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Blending talents for innovation: Team composition for cross-border R&D collaboration within multinational corporations

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Abstract
Despite the upsurge in cross-border R&D collaboration within multinational corporations (MNCs), firms often fail to realize the full potential of cross-border R&D teams. We examine under what conditions geographic diversity might lead to higher or lower innovation performance by focusing on the moderating roles of team composition. We first demonstrate that the geographic diversity of an MNC's research team has a curvilinear (inverted U-shaped) relationship with the team's innovation performance. Building upon group learning theory, we further claim that this non-linear relationship is strengthened by the technical experience heterogeneity of researchers but weakened by repeated collaboration among researchers. Our analyses on the top 25 multinational pharmaceutical companies and their 59,998 patents registered from 1981 to 2012 provide strong support for our hypotheses. When geographic diversity is relatively low, teams with different levels of technical experience and more fresh collaborators improve performance by amplifying the benefits of sourcing diverse knowledge. With high geographic dispersion, on the other hand, minimal experience heterogeneity and more instances of past collaboration lead to better performance by facilitating the integration of diverse knowledge. The results shed light on the importance of technical and social relationships among researchers in sourcing and integrating location-specific knowledge and ultimately enhancing team performance.
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INTRODUCTION

> We run hundreds of cross-border R&D projects. The positive thing in the cross-border projects is diversity. You engage different practices, different settings, and even different levels of experience across the world. The challenging piece, however, is complexity. For example, the more countries your team members come from, the more delays you may experience in running your project.
>
> – The Vice President at GlaxoSmithKline (1)

Cross-border R&D collaboration within multinational corporations (MNCs) has received significant academic attention in the international business research. A fundamental issue within this research concerns how firms can effectively access and combine knowledge assets around the world in their global value chains to compete successfully in global markets (Cantwell, 1989; Gupta & Govindarajan, 2000; Hymer, 1976; Kogut & Zander, 1993; Zaheer, 1995). Research suggests that MNCs can achieve competitive advantages through cross-border collaboration among their global R&D locations (Berry, 2014). Since knowledge spillover is, by nature, restricted to regional boundaries (Audretsch & Feldman, 1996; Jaffe, Trajtenberg, & Henderson, 1993), firms engaging in cross-border R&D activities are well positioned to access a variety of information and specialized knowhow in particular fields (Belderbos, Olffen, & Zou, 2011; DeCarolis & Deeds, 1999; Feldman & Florida, 1994; Shan & Song, 1997; Owen-Smith & Powell, 2004; Zucker, Darby, & Brewer, 1998).

The growing importance of cross-border collaboration within MNCs is well demonstrated by the surge in the number of cross-border patents – that is, inventions developed by a group of inventors that belong to the same firm yet reside in different countries – as shown in Figure 1. Until 1990, less than 7% ($n \approx 6500$) of US patents were globally developed patents. Beginning in the early 1990s, however, this number began increasing, reaching 20% ($n \approx 50{,}000$) in 2015.

Although there seems to be agreement on the potential value of cross-border R&D collaboration in MNCs' global value chains, firms often fail to realize the full potential of this mode of engaging in R&D. Although information technologies have reduced the burdens associated with distant communication, severe managerial challenges may still arise from geographic dispersion. As existing studies point out, geographically dispersed research teams experience more coordination problems (Cramton, 2001; Montoya-Weiss, Massey, & Song, 2001), crises of trust (Jarvenpaa & Leidner, 1999), and unhealthy subgroup dynamics (Armstrong & Cole, 2002; O'Leary & Mortensen, 2010) than other research teams. These challenges impede realization of the full potential for innovation in MNCs engaging in cross-border R&D collaboration. This may explain the inconclusive results in previous empirical studies on the relationship between geographic diversity and innovation performance (e.g., Ambos & Ambos, 2009; Ambos, Ambos, Eich, & Puck, 2016; Scalera, Perri, & Hannigan, 2018; Singh, 2008; Yamin & Otto, 2004). Conflicting patterns of theoretical predictions and empirical findings in these studies raise questions about the simplistic diversity–performance models used in prior research and prompt researchers to consider under what conditions geographic diversity might lead to higher or lower innovation performance.

To fill this gap in the literature, this study seeks to extend the stream of research on cross-border R&D collaboration of MNCs by examining the moderating role of team composition. Considerable research has emphasized that the composition of a team, or the nature and attributes of the team members, has a powerful influence on a wide range

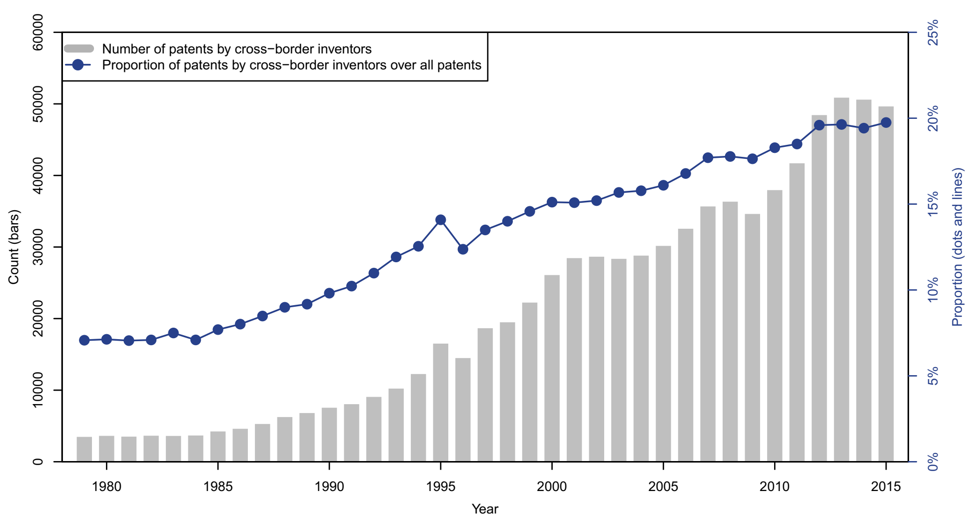

Figure 1 The number and proportion of US Patents by cross-border inventors, 1979–2015. *Source*: PatentsView.

of teamwork processes and outcomes (Apesteguia, Azmat, & Iriberri, 2012; Hoisl, Gruber, & Conti, 2017; Horwitz & Horwitz, 2007; Kozlowski & Bell, 2003). Having the right combination of members in a team, therefore, is an important starting point for management of cross-border R&D collaboration (Foss & Pedersen, 2019). Drawing on group learning theory (Argote, 2013; Edmondson, Dillon, & Poloff, 2007), we explore how the combination of experienced and inexperienced members (i.e., technical experience heterogeneity) and the combination of repeated collaborators and newcomers (i.e., repeated collaboration) moderate the baseline relationship between geographic diversity and innovation performance. These combinations have been widely studied in management research on team composition (Hambrick, Cho, & Chen, 1996; Gilson et al., 2013; Guimera, Uzzi, Spiro, & Amaral, 2005; Smith et al., 1994; Porac et al., 2004; Reagans, Argote, & Brooks, 2005; Skilton & Dooley, 2010; Williams & O'Reilly, 1998), but not yet in the context of cross-border collaboration, which is a completely different setting that necessitates a whole new set of technical and management skills.

Our baseline argument is that there is an inverted U-shaped relationship between the geographic diversity of a research team and its innovation performance. Diversity of researcher location provides the team with an opportunity to access and source heterogeneous location-specific knowledge. As the diversity level increases, however, challenges in coordination and commitment arise. We then articulate the roles of team composition in the cross-border setting. When an MNC research team includes inventors with different levels of technical experience, the team is more sensitive to both the positive and negative impacts of geographic diversity. This heterogeneity of technical experience increases the team's capacity to source external knowledge, which enhances the positive impact of geographic diversity, but also necessitates more intensive interactions and deeper understanding among members for integration of sourced knowledge; this aggravates its negative impact. Repeated collaboration, on the other hand, makes the team less sensitive to the positive and negative impacts of geographic diversity on innovation. While transactive memory and group identity developed during earlier collaborative projects may help resolve the present challenges in coordination and commitment among inventors in different locations during the integration process, knowledge overlap among members (via prior collaboration experience and mutual learning) and routinized problem-solving patterns may reduce the potential value of geographic diversity in terms of sourcing diverse knowledge.

