e.g. Harrison and Klein, 2007; Jehn et al., 1999; Pelled et al., 1999; Van Knippenberg et al., 2004). The influence of team composition or team structure on workplace performance has been an important issue in management studies (Gruenfeld et al., 1996; Harrison and Klein, 2007; Jackson, 1992). More recently, a growing body of work has started looking at how team composition affects team creativity and innovation (Lee et al., 2015; Singh and Fleming, 2010; Somech and Drach-Zahavy, 2013; Taylor and Greve, 2006).

Despite the evidence documented in these studies that teams composed of diverse members are likely to perform better in innovation and other creative tasks, there remains a gap in the literature that has yet to sufficiently capture the complexity of team composition, due to a lack of detailed examination of the distinction between *knowledge composition* and *member composition* (e.g. Lee et al., 2015; Singh and Fleming, 2010; Taylor and Greve, 2006). Specifically, many prior studies on team diversity with respect to knowledge-based attributes have focused on a team's overall cross-domain heterogeneity of knowledge (hereafter *knowledge heterogeneity*, or more concisely, *variety*) (e.g. Harrison and Klein, 2007; Lee et al., 2015; Singh and Fleming, 2010; Taylor and Greve, 2006). These studies treat a team as an integrated knowledge holder, and often simplify team composition on the premise that each team member brings in only one domain of knowledge to teamwork (Harrison and Klein, 2007).[1] In this case, variety becomes almost equivalent to another type of diversity—the team's heterogeneity among individual team members regarding each member's knowledge (hereafter *member heterogeneity*, or more concisely, *dissimilarity*).

However, the interchangeable use of a team's knowledge composition and member composition would be problematic when team diversity is examined under circumstances in which an individual team member has expertise in multiple knowledge domains. Imagine that two teams—Team A and Team B—have an equal level of variety across different knowledge domains. Team A comprises generalists (i.e. each member's knowledge spreads across multiple domains) whose knowledge domains share a lot in common, whereas Team B is composed of specialists (i.e. each member's knowledge concentrates within one domain) that are very dissimilar to each other. It does not seem difficult to

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[1] Harrison & Klein have made an assumption for variety: "within units, members differ from one another qualitatively—that is, on a categorical attribute V" (2007: 1204). This assumption implies that each team member's knowledge concentrates within only one category or domain.

https://doi.org/10.1016/j.respol.2019.03.020
Received 27 November 2015; Received in revised form 26 March 2019; Accepted 28 March 2019
Available online 03 April 2019

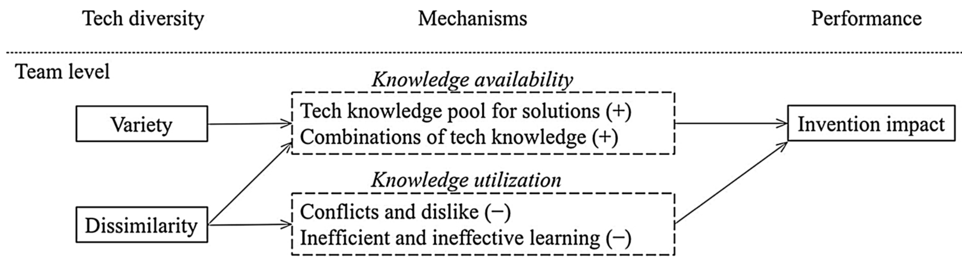

Fig. 1. The mechanisms of team technological diversity.

envision that the two teams with equivalent level of variety are likely to result in divergent creative outcomes, at least in terms of idea generation where all possible domains of task-relevant knowledge owned by each team member may contribute to variation, selection, and retention of ideas (Campbell, 1960; Girotra et al., 2010). In cases like this, focusing only on variety makes it incapable of distinguishing Team A from Team B, thereby reaching an inaccurate understanding of how team diversity influences innovation.

The conceptual differentiation between knowledge composition and member composition further leads to the differentiation between variety and dissimilarity, which will allow us to better appreciate the multifaceted influences of team diversity on innovation from the information-processing and communication perspectives (Jehn et al., 1999; Lee et al., 2015; Lovelace et al., 2001; Singh and Fleming, 2010; Taylor and Greve, 2006). Considering that new inventions often build upon accumulated knowledge and technique that are embedded in existing inventions, we employ the *impact* of an invention created from teamwork on subsequent inventions to evaluate the level of creativity inherent to the invention (Amabile, 1983; Baer, 2012). In particular, given that technological knowledge is the most direct and crucial source of inventions (Cohen and Levinthal, 1989), we focus on the influence of a team's technological diversity on invention impact. Specifically, we propose that the *availability* and *utilization* of knowledge matter in the team innovation process as they collectively characterize a team's ability to create or invent, which may be driven by the team's structural composition in both aspects of knowledge and member. First, based on prior work on creativity (Jehn et al., 1999; Lee et al., 2015; Singh and Fleming, 2010; Taylor and Greve, 2006), we contend that a team's technological variety and technological dissimilarity are positively associated with the availability of cross-domain knowledge for creative teamwork. Second, according to the perspective of cognitive communication, we posit that technological dissimilarity also plays a negative role in the utilization of knowledge throughout teamwork whereby, dissimilar team inventors tend to produce less impactful inventions because of the conflicts and learning obstacles in the team innovation process (Lovelace et al., 2001). As such, our paper intends to investigate the multifaceted relationship between team diversity and invention impact by clarifying the mechanisms relevant to the availability and utilization of knowledge, and thus provides a more full-fledged understanding of the role that team composition plays in innovation.