To test our questions empirically, we study the top 25 multinational pharmaceutical firms. In total, 59,998 inventions were developed and patented during the period between 1981 and 2012, from which we compile a list of researchers ("team members") and their researcher-level locations. We measure innovation performance by impact and novelty of patents. The results from a set of regression analyses and additional robustness checks support our predictions. We find an inverted U-shaped relationship between an MNC research team's geographic diversity and its innovation performance (in terms of both impact and novelty). Furthermore, this curvilinear slope increases with increased heterogeneity of experience on a given team but decreases with repeated collaboration among team members. To refine our conceptual ideas and confirm our empirical findings, we also conducted interviews with senior executives of global pharmaceutical companies such as GlaxoSmithKline (GSK) and Merck Sharp & Dohme (MSD) who have extensive experience with cross-border R&D projects. The results of this study contribute to a more nuanced understanding about how MNCs can enhance their innovation capabilities by appropriately composing and managing global teams that utilize geographically distributed human talent in their global value chains.

THEORY AND HYPOTHESES

Geographic Diversity and Innovation Performance

How is geographic dispersion of researchers associated with a team's innovation performance, defined as the creation of novel and impactful inventions? Prior research suggests that innovations are more novel and impactful when they combine broader knowledge across various technological domains (Nerkar, 2003; Rosenkopf & Nerkar, 2001; Sorenson & Fleming, 2004). As previously discussed, innovation performance is determined by two fundamental processes: (1) sourcing diverse knowledge and (2) integrating the knowledge sourced. The former is related to the potential of knowledge recombination, while the latter is related to the realization of that potential for the purposes of innovation (Zahra &

George, 2002). These two processes are jointly necessary for successful innovation (Grant, 1996; Singh, Kryscynski, Li, & Gopal, 2016). Research teams may not generate novel and impactful innovations if they cannot access diverse knowledge inputs, although they may be highly capable of integrating such knowledge inputs. Conversely, though teams may possess diverse knowledge inputs, their innovation outcomes may be poor if they do not effectively integrate those knowledge inputs. In this study, we discuss how the geographic diversity of an MNC research team is associated with sourcing and integrating diverse knowledge inputs, and, ultimately, how it affects its innovation performance.

The geographic diversity of a research team facilitates the sourcing process by allowing access to various location-specific intellectual assets (Berry & Kaul, 2015; Cantwell, 1989; Huang & Li, 2019; Kogut & Chang, 1991; Scalera, Perri, & Hannigan, 2018). Knowledge spillover exhibits localized patterns because it is difficult to transfer knowledge without frequent interpersonal interactions (Frost & Zhou, 2005; Jaffe, Trajtenberg, & Henderson, 1993; Song, Almeida & Wu, 2003; Song, 2014; Szulanski, 1996). As a result, valuable knowledge assets are unevenly distributed across geographic regions and difficult to acquire from outside a given location (Audretsch & Feldman, 1996; Iwasa & Odagiri, 2004; Jaffe, Trajtenberg, & Henderson 1993). Empirical studies in economic geography have shown that geographic expansion of MNCs aims to access information and capitalize on regional knowledge spillover (Audretsch & Feldman, 1996; DeCarolis & Deeds, 1999; Feldman & Florida, 1994; Shan & Song, 1997; Owen-Smith & Powell, 2004; Zucker, Darby, & Brewer, 1998). Thus, it is reasonable to suppose that geographically dispersed research teams would have better access to and superior ability to acquire valuable, irredundant knowledge inputs as compared to collocated teams.[1]

In 1997, for instance, Hitachi created a virtual research laboratory, called Hitachi European Telecommunications Lab, to conduct research in telecommunications systems and develop network systems software (Boutellier, Gassman, & von Zedtwitz, 2000). As shown in Figure 2, the laboratory spanned four locations, Cambridge (U.K.), Dublin (Ireland), Sophia-Antipolis (France), and Dallas (U.S.), each of which provided distinctive competences to the research. Dallas Laboratory, for example, possessed expertise in network design and network management, while Dublin Laboratory contributed resources for multimedia software. In this virtual research laboratory, scientists collaborated on research projects, thus improving their ability to identify, source, and utilize diverse knowledge better than others. This is consistent with Berry's (2014) finding from an analysis of U.S. patents that multinational inventions tend to combine a wider base of technological knowledge than single-country inventions. As geographical diversity increases, we therefore posit, the potential to source diverse knowledge and ultimately find innovative solutions will increase.

The marginal impact of geographic diversity, however, tends to decrease according to scale. In order for an MNC research team to realize its innovation potential, diverse location-specific knowledge sourced from each inventor must be transferred and assimilated within the team (Grant, 1996). Such integration processes, unfortunately, are not costless (Singh, 2008; Teodoridis, 2018). In contrast to the benefits of the increase in geographic diversity, the costs of knowledge integration grow exponentially (Lahiri, 2010). Coordination and commitment problems are the two main sources of such costs.

First, geographic diversity results in substantial costs in coordinating distributed researchers. Although the advancement of information technologies has reduced the cost of distant communication to some extent, it is still difficult and costly to communicate and coordinate between multiple individuals residing in distant regions (Gibson & Gibbs, 2006). Time zone differences, for instance, may create asynchronous communication environments, which can increase information overload and may reduce the synergy of team members (Montoya-Weiss, Massey, & Song, 2001). Lack of direct interactions may also increase coordination costs among geographically dispersed inventors (Kiesler & Cummings, 2002). According to Zander & Kogut (1995), direct interpersonal interactions play a crucial role in transferring complex and tacit information or knowhow in innovation processes, which is necessary for the success of R&D projects. In the setting of cross-border collaboration in which direct communication is lower in quality and less frequent, therefore, MNC research teams experience severe challenges in information exchange and coordination within the team, thus leading to underutilization of location-specific resources and capabilities of team members (Cox & Blake, 1991; Gluesing et al., 2003).[2]

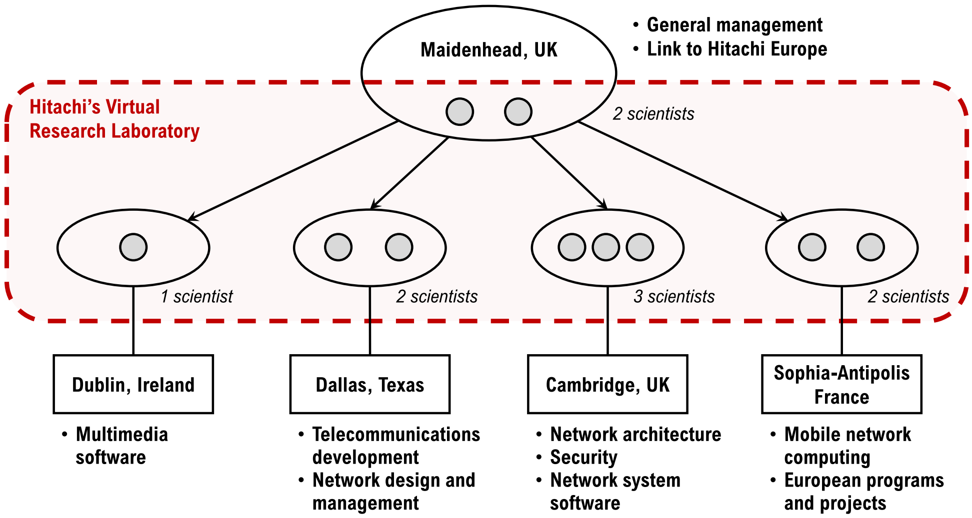

Figure 2 Hitachi's Global R&D Lab. *Source*: Excerpted from Figure I.5.3. of Boutellier, Gassman, & von Zedtwitz (2000: 96).

The challenges of coordinating geographically dispersed R&D are well illustrated by the case of Boeing's 787 Dreamliner project (Wilson & Doz, 2012). To develop a plane with new composite materials, 50 partners across the U.S., Europe, and East Asia were each charged with developing different subsections. Coordinating so many partners in dispersed locations, however, was extremely difficult, and subparts developed were not successfully integrated into the project as a whole. In the end, Boeing had to collocate its partners for 6 months in order to complete the project. Although the final product was developed successfully, it was delayed by almost 3 years, during which Boeing lost orders to the Airbus A350.

Second, geographic diversity of MNC research teams discourages members' willingness to commit their best resources. Studies show evidence of the so-called "out of sight, out of mind" effect, which clearly applies in the context of research collaboration (Armstrong & Cole, 2002). Zajonc's (1968) experiment, for instance, showed that the frequency of face-to-face meetings is significantly associated with positive affection and cooperative attitude. Similarly, Nardi & Whittaker (2002) pointed out that the sense of "presence" engenders social bonding with the person with whom one is communicating. It follows, then, that securing commitment from their inventors may be intrinsically challenging for geographically dispersed teams lacking frequent face-to-face interactions. Furthermore, according to Jehn, Northcraft, and Neale's (1999) in-depth field study in workgroups, group morale is significantly reduced in the form of lower job satisfaction, intent to remain, and commitment of group members, when members differ in terms of what they think the group's real task, goal, target, or mission should be. These findings are echoed in the literature on social categorization theory (Turner et al., 1987) and homophily (McPherson, Smith-Lovin, & Cook, 2001), which suggests that individuals prefer to cooperate with people who share similarities in various attributes, such as culture, education, or ethnicity. Therefore, geographically diverse research teams – in which members are less likely to have shared values, norms, or priorities – could face significant obstacles in terms of cooperation, commitment to the team's goals, and decision-making processes.

We posit that costs associated with geographic diversity grow exponentially, leading to a nonlinear, inverted U-shaped relationship between geographic diversity and team performance. As Barnard (1948: 108) pointed out, "the complexity of the relationships in any group increases with great rapidity as the number of persons in the group increases". Suppose the number of locations of inventors involved in a given R&D project increases from three to four. As shown in Table 1, the benefits of obtaining non-redundant knowledge increase by one unit (the number of additional locations), but the potential costs stemming from integration challenges increase by three units (the number of additional ties). All in all, as illustrated in Figure 3, we see that the linear benefits weighed against the exponential costs lead to a net relationship that exhibits an inverted U shape.

Table 1 Exponential increase in integration challenges with added geographic locations

Number of locations	Number of ties between locations	Increase in ties with each added location
1	0	0
2	1	1
3	3	2
4	6	3
5	10	4
6	15	5
7	21	6
8	28	7
9	36	8

We therefore predict that although an initial increase in the geographic diversity of an MNC research team may enhance its innovation performance, after a certain threshold is reached, further increases may cause a decline in performance. We hypothesize as follows.

Hypothesis 1: Innovation performance is maximized at a moderate level of geographic diversity; that is, the geographic diversity of an MNC research team has an inverted U-shaped relationship with its innovation performance.

Moderating Role of Team Composition

Team composition has been considered one of the most influential factors in shaping a team's cooperative behaviors and, ultimately, its performance (Apesteguia, Azmat, & Iriberri, 2012; Hoisl et al., 2017; Horwitz & Horwitz, 2007; Kozlowski & Bell, 2003; O'Leary & Mortensen, 2010). However, in the past, geographic dispersion and team composition have mostly been studied independently (Ambos et al., 2016). In the aforementioned Hitachi case, the method of combining scientists in four different locations must have influenced the innovation performance of the project, but we do not have a clear understanding as to how the mixture of specific inventors with varying backgrounds affected the team's innovation performance in the international collaboration context. Linking the two research streams in this study, we examine variations in knowledge sourcing benefits and integration challenges associated with geographic diversity according to different ways of combining inventors on a given team.

We focus on two distinct yet complementary dimensions: the technical and relational dimensions (Frost & Zhou, 2005; Song, Asakawa, & Chu, 2011). For the technical dimension, we examine the distribution of technical experience among team members, which is one of the classic variables in team composition research (Bantel & Jackson, 1989; Gilson, Lim, Luciano, & Choi, 2013; Smith et al., 1994; Williams & O'Reilly, 1998). For instance, Hambrick, Cho, & Chen (1996) investigated the influence of heterogeneity of experience on the top management team on the firm's behaviors and performance. In the context of research teams, it is more relevant to focus on an inventor's experience in a given technology field. Such technical experience significantly affects how inventors perceive and respond to external environments in accomplishing creative tasks (Shaw, 1976). Following this line of thought, we examine how differences in the technical experience of inventors within an MNC research team moderate the impact of geographic diversity.

As for the relational dimension, we shift our focus to prior interpersonal relationships among team members. In other words, we examine the extent to which team members have previous experience of collaboration with each other. Prior research suggests that repeated collaboration is an important determinant of team behavior and subsequent performance in creative processes such as R&D projects and scientific research (Guimera, Uzzi, Spiro, & Amaral, 2005; Porac et al., 2004; Skilton & Dooley, 2010). We expect to detect different behavioral influences between teams composed of already acquainted co-workers who have worked together in the past and those made up of unacquainted workers.

We theorize on the moderating effect of team composition building upon group learning theory. Viewing teams as problem-solving and information-processing systems, group learning theory explores how individuals generate, share, and combine knowledge within a group and what factors influence the outcome of their learning behavior (Argote, 2013; Edmondson, Dillon, & Roloff, 2007). Building upon major constructs identified by prior group learning research (i.e., divergent thinking, transactive memory, and team identity), we examine how team composition moderates sourcing benefits and integration challenges caused by geographic diversity. First, "divergent thinking", or the process of considering an issue from multiple perspectives, amplifies the benefits of sourcing diverse knowledge in geographically dispersed teams. As Janis (1972) pointed out, groups often tend to converge too quickly on prior familiar solutions without thorough

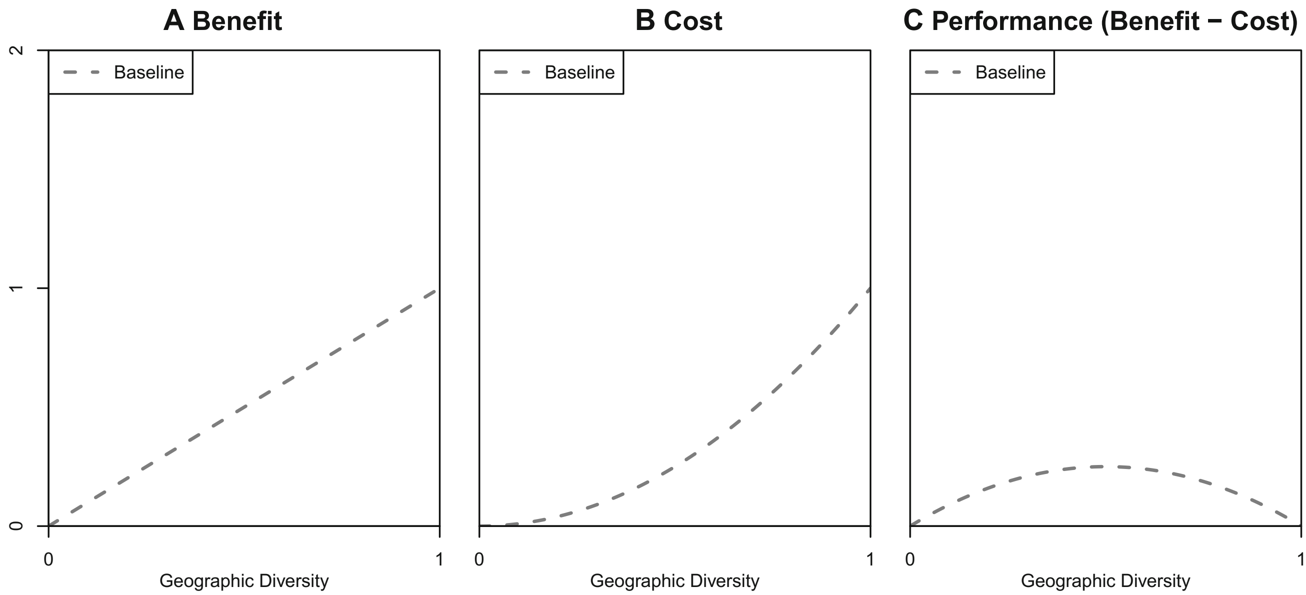

Figure 3 Expected inverted U-shaped relationship between geographic diversity and innovation performance.

consideration of alternatives and thus fail to generate creative and original solutions. Under this circumstance, having access to diverse knowledge inputs might not contribute enough to the innovation process of a research team (Nemeth & Kwan, 1987; Nemeth & Wachtler, 1983). Thus, the sourcing benefits of geographic diversity are highly contingent upon the team's ability to think divergently.

Second, a "transactive memory" system, or a basic understanding about "who knows what", reduces the coordination challenges in integrating geographic diversity. While collaborating, members tend to gain knowledge about which other members are good at performing which task or operating which tool (Argote, 2013). This meta-knowledge of who knows what promotes efficient coordination in the team by enabling them to match tasks and tools to members (Brandon & Hollingshead, 2004; Reagans, Argote, & Brooks, 2005). Research teams in which a transactive memory is well developed, therefore, may be more capable of mitigating potential problems of coordinating geographically dispersed R&D.