To address the gap in earlier research, we begin by reviewing the literature pertinent to our research and then build the conceptual framework to elucidate the mechanisms underlying our hypotheses. To test the effects, we conduct an empirical investigation with a large-scale sample of over half million U.S. utility patents from 1991 to 2005 invented by teams composed of at least two inventors. On the basis of the patent sample, we unpack the distinct effects of technological dissimilarity and technological variety on invention impact. Finally, our article is concluded with a discussion of findings and managerial implications from the results and potential future research directions.

2. Conceptual background and hypotheses

Creative products such as inventions are determined by at least two processes. On the one hand, novelty and usefulness are two key elements for evaluating the quality of an invention (Amabile, 1983; Baer, 2012). While novelty originates from the recombination of existing knowledge elements, useful inventions can be viewed as solutions to technological problems (Campbell, 1960; Simonton, 1999a,b; Weitzman, 1998). In such a view, the availability of diverse cross-domain knowledge enables a large technological knowledge pool for knowledge recombination and problem-solving (Hülsheger et al., 2009; Stewart, 2006), thereby enhancing the potential of producing creative inventions (Jehn et al., 1999; Lee et al., 2015; Singh and Fleming, 2010; Taylor and Greve, 2006). On the other hand, given that teamwork performance is greatly shaped by how well people work together, a team's creative outcomes are characterized by its creative ability embedded in interpersonal relations within the team that can affect the utilization of knowledge (Harrison and Klein, 2007; Jehn et al., 1999; Lovelace et al., 2001; Williams and O'Reilly, 1998). We summarize the mechanisms relevant to the availability and utilization of knowledge in team innovation, as well as their associations with technological dissimilarity and technological variety in Fig. 1, and elaborate how creative products such as inventions are influenced by these mechanisms in the following subsections.

2.1. The effect of technological variety on invention impact

Research on task-relevant cognitive diversity has primarily focused on how variety along knowledge-based attributes such as knowledge, expertise, and function influences work performance (Harrison and Klein, 2007), given the importance of cross-domain knowledge in complex problem-solving and creative activities (Lee et al., 2015; Singh and Fleming, 2010; Taylor and Greve, 2006). These studies, addressing not only teams but also individual creative workers, often theorize from an information-processing perspective, arguing that creators from different disciplines have the advantage of endorsing greater availability of various information. As variety of technological knowledge increases, creators tend to have a broader cognitive and behavioral repertoire, through which cross-domain knowledge gets combined and hence leads creators to derive novel ideas and thus create high-quality products (Campbell, 1960; Simonton, 1999a,b; Weitzman, 1998). Therefore, creative products emerging from teams with diverse knowledge are more likely to be novel and useful (Lee et al., 2015), thereby exerting higher impact on subsequent creative products. In line with this proposition, most empirical examinations reviewed earlier have demonstrated a positive effect of variety on creative outcomes. For example, Taylor and Greve (2006) found that more diverse knowledge across a greater number of comic genres resulted in higher mean and deviation of outcomes for both teams and single creators. Similarly, based on the data of scientific publications, Lee et al. (2015) revealed that teams with high variety across scientific fields were more likely to succeed publishing high-impact papers. Mostl relevant to our context of technological innovation, Singh and Fleming (2010) showed that the number of technology domains identified in a past patent profile was positively associated with highly cited patents and negatively associated with patents that had received no citations. Hence, we hypothesize:

H1 Technological variety of team inventors will have a positive effect on the impact of an invention from a team (knowledge availability effect).

2.2. The effect of technological dissimilarity on invention impact

Technological dissimilarity tends to have mixed influences on invention impact. On the one hand, regarding the availability of knowledge, when dissimilar individuals form a team and collaborate, they have the resource advantage of pooling together different perspectives and expertise (Hülsheger et al., 2009; Stewart, 2006) whereby novel ideas may originate from the recombination of existing knowledge elements (Campbell, 1960; Simonton, 1999a, b; Weitzman, 1998). Teams, as information-processing agents, are better able to solve complex tasks and thus produce high-quality inventions that are potentially impactful to subsequent relevant inventions (Lee et al., 2015; Singh and Fleming, 2010; Taylor and Greve, 2006). On the other hand, considering the utilization of knowledge, dissimilarity may be detrimental to the transformation of the information-processing advantage to high-quality inventions. First, the informational and cognitive differences may produce emotional conflicts and dislikes among team members, which tend to hurt team cohesion as dissimilarity becomes quite salient (Lovelace et al., 2001). Despite that the conflicts induced by dissimilarity may not be as destructive as those caused by separation of value, belief, and attitude between subgroups (Harrison and Klein, 2007; Jehn et al., 1999; Williams and O'Reilly, 1998), they may still hinder collaborative process by creating difficulty in information exchange and integration (Van Knippenberg et al., 2004), thereby affecting the final creative products invented by a team. Second, dissimilarity may also lead to inefficient and ineffective learning (Grant, 1996; March, 1991). The extent that different knowledge shared or communicated by team members can be understood and utilized in collaboration largely depends on whether or not one successfully perceives and incorporates the knowledge offered by other members within the team given the specialization in knowledge acquisition (Grant, 1996). Therefore, efficient and effective learning takes place on the basis of collaborators' mutual knowledge, which necessitates knowledge integration by encouraging collaborators to share and combine knowledge that is not common in the team (Clark and Wilkes-Gibbs, 1986; Clark and Marshall, 2002; Dixon, 2000). Thus, when collaborators hold vastly dissimilar technological knowledge, they may not be able to communicate their unique knowledge to the rest of the team due to the lack of common knowledge background even though the unique knowledge may have a great potential to get combined and generate creative outcomes. Given these obstacles in the utilization of the knowledge, we expect that an increase in dissimilarity may lead to a diminishing marginal benefit, resulting from the availability of diverse cross-domain knowledge that enhances information-processing advantage. The process loss due to poorer knowledge utilization may even outweigh the benefit beyond a point where team members become too dissimilar to collaborate cohesively in the team innovation process, and therefore lead to an inverted U-shaped relationship between dissimilarity and invention impact. We therefore hypothesize:

H2 Technological dissimilarity between team inventors will have an inverted U-shaped effect on the impact of an invention from a team (knowledge availability and utilization effects).

To sum up, the role of technological dissimilarity and technological variety differs in their associations with the availability and utilization of knowledge in team innovation. Variety influences team innovation by enhancing the availability of diverse technological knowledge. By contrast, dissimilarity involves the same mechanisms that underlie the effect of variety and other mechanisms regarding the utilization of knowledge determined by interpersonal knowledge differences. Put differently, variety will consistently encourage a team to produce high-quality inventions by enhancing the availability of diverse cross-domain knowledge, whereas dissimilarity will elicit an inverted U-shaped effect by affecting both the availability and the utilization of knowledge. Moreover, dissimilarity and variety have overlapping mechanisms with regard to the availability of knowledge because the team-level variety across technological domains will increase when a team is composed of inventors each with a profile of technological knowledge dissimilar to others.[2] In this regard, if we control for variety when examining the effect of dissimilarity on invention outcomes, the positive effect of dissimilarity via enhancing knowledge availability can be ruled out. By doing so, we can disengage the negative effect underlain by the mechanism regarding knowledge utilization from the intertwined positive effect regarding knowledge availability.

3. Methodology

3.1. Data collection and sample

We used data from the U.S. Patent and Trademark Office (USPTO) to empirically examine our hypotheses. Patents are creative outcomes from inventive activities, and patent data have been considered as a convincing source of information to evaluate technological innovation in economics and management studies (e.g. Kang et al., 2014; Mowery et al., 1998; Singh, 2005; Singh and Fleming, 2010). Specifically, we employed a dataset from Harvard Institute for Quantitative Social Science, which was provided by Lai et al. (2015). Individual inventors were identified with universal unique identifiers processed through an algorithm originally developed by Torvik et al. (2005), despite that the name disambiguation may not be 100% accurate.

Finally, the sample comprises 384,009 teams (or 493,730 teams if we treat same groups of inventors observed in different years as distinct teams) across 587,023 observations, each representing a granted utility patent that was applied for during 1991–2005. All citations used in computing the relevant variables were made by 2010.

3.2. Measures and statistical method

3.2.1. Invention impact

The dependent variable is measured by forward citations received from subsequent patents by 2010. Previous studies have acknowledged the validity of the correlation between the importance of an invention and its forward citations (Albert et al., 1991; Hagedoorn and Cloodt, 2003; Harhoff et al., 1999; Jaffe et al., 1993; Lanjouw and Schankerman, 2004; Trajtenberg, 1990).

3.2.2. Dissimilarity

We compute a cosine index for each dyad of inventors within a team, and then average the sum of all cosines to generate the proxy of dissimilarity for the team. The cosine index for each dyad of inventors is defined as follow:

$$d = 1 - \frac{k_A \bullet k_B}{|k_A||k_B|}$$

where k_A and k_B are prior knowledge vectors for inventor A and inventor B, respectively. Each dimension in the prior knowledge vectors refers to a subclass under the U.S. patent classification (USPC). Note that $\bullet$ refers to dot product and || is the magnitude of the vector. The

[2] Another direct source of a team's variety is each team member's intrapersonal variety, which has been highlighted in a few studies on functional diversity (e.g. Bunderson and Sutcliffe, 2002; Walsh, 1988).

prior knowledge includes all utility patents within the past ten years.

3.2.3. Variety

We employ a Herfindahl index to measure the distribution of a team's prior patents across USPC subclasses. Specifically, we measure a team's knowledge profile by including all granted patents applied for within the past ten years, and then compute a Herfindahl index based on the profile. The index is defined as follows:

$$v = 1 - \sum_{i=1}^{n} p_i^2$$

where p_i refers to the proportion of USPC subclass of technology i in the profile of a team. Besides, we also generate alternative proxies to re-estimate all models, followed by the main examinations.

3.2.4. Control variables

We include variables to control for characteristics of *team* (i.e., *size*, *average fields*, *average experience*, *repeat experience*, and *year dummies*) and *patent* (i.e., *fields*, *claims*, *references*, and *technology dummies*).

3.2.4.1. Team size. We employ the number of inventors to proxy and control for team size. It tends to correlate with other factors such as patent applicants' role (Balconi et al., 2004), as well as to affect the novelty of team outcomes (Lee et al., 2015).