Third, "group identity" also helps mitigate the integration challenges of cross-border R&D teams, especially the challenges related to member commitment. According to social identity theory (Tajfel, 1974; Turner, 1975), individuals tend to categorize themselves and others into two distinct groups: the "ingroup" and the "outgroup". Although the distinction most often exists between teams, it can also occur among subgroups within a single team (Gibson & Vermeulen, 2003). Prior research shows that a strong shared identity among team members is related to increased satisfaction, higher cooperation, and reduced conflicts in the group (Williams & O'Reilly, 1998). Considering that geographic diversity discourages members' willingness to commit their best resources, we argue for a strong team identity as a solution to overcome such challenges in cross-border R&D collaboration (Ambos et al., 2016).

We now investigate how the technical and social dimensions of team composition moderate the impact of geographic diversity on innovation performance by shaping divergent thinking, transactive memory, and team identity of MNC research teams.

Heterogeneity in technical experience

We examine the moderating role of technical experience heterogeneity – that is, whether the team is composed of both technically experienced and inexperienced members or of those with similar levels of technical experience (Perretti & Negro, 2007).[3] According to our interviews with executives in global pharmaceutical firms, firms mix experienced and inexperienced inventors for various reasons. For instance, they include rookie inventors to incorporate new knowledge and approaches to problems. Mentoring is another reason for having experienced and inexperienced researchers on the same team; through collaboration, junior researchers learn from senior researchers new skills, knowledge, and know-how that cannot be easily obtained from the "market" (Aryee, Wyatt, & Stone, 1996; Becker, 1964).[4]

How can the combination of those experienced and inexperienced members moderate the impact of geographic diversity on innovation performance? First, heterogeneity in technical experience can amplify the benefits of sourcing diverse knowledge in geographically diverse teams by facilitating divergent thinking. Prior studies suggest that experienced and inexperienced inventors tend to possess different perspectives, skill sets, and types of creativity that complement each other in the process of learning and utilizing new knowledge (Bell, Villado, Lukasik, Belau, & Briggs, 2011; Gilson et al., 2013). Researchers with less invention experience tend to be better at embracing fresh ideas and bringing them to a project because they are less socialized to established and predominant norms and values in innovation activities (Jones, 1986; Perretti & Negro, 2007). Inventors who recently received their degrees, for instance, tend to be more open to using state-of-the-art technologies based on the newest academic research, which often deviate from established norms and methods of invention and innovation. Inventors lacking industrial R&D experience, however, may fail to materialize their preliminary ideas into tangible outcomes (Amabile, 1983; Levine, Choi, & Moreland, 2003). As noted by Simon (1981), it is veterans, or experienced inventors, who are better at finding impactful and feasible applications of such knowledge. We posit that the complementary skill sets and perspectives of experienced and less experienced inventors facilitate divergent thinking in the innovation process and increase the benefit of diverse location-specific knowledge inputs. An MNC research team with homogeneous technical experience, on the other hand, may not receive the same benefit due to a lack of divergent thinking. The benefits of geographic diversity increase with heterogeneity in technical experience on an MNC research team, as presented in Panel (A) of Figure 4.

Heterogeneity of technical experience, on the other hand, makes the MNC research team more sensitive to challenges in integrating diverse knowledge, challenges which tend to be amplified by geographic diversity. Inventors with differing technical experience are also likely to differ with respect to their expertise and perspectives as well as their attitudes and values (Bantel & Jackson, 1989). As a result, more time is needed to achieve consensus as team heterogeneity increases (Hambrick, Cho, & Chen, 1996). To mitigate this problem, it is necessary to have intensive, high-quality interactions within the group (Argote, 2013; Kogut & Zander, 1996; Thompson, 1967). Gilson et al. (2013) showed that experience heterogeneity enhances creativity *only* if there is extensive interaction within the team. In the context of cross-border collaboration, however, interaction among team members is much more difficult and costly. Coordination issues due to geographic diversity are exacerbated and become more severe when individuals with heterogeneous experience undertake specialized tasks as a team. Technically heterogeneous teams have greater knowledge gaps, more disparate skills, and more divergent perspectives, which hampers accurate and efficient communication (Carlson & Zmud, 1999; Ngwenyama & Lee, 1997). According to prior research, the resulting inefficient communication deters the development of transactive memory systems, which are necessary to facilitate efficient coordination of geographically dispersed R&D (Hollingshead & Brandon, 2003; Lewis, 2004). Teams with members who possess similar experience and comparable knowledge, on the other hand, can build transactive memory systems more readily and thus are less affected by difficulties that arise from geographic diversity.

In addition, in experience-heterogeneous teams, problems with lower commitment arise more frequently and are often more aggravated by geographic diversity than in homogeneous teams because of a lack of team identity. Prior research suggests that similarities in salient perceptual dimensions influence the group identity of a team (Amiot, Terry, & McKimmie, 2012; Eckel & Grossman, 2005; Tajfel, 1982). For instance, status differentials among individuals may facilitate or hinder the formation of identity in the group (Commins & Lockwood, 1979; Hagendoorn & Henke, 1991; Sachdev & Bourhis, 1987). This implies that research teams with high levels of experience heterogeneity (e.g., veterans and rookies) should find it more difficult to develop group identity than those with similar levels of experience (Williams & O'Reilly, 1998). Smith et al. (1994), in a study of 53 top management teams, found that heterogeneity of experience at the industry and

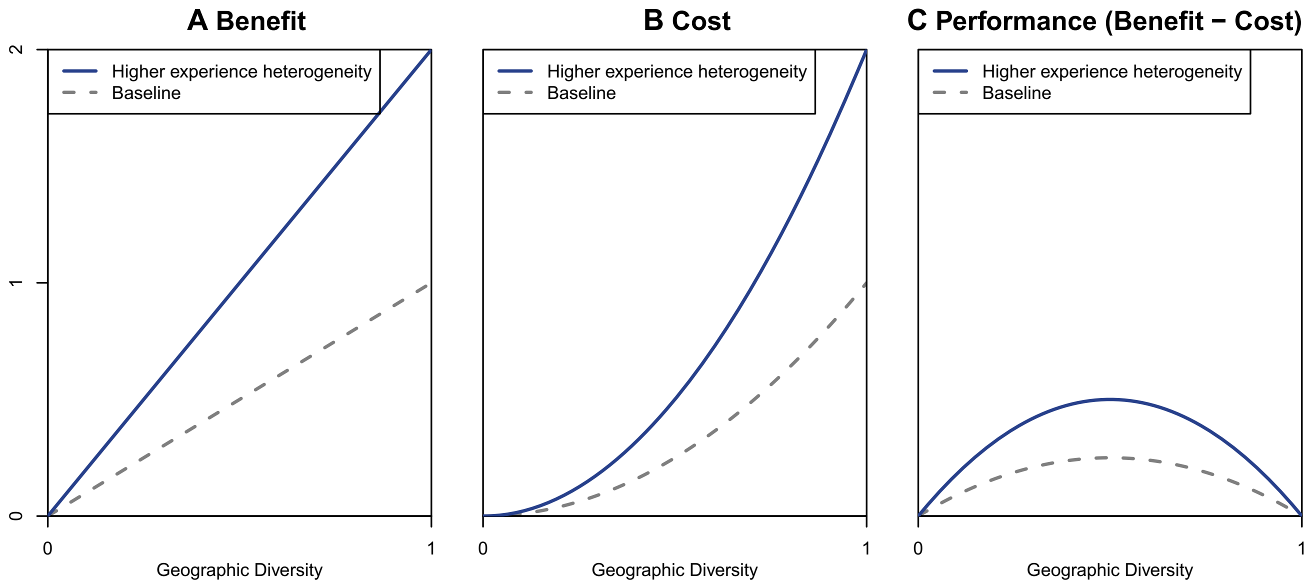

Figure 4 Expected moderating effects of experience heterogeneity.

company levels is negatively related to group cohesiveness and commitment to the team. Consequently, challenges with commitment are magnified when technically heterogeneous members work together from distant locations. In other words, the marginal cost of geographic diversity becomes greater as experience heterogeneity increases, as illustrated in Panel (B) of Figure 4.

The overall effect of heterogeneity of technical experience on a research team is illustrated in Panel (C) of Figure 4. As heterogeneity of technical experience increases, the team becomes more sensitive to both benefits and challenges of high geographic diversity on innovation performance. We hypothesize as follows.

> **Hypothesis 2:** Experience heterogeneity within an MNC research team increases the influence of geographic diversity on innovation performance; that is, as the level of experience heterogeneity increases, the inverted U-shaped curve between geographic diversity and innovation performance becomes steeper.