3.2.4.2. Team average fields. We first count the number of distinct USPC subclasses each member's prior patents covered and then compute the average number of subclasses across all team members. It is similar to intrapersonal functional diversity measured at the team level (Bunderson and Sutcliffe, 2002; Walsh, 1988). A team with each member having expertise in more technology fields prior to the current task was found to perform better in innovation (Singh and Fleming, 2010).

3.2.4.3. Team average experience. This variable averages the sum of experience years of each collaborating inventor on a team since he or she was observed on any patent for the first time. This variable measures experience by time on prior R&D tasks in particular, which tends to directly affect job performance of current R&D tasks (Quińones et al., 1995).

3.2.4.4. Team repeat experience. We count the number of years a team exists in patent data to proxy its repeat experience. Repeat collaboration in prior projects has been argued to suppress teams' creative abrasion (Skilton and Dooley, 2010), and was found to lead to low-quality patents (Singh and Fleming, 2010).

3.2.4.5. Patent fields. We count the number of USPC subclasses on a patent. The more patent subclasses USPTO assigns to a patent, the broader technological knowledge the patent represents. Lerner (1994) found a positive correlation between broad-scope patents and the value of firms in biotechnology industry.

3.2.4.6. Patent claims. The claims on a patent specification represent exclusive intellectual property rights that the patent claims in order to protect an invention (Lanjouw and Schankerman, 2004). The number of claims indicates the width or scope of the invention's protection (Jaffe et al., 2005), and was found to positively correlate with patent quality (Tong and Frame, 1994).

3.2.4.7. Patent references. This variable refers to the number of backward citations to "prior art," which indicates how many prior patents are related to the observed patent. It has been used to indirectly proxy the absorptive capacity of the patent applicant (Rothaermel and Thursby, 2005).

3.2.4.8. Year dummies and technology dummies. Previous research has suggested systematic differences across technologies and time (Hagedoorn, 1993; Hall et al., 2001; Jaffe et al., 2005; Rumelt, 1991; Schmalensee, 1985). Thus, our analysis includes fourteen year dummies (1992–2005) and five HJT technology sector dummies proposed by Hall et al. (2001), in order to control for the fixed effects of technology and time (Judge, 1985).

In the main analysis, we employ negative binominal model because the measure of invention impact has a large portion of small non-negative integer counts (Hausman et al., 1984). The analysis is conducted on patents with each observation representing one patent invented by a team in a year. In this case, because a team can have multiple patents during a year, we cluster errors by team in such a way that treats same groups of inventors observed in different years as distinct teams (493,730 teams). In addition, an alternative clustering approach that treats same groups of inventors observed in different years as one team is also used to examine if the results are consistent (384,009 teams).

4. Results

4.1. Main results

Table 1 reports the descriptive statistics for all major variables. The correlation coefficients of each pair of focal predictors are small except for that between dissimilarity and variety.

We investigate the effects of dissimilarity and variety on invention impact, and present the estimates in Table 2. We include only control variables in model (1), and then respectively examine the main effects of variety and dissimilarity on invention impact in models (2)–(4). Model (2) reports the effect of variety on invention impact, showing a significant positive estimate that supports H1 ($\beta = 0.198, p < 0.001$). As for the effect of dissimilarity on invention impact, we include dissimilarity and its square term in models (3) and (4). The estimates for dissimilarity ($\beta = 0.209, p < 0.001$) and its square term ($\beta = -0.119, p < 0.001$) are both significant in model (4), and their signs suggest an inverted U-shaped relationship between dissimilarity and invention impact. Further, based on these estimates, we find that invention impact will be maximal when dissimilarity has a moderate value of 0.88. This value is greater than the mean of dissimilarity and close to its upper bound in our sample, suggesting that the net effect of dissimilarity on invention impact becomes significantly negative when team members are very dissimilar. These results support H2.

Next, we include both dissimilarity and variety in model (5), and find that the inclusion of variety in addition to dissimilarity significantly reduces the significance level of the estimate of dissimilarity ($\beta = -0.014, p = 0.344$) as compared to columns (3). We notice that, albeit insignificant, this estimate of dissimilarity is negative. This result suggests that a significant portion of the positive effect of dissimilarity on invention impact is ruled out after controlling for variety but the remaining negative effect of dissimilarity *per se* is weak.[3] Further, we include variety in addition to dissimilarity and its square term in model (6) to examine how the inverted U-shaped influence of dissimilarity on invention impact would be affected by controlling for variety. Both estimates of dissimilarity and its square term are insignificant.

We also examine the interaction of variety and dissimilarity. Because variety and dissimilarity correlate significantly, a model that includes the interaction term of the two continuous variables may not present the result clearly. Instead, we dichotomize the two continuous variables by their sample medians and compare the effects of four groups of teams classified from the interaction of high variety and high dissimilarity in model (7). The result shows the following findings. Patents invented by teams with both high variety and high dissimilarity

[3] We discuss an alternative explanation for this insignificant, negative effect of dissimilarity on invention impact in the final section.

Table 1
Descriptive statistics.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Impact										
(2)	Variety	0.004 (0.007)									
(3)	Dissimilarity	0.004 (0.003)	0.523 (0.000)								
(4)	Team size	0.008 (0.000)	0.162 (0.000)	−0.050 (0.000)							
(5)	Team average fields	−0.008 (0.000)	0.340 (0.000)	0.051 (0.000)	0.022 (0.000)						
(6)	Team average experience	−0.048 (0.000)	0.364 (0.000)	0.156 (0.000)	0.007 (0.000)	0.303 (0.000)					
(7)	Team repeat experience	−0.014 (0.000)	0.015 (0.000)	−0.539 (0.000)	−0.109 (0.000)	0.319 (0.000)	0.209 (0.000)				
(8)	Patent fields	0.014 (0.000)	0.057 (0.000)	0.003 (0.016)	0.068 (0.000)	0.062 (0.000)	0.023 (0.000)	0.037 (0.000)			
(9)	Patent claims	0.123 (0.000)	0.030 (0.000)	0.021 (0.000)	0.010 (0.000)	0.052 (0.000)	0.004 (0.006)	−0.006 (0.000)	0.051 (0.000)		
(10)	Patent references	0.104 (0.000)	0.007 (0.000)	−0.081 (0.000)	0.056 (0.000)	0.063 (0.000)	0.043 (0.000)	0.121 (0.000)	0.028 (0.000)	0.169 (0.000)	
	Mean	10.744	0.809	0.601	3.098	0.932	0.857	1.111	4.914	17.329	1.477
	S.D.	21.302	0.206	0.305	1.579	1.378	0.493	1.368	3.881	14.724	2.832
	Min	0.000	0.000	0.000	2.000	0.100	0.100	0.000	1.000	0.000	0.000
	Max	1047.000	0.997	1.000	75.000	28.100	8.500	10.000	166.000	887.000	96.500

n = 587,023. Significance levels appear below correlations. Team average fields, team average experience, and patent references are in 10 s.

have the highest level of impact (β = 0.075, $p < 0.001$). The second best group involves teams with high variety but low dissimilarity (β = 0.059, $p < 0.001$), followed by the third—low variety but high dissimilarity (β = 0.026, $p < 0.001$). The baseline group, low variety and low dissimilarity, produces the lowest impact inventions.

The estimates for the control variables also yield interesting findings (see the sixth column of Table 2). First, team size is positively associated with invention impact (β = 0.015, $p < 0.001$), similar to prior findings on scientific teams (Lee et al., 2015). Second, consistent with Singh and Fleming (2010), team members that have broad technological knowledge in the past will facilitate invention impact (β = 0.030, $p < 0.001$). Third, past experience impedes teams from generating creative inventions (β = −0.078, $p < 0.001$). Fourth, repeat collaboration has a negative effect on invention impact (β = −0.010, $p < 0.001$). These results on team experience are in line with prior studies (e.g. Skilton and Dooley, 2010), suggesting that creative outcomes may be suppressed within an experienced team, especially when the team comprises members who have collaborated repeatedly in prior tasks. Finally, the positive estimates of patent characteristics such as fields (β = 0.011, $p < 0.001$), claims (β = 0.015, $p < 0.001$), and references (β = 0.094, $p < 0.001$) are consistent with prior findings in the literature (e.g. Singh and Fleming, 2010).

4.2. Additional analyses

4.2.1. Number of team patents as innovation performance

One may still doubt that variety and dissimilarity are different measures on the same construct, since our main analysis has not explicitly elicited contrasting effects of the two variables. To address this concern, we employ the number of team patents as an additional dependent variable to show the divergent influences of variety and dissimilarity on team innovative performance measured by this particular variable. Consistent with our model, dissimilarity has mixed influences on innovation. On the one hand, considering the availability of knowledge, dissimilarity increases cross-domain combinations. On the other hand, considering the utilization of knowledge, dissimilarity results in team conflicts and learning obstacles that may harm team productivity. The two aspects conceptually represent opposite effects of dissimilarity on the number of team patents. Despite the difficulty of directly measuring knowledge availability and utilization based on our data, we can control for variety (i.e., positive channel) to check if dissimilarity has a significantly negative effect (i.e., negative channel) on the number of team patents. Columns (1)–(3) of Table 3 illustrate the result from negative binomial models that test the influences of variety and dissimilarity on the number of team patents. The two variables both exhibit significant positive effects on the number of team patents when they are included independently in columns (1) and (2) (β = 1.855, $p < 0.001$; β = 0.095, $p < 0.001$). However, interestingly, as we include both variables in column (3), the effect of dissimilarity turns to be significantly negative (β = −0.852, $p < 0.001$) whereas variety remains significantly positive (β = 2.611, $p < 0.001$). Consistent with our earlier arguments, we can infer that dissimilarity has mixed effects on the number of team patents. The negative effect of dissimilarity manifests when the positive influence of variety is controlled for.[4]

[4] We acknowledge that, given the limitation in terms of directly measuring knowledge availability and utilization based on patent data, the channel for the negative effect of dissimilarity is almost impossible to be directly examined. Nonetheless, we control for variety (and other control variables) to rule out the positive effect of dissimilarity as much as possible, thereby indirectly showing the evidence of the negative effect and proving the distinction between dissimilarity and variety. We thank anonymous reviewers for helping us clarify the distinction.

Table 2
The estimates for the effects of variety and dissimilarity on invention impact.