Repeated collaboration among inventors

Repeated collaboration among inventors within an MNC research team is another important compositional factor that moderates the relationship between geographic diversity and innovation performance. The moderating effect of repeated collaboration is expected to be opposite to that of experience heterogeneity: the greater the degree of repeated collaboration among team members, the weaker the impact of geographic diversity on the team's performance.

Repeated collaboration makes it difficult for an MNC research team to benefit from various location-specific knowledge for two reasons. First, repeated collaboration homogenizes the knowledge pool of the team (Guimera, Uzzi, Spiro, & Amaral, 2005; Porac et al., 2004). For a given level of geographic diversity, the magnitude of knowledge diversity itself is small for repeated collaborators because team members tend to provide redundant information over time. Second, repeated collaboration impedes the process of divergent thinking in completion of innovation tasks. As pointed out by Skilton and Dooley (2010), frequent collaborators tend to converge too quickly on prior familiar solutions rather than carefully discussing diverse alternatives before they come to a conclusion. In other words, a research team packed largely with repeated collaborators is less likely to utilize diverse knowledge in their problem solving. Inventors who repeatedly work together on the same team may not fully enjoy the knowledge benefits arising from geographic diversity. Therefore, as illustrated in Panel (A) of Figure 5, knowledge benefits provided by geographic diversity are significantly reduced for MNC research teams consisting of collaborators who have worked together in the past.[5]

Although repeated collaboration is detrimental with respect to the benefits of sourcing diverse knowledge in MNC research teams with high

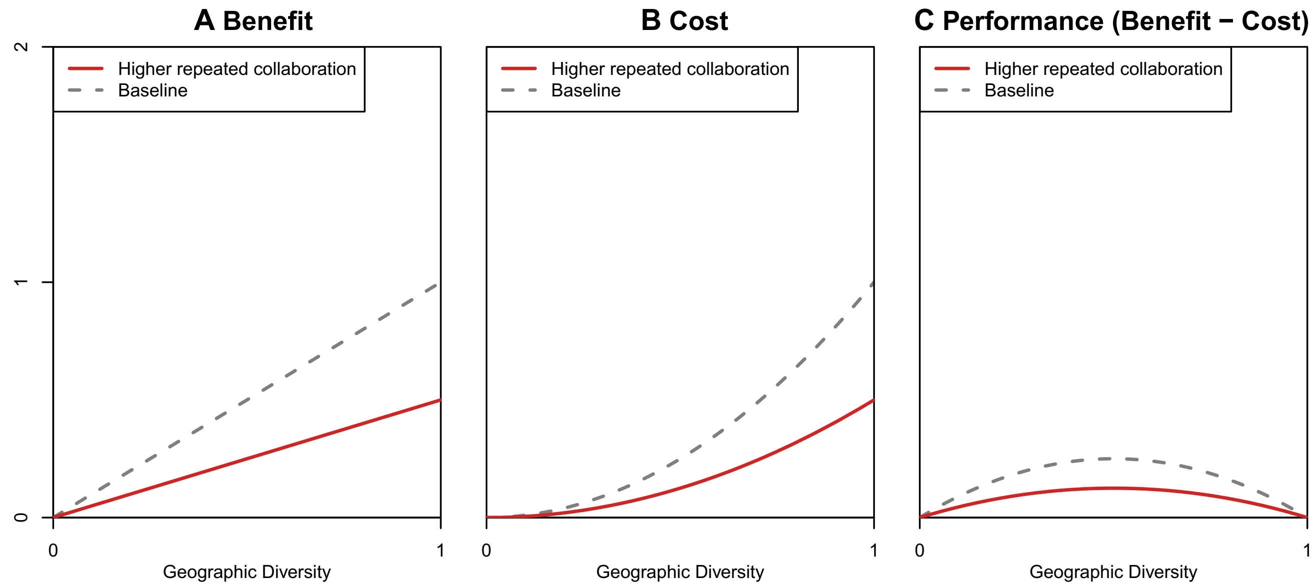

Figure 5 Expected moderating effects of repeated collaboration.

geographic diversity (i.e., in terms of sourcing and combining diverse location-specific knowledge), it is beneficial in terms of mitigating the challenges in integrating diverse knowledge arising from geographic diversity (i.e., coordination and commitment challenges). As professionals work together, they accumulate a common knowledge base and reach a deep understanding of previously unfamiliar contexts (Baba et al., 2004). Shared knowledge contributes to efficiency and effectiveness when researchers communicate ideas and share tacit knowledge within groups or organizations (Kogut & Zander, 1996). These members may develop special terms and customs over time to communicate and coordinate effectively with one another. In addition, during prior interactions, a well-functioning transactive memory system may already have developed (Liang, Moreland, & Argote, 1995; Faraj & Sproull, 2000; Rosen, Furst, & Blackburn, 2007). Thus, MNC research teams in which inventors have prior experience of collaboration with each other can overcome coordination and communication challenges stemming from geographic dispersion more effectively than teams consisting of all new members.

Furthermore, shared collaboration experience can resolve challenges in commitment that may arise when inventors in a team are geographically dispersed. Mutual trust and a strong team identity develop as members learn about the skills, personal values, and behavioral habits of others through repeated interaction (Argote, 2013). Studies suggest that interpersonal interactions could facilitate social identification processes among group members (Mansour-Cole, 2001). Hinds & Mortensen (2005), for instance, found that spontaneous communication could contribute to developing group identity among geographically distributed workers. Group identity should therefore emerge more easily among repeated collaborators.

This is particularly important for MNCs in which geographically dispersed team members lack common backgrounds. When members of a team trust each other, they can be confident that they will get appropriate returns from their commitment (Jones & George, 1998). Consider the example of Snecma, a French aerospace engine company. Snecma visited the USSR's Moscow Aviation Institute (MAI) over several decades during the Cold War period. Despite the political and sociocultural gaps between the two countries, the repeated collaboration of Snecma scientists with the USSR scientists alleviated tensions and cultural gaps and resulted in a series of innovations which other competitors in the West could not achieve (Doz & Wilson, 2014).

This is also consistent with the empirical findings of Hinds & Mortensen (2005). Their field study on 43 teams from one MNC showed that shared identity within a team reduces the impact of geographic dispersion on team conflicts. Even when the level of geographic diversity is excessively high, research teams with abundant repeated collaboration experience have fewer difficulties in motivating their dispersed members to commit themselves to their tasks. As illustrated in Panel (B) of Figure 5, the costs arising from geographic diversity are significantly reduced for MNC research teams with considerable collaboration experience among team members.

Repeated collaboration is, however, detrimental to geographically dispersed collaboration in that it undermines sourcing benefits provided by geographic diversity; yet it is also helpful in that it aids in overcoming integration challenges associated with geographic dispersion. Therefore, MNC research teams with frequent repeated collaboration among team members are less influenced by both the positive and negative impacts of geographic diversity on their innovation performance, as illustrated in Panel (C) of Figure 5. Hence, we propose the following hypothesis:

> **Hypothesis 3:** Repeated collaboration among members of an MNC research team decreases the influence of geographic diversity on innovation performance; that is, as the level of repeated collaboration increases, the inverted U-shaped curve between geographic diversity and innovation performance becomes flatter.

METHODS

Data and Sample

We analyze U.S. patents issued by global pharmaceutical firms from 1981 to 2012. Pharmaceutical firms strive to develop technological innovations and create new medicines in order to alleviate a broad range of health problems. The pharmaceutical industry offers an optimal setting for our study for the following reasons. First, geographic dispersion of R&D activities is evident in this industry. The extensive globalization of R&D activities in the pharmaceutical industry guarantees abundant cases of geographically dispersed collaboration for innovation. Second, the high propensity to patent of pharmaceutical firms offers a great opportunity to measure and study geographic diversity and team composition of research teams in an objective manner. Since U.S. law obliges patent applicants and their patent attorneys to provide detailed information about the residence of inventors, we can observe and measure the geographic diversity of a team by analyzing patent documents. In addition, by tracking prior patenting activities of every single inventor on a research team, we can operationalize team composition variables, such as experience heterogeneity and repeated collaboration. Patent archival data enable us to conduct a quantitative analysis with a large sample, avoiding the self-reporting bias inherent in survey methods.

We conduct our regression analysis at the patent level, regarding inventors listed in a given patent document as a research team. The final sample used in the analysis is determined as follows. First, we identified the top 25 pharmaceutical companies in 2013 (in terms of sales) from the records of *Pharmaceutical Executive*, a specialized magazine focusing on the pharmaceutical industry. Table 2 briefly summarizes the financial information of the sample firms in 2013. Second, as illustrated in Figure 6, we tracked major mergers and acquisitions (M&A) of the firms during the sample period and identified 46 pre-M&A firms. We then identified 86,750 patents registered by these firms. We dropped patents registered by a single inventor to ensure that the R&D activities included in our sample reflect collaborative efforts. We further dropped patents where we cannot observe their assignee firm's revenue, a measure of firm size. The resulting final sample for our regression analysis contains 59,998 inventions in the top 25 pharmaceutical firms from 1981 to 2012.

Measurement

Innovation performance: impact and novelty

We measure the innovation performance of research teams in two different dimensions: *impact* and *novelty*. First, the scientific impact of innovation is the extent to which a given innovation influences future innovation. This is measured by the number of forward (future) citations that each patent has received. To take into account the fact that old patents have a greater chance of being cited than new patents, we count forward citations received in the first 10 years after patent filing. We also include year-fixed effects in our regression models, which further address the concerns of secular increases in citation frequency.

Second, the novelty of innovation captures how much a given innovation draws on knowledge that has rarely been used before in inventions in the same field (i.e., unprecedented combinations). We draw on Eggers & Kaul's (2018) measure of novelty, which identifies "inventions that draw on knowledge that is fundamentally new to the field" (Eggers & Kaul, 2018: 74). We first measure novelty at the patent-backward citation level. For each patent, we look at its backward citations and their technology

Table 2 Top 25 global pharmaceutical firms in 2013

Name	Headquarters location	Sales*	US sales (%)	R&D*	Employees	Patents**	Countries***
Pfizer	New York, NY, USA	47,404	39.14	7046	77,700	827	14
Novartis	Basel, CH	45,418	31.84	8831	135,696	779	11
Merck & Co	Whitehouse Station, NJ, USA	41,143	41.44	7911	76,000	556	7
Sanofi	Paris, FR	38,370	31.66	6118	112,128	671	9
Roche	Basel, CH	37,542	37.01	8032	85,080	785	14
GlaxoSmithKline	Brentford, UK	33,107	32.94	5256	99,451	528	10
AstraZeneca	Cambridge, UK	27,064	39.07	4452	51,500	430	7
Johnson & Johnson	New Brunswick, NJ, USA	23,491	49.59	5362	128,100	129	9
Abbott Laboratories	Abbott Park, IL, USA	23,119	28.69	2900	69,000	803	10
Eli Lilly	Indianapolis, IN, USA	18,509	55.77	5075	37,925	282	1
Teva Pharmaceutical	Petach Tikva, IL	17,681	51.50	1283	44,945	200	6
Amgen	Thousand Oaks, CA, USA	16,639	77.53	3318	20,000	369	3
Takeda	Tokyo, JP	15,173	22.08	3721	31,230	262	6
Bayer	Leverkusen, DE	14,734	20.80	2523	112,400	1002	15
Boehringer Ingelheim	Ingelheim am Rhein, DE	13,686	36.67	3012	47,492	443	7
Novo Nordisk	Bagsvaerd, DK	13,478	46.70	1882	38,436	102	3
Bristol-Myers Squibb	New York, NY, USA	13,155	50.77	3715	28,000	544	3
Daiichi Sankyo	Tokyo, JP	11,019	24.13	2287	32,790	49	1
Astellas Pharma	Tokyo, JP	10,835	25.20	2224	17,649	112	2
Gilead Sciences	Foster City, CA, USA	9398	59.77	1683	6100	123	7
Baxter International	Deerfield, IL, USA	8857	42.68	1015	61,000	219	3
Otsuka	Tokyo, JP	8385	41.30	1870	28,288	118	2
Merck KGAA	Darmstadt, DE	7709	21.50	1552	77,000	595	4
Mylan LV	Canonsburg, PA, USA	6697	57.42	389	20,000	12	3
Eisai	Tokyo, JP	6181	26.70	1424	10,419	186	2

Sources: *Pharmaceutical Executive* and annual reports
*In million U.S. dollars.
**Number of U.S. patents granted to the firm from 2008 to 2012.
***Number of countries of assignees in U.S. patents granted to the firm from 2008 to 2012.

classes (United States Patent Classification). For a citation made by a patent in class i to a patent in class j, we take all other patents in class i in the prior 5 years and calculate the percentages of their backward citations that referred to patents in class j. That is,

$$LINK_{tij} = \frac{\sum_{t=-5}^{-1} citations_{tij}}{\sum_{t=-5}^{-1} citations_{ti}}$$

Patent-level novelty is then calculated as 1 minus the lowest (rarest) *LINK* in the patent. This measure captures the rarest technological link made by a given patent compared to all the other patents in the same technology class. This variable is not identifiable for patents that either cited no other patents (one case in our sample) or cited old patents whose technology class is not adequately defined (8283 cases in our sample). This reduces our sample size for novelty analysis to 51,705 patents (86 percent of the full sample).

Geographic diversity

The USPTO database provides information about the residence of each inventor at two levels: the city level and state/country level. We first operationalize geographic diversity using the Blau index of diversity, $Diversity_i = 1 - \sum_{l=1}^{L} p_{il}^2$, where p_{il} is the proportion of inventors on research team i in state/country-level location l, and L is the number of locations (Berry, 2014). We then account for Hall's (2000) argument that the index based on a small number of inventors tends to be biased downward. In other words, diversity is underestimated when the number of inventors involved in a patent is small. We correct for this potential bias as follows:

$$Geographic\ Diversity_i = Diversity_i \times \frac{N}{N-1},$$

where $Diversity_i$ indicates the Blau index of diversity mentioned above, and N refers to the number of inventors on the patent.

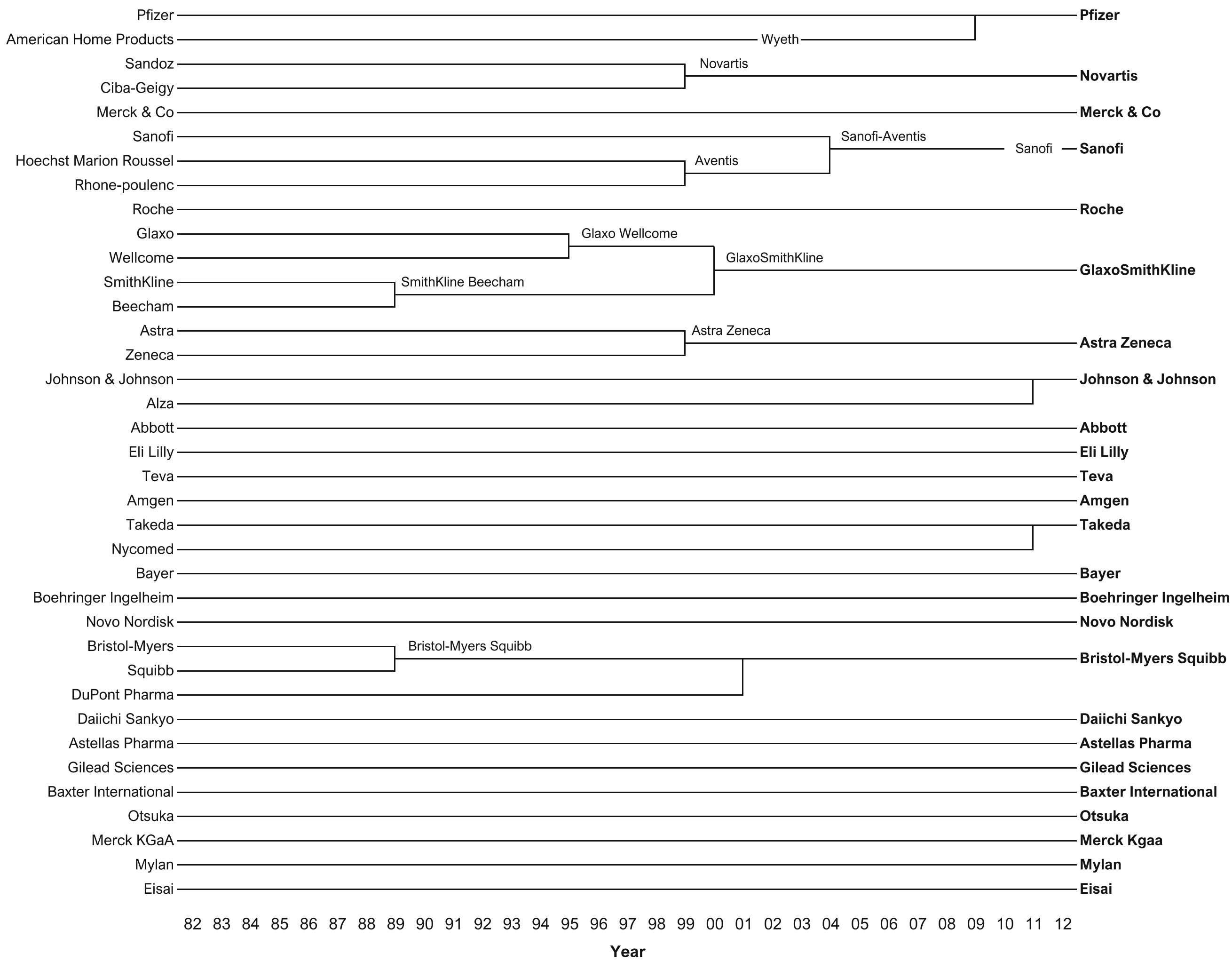

Figure 6 Major M&A events of sample firms.