Variables	(1) Impact	(2) Impact	(3) Impact	(4) Impact	(5) Impact	(6) Impact	(7) Impact
Variety		0.198***			0.209***	0.233***	
		(0.016)			(0.020)	(0.024)	
Dissimilarity			0.082***	0.209***	−0.014	−0.112	
			(0.012)	(0.037)	(0.015)	(0.059)	
Dissimilarity square				−0.119***		0.081	
				(0.032)		(0.044)	
High variety X high dissimilarity							0.075***
							(0.008)
High variety X low dissimilarity							0.059***
							(0.009)
Low variety X high dissimilarity							0.026**
							(0.008)
Team size	0.019***	0.015***	0.021***	0.019***	0.015***	0.015***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Team average fields	0.038***	0.030***	0.035***	0.034***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Team average experience	−0.053***	−0.077***	−0.065***	−0.065***	−0.077***	−0.078***	−0.070***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Team repeat experience	−0.012***	−0.008***	0.000	−0.001	−0.010***	−0.011***	−0.005
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Patent fields	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent claims	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patent references	0.094***	0.094***	0.094***	0.094***	0.094***	0.094***	0.094***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	1.959***	1.838***	1.904***	1.888***	1.840***	1.844***	1.944***
	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
Observations	587,023	587,023	587,023	587,023	587,023	587,023	587,023
Team clusters	493,730	493,730	493,730	493,730	493,730	493,730	493,730
Chi-squared	78313	78146	78265	78311	78148	78117	78358
df	26	27	27	28	28	29	29

Cluster-robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
All models include year and technology dummies (not displayed).
The estimates for the effects of variety and dissimilarity on number of patents and extreme-impact patents.

Table 3
The estimates for the effects of variety and dissimilarity on number of patents and extreme-impact patents.

Variables	(1) Number of patents	(2) Number of patents	(3) Number of patents	(4) Top 10% cited	(5) Non-cited
Variety	1.855***		2.611***	0.386***	−0.179***
	(0.037)		(0.038)	(0.071)	(0.026)
Dissimilarity		0.095***	−0.852***	−0.112	−0.008
		(0.012)	(0.011)	(0.058)	(0.025)
Team size	0.278***	0.304***	0.240***		−0.004
	(0.001)	(0.002)	(0.001)		(0.003)
Team average fields	0.519***	0.696***	0.504***	0.092***	0.002
	(0.013)	(0.013)	(0.012)	(0.014)	(0.004)
Team average experience	0.206***	0.317***	0.258***	−0.150***	0.001
	(0.006)	(0.006)	(0.006)	(0.028)	(0.009)
Team repeat experience	0.094***	0.068***	−0.010***	−0.033*	0.025***
	(0.002)	(0.002)	(0.002)	(0.014)	(0.005)
Patent fields				0.022***	−0.011***
				(0.003)	(0.001)
Patent claims				0.019***	−0.021***
				(0.001)	(0.000)
Patent references				0.081***	−0.123***
				(0.006)	(0.004)
Constant	0.002	1.185***	0.095***	−3.772***	−1.797***
	(0.026)	(0.011)	(0.025)	(0.065)	(0.037)
Observations	587,023	587,023	587,023	302,893	637,738
Team clusters	493,730	493,730	493,730	249,757	534,875
Chi-squared	199233	201255	268913	6312	65563
df	19	19	20	27	28

Cluster-robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
All models include year and technology dummies (not displayed).

4.2.2. Team size, variety, and dissimilarity

Based on Table 2, we additionally check how team size is related with variety and dissimilarity, given prior studies showing that increasing team size is a plausible means for a team to pool necessary resources, knowledge, and expertise for creative and complex tasks (Lee et al., 2015; Stahl et al., 2010; Stewart, 2006). Consistent with these studies, we find an insignificant reduction in the effect of team size on invention impact after variety is included in the model, suggesting that substantial positive effect of team size on invention impact is *not* working through the channel of variety in our sample.[5] Furthermore, we also find that large-size teams are *not* necessarily associated with dissimilar members, but rather involve similar members regarding their technological expertise ($\rho = -0.050$, $p < 0.001$, in Table 1). Since our proxy of dissimilarity measures the average score of every inventor-dyad difference of the team members, these results on team size suggest that team organizers may explicitly avoid selecting team members that are too dissimilar to each other when assembling a large team.

4.2.3. Intrapersonal variety

The team-level variety is determined by at least two diversities measured at the individual level: interpersonal dissimilarity and intrapersonal variety. In the main analysis, we examined the former (i.e. technological dissimilarity) while controlling for the latter (i.e. team average fields). A handful of studies on managers' functional diversity have focused on intrapersonal variety (Bunderson and Sutcliffe, 2002; Walsh, 1988). To reach a more thorough understanding, we report the relevant results regarding this construct based on our sample. By comparing the estimate of team average fields in columns (3) and (5) of Table 2, we find that it decreases from 0.035 to 0.030 while the significance level remains unchanged ($p < 0.001$), suggesting a weak indirect effect of intrapersonal variety on invention impact through team-level variety.