Experience heterogeneity

Successful patent registration can effectively reflect the technical experience of an individual or an organization (Ahuja & Katila, 2001; Li & Simerly, 2002). In order to measure the experience heterogeneity of a given research team, we track prior patenting activities of every inventor on every team. We operationalize inventors' technical experience by counting the number of successful patent registrations for each individual. Accounting for the effects of obsolescence of old technologies, we limit the analysis to patents that were registered within the previous 5 years. We additionally conduct sensitivity tests with longer time windows. As a next step, we operationalize the experience heterogeneity of a research *team* by computing the variance of each inventor's technical experience as follows:

$$Experience\ Heterogeneity_i = \frac{\sum_{j=1}^{N}\left(Experience_{ij} - \overline{Experience_i}\right)^2}{N},$$

where $Experience_{ij}$ represents the technical experience of inventor j of patent i, and N refers to the number of inventors on the team.

Repeated collaboration

To measure the extent of (prior) repeated collaboration within a research team, we follow the approach of Reagans, Argote, and Brooks (2005). We first identify dyadic pairs between inventors within the team and then count the number of instances of prior collaboration of each pair in former patenting activities over the past 5 years. We again conduct sensitivity tests with longer time windows. Repeated collaboration of a research team is calculated by dividing the total number of instances of prior collaboration among members of a research team by the number of all possible dyadic pairs within the team:

$$\text{Repeated Collaboration}_i = \frac{\sum_{k=1}^{K} \text{Pair}_{ik}}{K},$$

where $Pair_{ik}$ indicates the number of prior instances of collaboration experience of pair k on patent i, and K refers to the number of all possible dyadic collaboration pairs, calculated by $\frac{N(N-1)}{2}$.

Control variables

To isolate the effects of geographic diversity and team composition, we include control variables at various levels. First, we take team characteristics into account. One could argue that geographically dispersed teams are composed of the best (or worst) inventors in each location and thus tend to have higher (lower) capabilities than collocated teams. We take these possibilities into account by including two control variables on team capabilities (Singh, 2008): *the number of inventors* and *the sum of inventors' patenting experiences*. In addition, *the number of locations* is controlled for to validate our use of the Blau index that measures geographic diversity. This variable also takes into account that team-level geographic diversity increases the number of contact points (i.e., locations) for a given invention and thereby mechanically increases its impact (e.g., forward citations). In addition, we also consider that inventors may move around to multiple locations in their careers, and that the resulting experience may affect both our independent and dependent variables. To mitigate this concern, we include in our regression models *the number of mobile inventors* who had changed their residence across states or countries. We further control for the abundance of regional resources by including *the number of patents in regions*, a variable that counts the sum of drug patents in the prior 5 years in cities in which inventors reside. Furthermore, our *average linguistic distance* variable controls for heterogeneity associated with linguistic distance between languages that members use. Prior research suggests that language differences impose significant barriers to coordination of tasks in MNCs (Harzing & Feely, 2008; Luo & Shenkar, 2006; Tenzer, Pudelko, & Harzing, 2014). To partial out the effect of language differences, we first identify all official languages of each inventor's residence (country). Following prior studies (Ambos & Ambos, 2009; Chen, Sokal, & Ruhlen, 1995), we then calculate linguistic distance between the languages (i.e., the number of branches on the language tree necessary to connect the two focal languages) using the *Ethnologue Database*. In cases where a country has multiple official languages (e.g., Switzerland), we use the mean value of the distance for all the official languages. Then, the control variable is constructed by averaging the values over all inventor pairs involved in a patent.

Second, we control for various patent-level characteristics. To isolate the effects of the technological complexity of each innovation output, our model includes *the number of backward citations*, which is the total number of U.S. patents that a focal patent cites (Fleming, 2001). We also include *the average age of backward citations* to control for various patterns of knowledge creation (Nerkar, 2003). To rule out the effects of path dependency on a firm's innovation activity, we include *the self-citation ratio* as a control (Song et al., 2003). Furthermore, we posit that firm-level joint patenting may affect both the geographic diversity of a research team and the team's innovation performance (Kim & Song, 2007). We thus control for *the number of assignees* of each patent in the model.[6] *The number of claims* – which define the invention and the scope of the protection conferred by a patent – is also controlled for, as it is related to the strategic value of the patent (Lanjouw & Schankerman, 1999). Prior studies also show that a single invention could be patented in multiple countries and this could be correlated to the quality of the invention (Criscuolo, 2006; Martínez, 2010). To control for this effect, we include a dummy variable (*US Only*) that equals one if the invention was patented only in the US and zero otherwise.

Third, we include firm-level controls. We control for *firm size*, measured by sales (billion U.S. dollars) of the firm in each year, and *firm age*, the number of years from the very first year in which a patent was granted. Lastly, we include firm, technology, and year dummies (see the following section for more detail).

Estimation

We obtain our estimates using ordinary least squares (OLS) models. One concern may arise that one of our outcome variables, *impact*, is a count variable. OLS is known to provide good estimates even for count variables. OLS estimates and the marginal effects of non-linear models are shown to be very similar (Angrist & Pischke, 2009). Although the use of OLS for count outcomes generally leads to violation of the assumption of homogeneity of error variance, we can adjust for it by using robust standard errors (White, 1980). In addition, OLS has several advantages over non-linear models. First, it provides consistent estimates without distributional assumptions of error terms. Second, OLS allows for more straightforward interpretation of the implied marginal effects from our parameter estimates. This is particularly important in our research setting where the three-way interactions among independent variables are estimated. As a robustness check, we also run negative binomial models. The results are consistent and qualitatively very similar to our main specification.

A major concern in estimating the effects of geographic diversity and team composition on innovation performance is that unobservable team characteristics may affect the results. Failure to address this endogeneity may confound our estimates. For example, MNCs typically have different ways of organizing and supporting research teams; if one MNC fully subsidizes travel expenses for cross-border teams to mitigate the impact of geographic distance while others do not, this unobserved, firm-specific characteristic may bias our estimates. Innovation performance of teams may also vary across different technological fields. Some fields inherently require more diverse inventors than other fields. We therefore include firm dummies to address the former issue and patent class dummies to reduce the effects of the latter. Furthermore, we include year dummies to account for any year-specific shocks. This also controls for the age of patents (to ensure that we do not favor older patents when counting patent forward citations) and the effects of technological trends over time (Singh, 2008). Thus, we estimate the OLS model including firm-fixed, technology class-fixed, and year-fixed effects to control for unobserved heterogeneity. The resulting *full* specification (Models 3 and 6 in Table 3) is as follows:

$$\begin{aligned} y_i = {} & \beta_0 + \beta_1\, \mathit{Geographic\ Diversity}_i + \beta_2\, \mathit{Geographic\ Diversity}_i^2 \\ & + \beta_3\, \mathit{Experience\ Heterogeneity}_i + \beta_4\, \mathit{Repeated\ Collaboration}_i \\ & + \beta_5\, \mathit{Geographic\ Diversity}_i \times \mathit{Experience\ Heterogeneity}_i \\ & + \beta_6\, \mathit{Geographic\ Diversity}_i^2 \times \mathit{Experience\ Heterogeneity}_i \\ & + \beta_7\, \mathit{Geographic\ Diversity}_i \times \mathit{Repeated\ Collaboration}_i \\ & + \beta_8 \mathit{GeographicDiversity}_i^2 \times \mathit{RepeatedCollaboration}_i \\ & + \boldsymbol{x}_i\gamma + \delta_{firm} + \mu_{class} + \tau_{year} + \varepsilon_i, \end{aligned}$$

where y_i represents the expected innovation performance of research team i, x_i refers to the control variables of team i, δ_{firm} represents firm dummies,[7] μ_{class} represents patent class dummies, τ_{year} represents year dummies, and ε_i is an error term. To account for heteroskedasticity of the errors, as discussed above, we use robust standard errors.