4.2.4. Variance of creative performance

Possibly, one may argue that diverse knowledge can lead to an increase in the variance but not the mean of creative performance. For example, Taylor and Greve (2006) found that more diverse knowledge across a greater number of comic genres resulted in higher mean and deviation of outcomes for a team. Aside from our focus on the mean performance in this paper, we apply Taylor and Greve (2006)'s approaches to our sample with team as the unit of analysis and find a similar result that variety is positively associated with both the mean and the deviation of patent citations. Further, based on logit models in columns (4) and (5) of Table 3, we find that only the best extreme (i.e. top 10% cited patent) is invented by teams with diverse technological knowledge ($\beta = 0.386$, $p < 0.001$) and that the worst extreme (i.e. lowest 17% non-cited patents) is associated with smaller variety ($\beta = -0.179$, $p < 0.001$). Similarly, we also examine the effects of dissimilarity on the two extremes in columns (4) and (5), respectively, while controlling for variety and other variables, and find insignificant estimates of dissimilarity for both extremes ($\beta\_best = -0.112$, $p > 0.05$; $\beta\_worst = -0.008$, $p > 0.05$).

4.2.5. Alternative measures

Variety in the literature has been measured in different ways. To ensure the robustness of the results, we re-check our hypotheses with two popular alternative measures of variety, based on the specification of model (5) in Table 2. One measure is the logarithm of the number of distinct USPC subclasses used by the team members within the past ten years. Then, we use an unbiased Herfindahl index, proposed in prior studies (e.g. Hall, 2002; Hall and Trajtenberg, 2006), as another alternative measure of variety. The coefficients of variety from both re-estimations are primarily consistent with those shown earlier, except for the slightly inconsistent estimates on dissimilarity ($\beta\_dissimilarity = -0.009$, $p = 0.494$, $\beta\_variety = 0.065$, $p < 0.001$, for the first measure; $\beta\_dissimilarity = 0.022$, $p = 0.172$, $\beta\_variety = 0.118$, $p < 0.001$, for the second measure), holding other variables constant.

4.2.6. Alternative error clustering methods

Team identification was earlier done by team-year. In other words, we treated the same groups of inventors observed in different years as distinct teams. Alternatively, we examine all models while clustering errors by team instead of team-year. In this case, the number of team clusters becomes 384,009 instead of 493,730. The estimates remain robust in spite of minor significance changes caused by the changes of error terms. Further, we cluster errors by organization (identified by primary organizational assignee on patents) and by organization-year, respectively. Accordingly, the models identify 25,316 organization clusters and 65,499 organization-year clusters from 457,514 patents, respectively. The estimation from both tests yields similar results to those from the main analysis (e.g. $\beta\_dissimilarity = -0.017$, $p > 0.1$, $\beta\_variety = 0.178$, $p < 0.001$, based on the specification of the fifth model in Table 2).

5. Discussion and conclusion

Theoretical models and empirical findings in the literature on team diversity regarding knowledge-based attributes have previously built upon intertwined mechanisms that have ambiguous effects on creative performance (e.g. Harrison and Klein, 2007; Lee et al., 2015; Taylor and Greve, 2006; Van Knippenberg et al., 2004). However, similar to prior research on managers with intrapersonal multi-function backgrounds (Bunderson and Sutcliffe, 2002; Walsh, 1988), in a usual situation where an inventor holds knowledge across multiple technological domains, member composition with respect to distinct knowledge domains and knowledge composition across these domains can no longer be equaled, thereby calling for a differentiation between dissimilarity and variety in research on team composition.

On the basis of such a conceptual differentiation, our findings based on patent data demonstrate that technological dissimilarity has an inverted U-shaped effect on invention impact, in which the positive effect dominates until a medium level of dissimilarity beyond which the negative effect begins to prevail. We further unpack this multifaceted effect of dissimilarity on invention impact and show that the positive effect of dissimilarity through enhancing the availability of diverse cross-domain knowledge is significantly reduced if technological variety that conceptually share the same mechanisms regarding knowledge availability is controlled for. Note that when considering the utilization of knowledge, however, variety cannot explain the downside of dissimilarity such as triggering team conflicts (Lovelace et al., 2001) and discouraging learning (Grant, 1996; March, 1991), which may not be salient given that our results show a weak negative effect of dissimilarity on invention impact after controlling for variety.

One possible explanation for this weak negative effect of dissimilarity is that some mechanisms associated with the utilization of knowledge may simultaneously have certain positive effect on invention impact. For example, differences in terms of members' informational or knowledge backgrounds may trigger task-relevant discussion, which in turn enhances intragroup communications and thus helps filtering low-quality ideas (Jehn et al., 1999; Singh and Fleming, 2010; Williams and O'Reilly, 1998). The potential positive effect may offset a portion of the negative effect induced by conflicts (Lovelace et al., 2001) and obstacles in learning (Grant, 1996; March, 1991) as conceptualized earlier but is hard to be separated from the negative effect, leaving the net effect weak and insignificant. If this alternative explanation is true, the net effect of dissimilarity regarding knowledge

[5] Note that, similar to the scientific paper impact examined in Lee et al. (2015), invention impact in our study is determined not only by team and patent characteristics, but also by many other factors. We thank anonymous reviewers for kindly indicating this point.

utilization may not be consistently unidirectional. For example, it may depend on the criteria of how we evaluate innovation performance. As we demonstrated in the first additional analysis, when innovation performance is measured by the number of team patents, the net effect of dissimilarity regarding knowledge utilization becomes significantly negative, suggesting that the detrimental influence of dissimilarity on innovation is more likely to be revealed in terms of the quantity of invention being created.

Indeed, our differentiation of the two types of team diversity—-dissimilarity and variety—has important contributions to the diversity literature. Harrison and Klein (2007) identifies separation and variety as two distinct types of diversity, which are similar but have conceptual and operational differences as contrasted with technological dissimilarity and technological variety proposed in our paper. First, Harrison and Klein define variety based on team members while assuming they "differ from one another qualitatively … on a categorical attribute" (2007: 1204), which inevitably intertwines the mechanisms relevant to interpersonal interactions with those involving recombinant opportunities of diverse knowledge, whereas our study disentangles member composition from knowledge composition and accordingly their distinctive underlying mechanisms regarding the availability and utilization of knowledge. Second, separation is defined as "along a single continuous attribute" (Harrison and Klein, 2007: 1203), which is mute on attributes consisting of multiple dimensions such as technology that contains various technological domains. This kind of attributes needs a more complicated indicator such as the cosine index employed in the present study, which can capture interpersonal differences regarding multiple dimensions. These adaptions allow us to investigate the distinctive influences of the two types of diversity with respect to technological knowledge in the present paper.

Additional analyses also lead to interesting findings. First, we find that substantial positive effect of team size on invention impact is not mediated by increased variety. Rather, one may predict that other mechanisms such as external social network of members outside the team may contribute to the effect. Second, we find that large-size teams are actually associated with technologically similar members rather than dissimilar ones, suggesting that team organizers may systematically avoid potential cognitive cost and process loss introduced by dissimilarity. Probably, this could be an effective way to keep a balance between increased recombinant opportunities from a team's diverse knowledge and increased potential process loss owing to large team size.

Our findings have important implications for practitioners such as R &D team managers and inventors. Team managers should be aware of the importance of dissimilar members as a source of diverse cross-domain knowledge held by teams, while understanding the downside of such dissimilarity in utilizing the recombinant potential of diverse knowledge. Taken together, for team innovative activities, albeit having multifaceted influences, assembling members who hold dissimilar technological knowledge tends to be a viable direction to creativity.

Despite the contributions discussed above, conclusions drawn from our project should take into account the following limitations. First, as we employed patents in our empirical context, we observed only successfully granted patents that could not represent all inventions. This limitation, however, may not be crucial in our study because being on a team guarantees inventors' patent quality (and thus considerable grant rate) to a great extent (Singh and Fleming, 2010). Second, we have not completely disentangled all intertwined hidden effects of dissimilarity, and have yet to untouch the various conditions under which the mixed effects of dissimilarity could be altered and as a result creative outcomes could be improved. Solving these two puzzles would be of great use for practitioners but it may also pose some challenge, because the multifaceted effects of dissimilarity are relatively small and context-sensitive. Future studies may explore along this direction by following the trail blazed by the present study.

Moreover, caution must be exercised when one attempts to generalize the reasoning and findings based on a dyadic construct such as dissimilarity that represents a bilateral relationship in the present study to collaboration that involves more than two members. Despite that an average measure at the aggregated team-level was employed in our study, it is possible that some multilateral details among individuals in a multi-member team remain overlooked. Also, the black box of idea generation and implementation processes needs to be unpacked in greater details in future studies. There are basically two directions. For one thing, process variables need to be measured to explore the mediating mechanisms within the processes. For another, team members' collaborative mode (Girotra et al., 2010) in the processes may play an important role that interacts with factors at individual, team, and organization levels.[6] Advances in both directions towards processes may enrich our understanding on the interactionist model of organizational creativity (Perry-Smith and Shalley, 2003; Shalley et al., 2009; Woodman et al., 1993; Zhou and Hoever, 2014). Finally, future work may also look at the contingent effects of distinct types (and their combinations) of organizations, such as firms, universities, institutions, and governments, and explore how diversity may elicit differential influences on creative outcomes in these organizational environments. Research along this direction should be interesting and may contribute to a few lines of literature such as university-industry linkage (e.g. Rothaermel and Thursby, 2005). However, much greater efforts need to be taken to scope with issues for various types of organizations given that the raw patent data are neither clean nor representative enough to actual interorganizational collaboration (Walsh et al., 2016).

Although more research is expected, this paper advances our understanding of how team diversity, with respect to team inventors' prior technological knowledge, affects creative outcomes. Practitioners will benefit from the present study in managing team innovation, provided that they carefully configure team composition on the basis of team members' technological knowledge.

Acknowledgements

We gratefully acknowledge the valuable comments and suggestions from Editor John Walsh and two anonymous referees. We would like to thank Jianwei Dang, Yunhui Huang, Haiyang Li, Nariaki Nishino, Sotaro Shibayama, Jun Suzuki, Xiao Zhang for their helpful comments on earlier versions of this article. Earlier versions of this paper were presented at seminars, held by Sun Yat-sen University and Shanghai Jiaotong University, and we would like to thank the seminar participants for their feedback on the paper. This project was funded by National Natural Science Foundation of China, granted to Dong Huo (#71503123and #71711540044) and Han Gong (#71502081).

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[6] Collaborative mode here is referred to as *group structure* or *organizational structure* in Girotra et al. (2010). Two modes were defined in their study as "*team* structure, in which the group works together in time and space," and "the *hybrid* structure, in which individuals first work independently and then work together" in the process of idea generation.

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