RESULTS

Descriptive Statistics and Main Results

Table 3 provides the descriptive statistics and correlations of the variables in our model. None of the variables exhibits large correlations except for those between *Geographic Diversity* and *Number of Locations* (0.839), between *Experience Sum* and *Experience Heterogeneity* (0.614), and between *Experience Sum* and *Team Size* (0.640). We conduct the variance inflation factor (VIF) test to check for multicollinearity based on the OLS model. The highest VIF score is 4.95 (mean VIF = 1.90), suggesting no serious multicollinearity problem in our model. Following the suggestion of Cronbach (1987), we also center our key independent variables by subtracting mean values from each individual value before generating interaction terms. This method reduces the correlation between separate and interactive effects, thus reducing the possibility of reporting meaningful interactions as non-significant. *Experience Heterogeneity* is standardized due to its large variance.

Table 4 shows the results of our OLS regression analyses. Models 1 and 4 include the control variables only, thus serving as a benchmark for comparison with the other models derived from our theory. Models 2 and 5 test Hypothesis 1, which predicts that the geographic diversity of a research team has an inverted U-shaped relationship with its innovation performance. In Model 2 examining the impact of innovation, the coefficient of *Geographic Diversity* is positive and significant ($\beta = 2.251$, p value $= 0.016$), while the coefficient of *Geographic Diversity*^{2} is negative and also significant ($\beta = -2.907$, p value $= 0.035$). In support of Hypothesis 1, the results indicate that an increase in the geographic diversity of an MNC research team initially enhances the impact of the team's innovation, but when the level of diversity exceeds a certain point (i.e., geographic diversity is 0.561), a further increase actually reduces that impact. The estimated maximum level of innovation impact is thus shown to be 14.06 percent greater than its minimum level. In Model 5 examining the novelty of innovation, the coefficient of *Geographic Diversity* is positive and highly

Table 3 Descriptive statistics and correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9
1. Impact of innovation	6.707	15.765									
2. Novelty of innovation	0.839	0.230	0.074								
3. Geographic diversity	0.174	0.308	0.031	0.013							
4. Experience heterogeneity	100.067	377.589	− 0.026	− 0.014	− 0.071						
5. Repeated collaboration	2.119	3.991	− 0.038	− 0.025	− 0.053	0.419					
6. Team size	4.029	2.488	0.026	− 0.004	0.076	0.054	0.059				
7. Sum of experience	29.831	51.324	− 0.026	− 0.018	− 0.038	0.618	0.640	0.436			
8. Number of locations	1.342	0.630	0.040	0.017	0.839	− 0.062	− 0.045	0.353	0.059		
9. Number of mobile inventors	0.420	0.797	0.017	0.008	0.219	0.021	0.110	0.418	0.262	0.365	
10. Number of patents in regions	462.823	726.347	− 0.014	− 0.023	− 0.001	0.066	0.076	0.570	0.291	0.151	0.242
11. Linguistic distance	0.832	2.005	− 0.025	0.005	0.357	− 0.038	− 0.039	0.014	− 0.029	0.303	0.086
12. Number of backward citations	10.113	35.179	0.122	0.142	0.038	0.007	0.080	0.051	0.069	0.059	0.071
13. Age of backward citations	9.738	8.022	− 0.019	0.120	0.016	− 0.043	− 0.071	0.022	− 0.047	0.027	0.017
14. Self-citation ratio	0.164	0.279	− 0.054	− 0.098	− 0.033	0.107	0.158	0.036	0.174	− 0.029	0.016
15. Number of assignees	1.007	0.228	0.018	0.029	0.119	− 0.007	− 0.008	0.070	0.012	0.132	0.031
16. Number of claims	14.448	13.612	0.134	0.051	0.066	− 0.063	− 0.055	0.082	− 0.047	0.091	0.080
17. US only	0.040	0.195	− 0.002	− 0.025	0.028	− 0.020	− 0.034	− 0.083	− 0.057	− 0.006	− 0.036
18. Firm size	19.691	16.171	− 0.042	0.023	0.036	0.150	0.083	0.126	0.196	0.063	0.082
19. Firm age	25.379	8.054	− 0.014	0.063	0.131	− 0.005	0.023	0.194	0.109	0.179	0.169

Variable	Mean	SD	10	11	12	13	14	15	16	17	18
1. Impact of innovation	6.707	15.765									
2. Novelty of innovation	0.839	0.230									
3. Geographic diversity	0.174	0.308									
4. Experience heterogeneity	100.067	377.589									
5. Repeated collaboration	2.119	3.991									
6. Team size	4.029	2.488									
7. Sum of experience	29.831	51.324									
8. Number of locations	1.342	0.630									
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13. Age of backward citations	9.738	8.022	0.003	0.012	0.104						
14. Self-citation ratio	0.164	0.279	0.036	− 0.007	− 0.068	− 0.254					
15. Number of assignees	1.007	0.228	0.076	0.064	0.058	− 0.037	− 0.001				
16. Number of claims	14.448	13.612	0.049	0.003	0.103	0.026	− 0.071	0.030			
17. US only	0.040	0.195	− 0.060	− 0.037	− 0.020	− 0.024	− 0.018	− 0.006	− 0.017		
18. Firm size	19.691	16.171	0.090	− 0.041	0.037	0.113	0.049	0.036	− 0.057	− 0.107	
19. Firm age	25.379	8.054	0.158	− 0.020	0.108	0.139	0.097	0.091	0.045	− 0.121	0.469

significant ($\beta = 0.031$, p value = 0.007), while the coefficient of *Geographic Diversity*^{2} is negative and also highly significant ($\beta = -0.059$, p value < 0.001), which also supports our Hypothesis 1. The results indicate that the novelty of innovation is maximized when geographic diversity is 0.444. The estimated maximum level of innovation novelty is thus shown to be 2.18 percent greater than its minimum level. Figure 7 illustrates the estimated inverted U-shaped relationship between geographic diversity and innovation performance with 95% confidence intervals.

In Models 3 and 6, we test Hypothesis 2. In Model 3 examining the impact of innovation, the coefficient of *Geographic Diversity* × *Experience Heterogeneity* is positive and highly significant ($\beta = 2.699$, p value = 0.002), while the coefficient of *Geographic Diversity*^{2} × *Experience Heterogeneity* is negative and highly significant ($\beta = -4.584$, p value = 0.004). The negative moderation of the quadratic term implies that the relationship between geographic diversity and innovation impact *strengthens* as heterogeneity of technical experience of team members increases. In other words, the slope of the inverted U-shaped curve of the relationship becomes *steeper* (Haans, Pieters, & He, 2016). Specifically, the marginal impact on innovation impact of the geographic diversity of an MNC research team at its minimum level (i.e., geographic diversity = 0) is estimated to increase from 1.056 to 5.347 (more enhancing) when the level of experience heterogeneity increases by one standard deviation around its mean value.[8] On the other hand, the marginal impact of geographic diversity at its maximum level (i.e., geographic diversity = 1) is estimated to decrease from -0.346 to -5.222 (more reducing) when the level of experience heterogeneity increases by one standard deviation around its mean value.

In Model 6 examining the novelty of innovation, the coefficient of *Geographic Diversity* × *Experience Heterogeneity* is also positive and highly significant ($\beta = 0.054$, p value < 0.001), while the coefficient of *Geographic Diversity*^{2} × *Experience Heterogeneity* is negative and highly significant ($\beta = -0.066$, p value = 0.006). More specifically, the marginal impact on innovation novelty of the geographic diversity of an MNC research team at its minimum level (i.e., geographic diversity = 0) is estimated to increase from 0.016 to 0.091 (more enhancing) when the level of experience heterogeneity increases by one standard deviation around its mean value. On the other hand, the marginal impact of geographic diversity at its maximum level (i.e., geographic diversity = 1) is estimated to decrease from -0.039 to -0.096 (more reducing) when the level of experience heterogeneity increases by one standard deviation around its mean value. These results imply that increasing the level of experience heterogeneity amplifies both positive and negative impacts of geographic diversity on innovation performance, which supports Hypothesis 2.

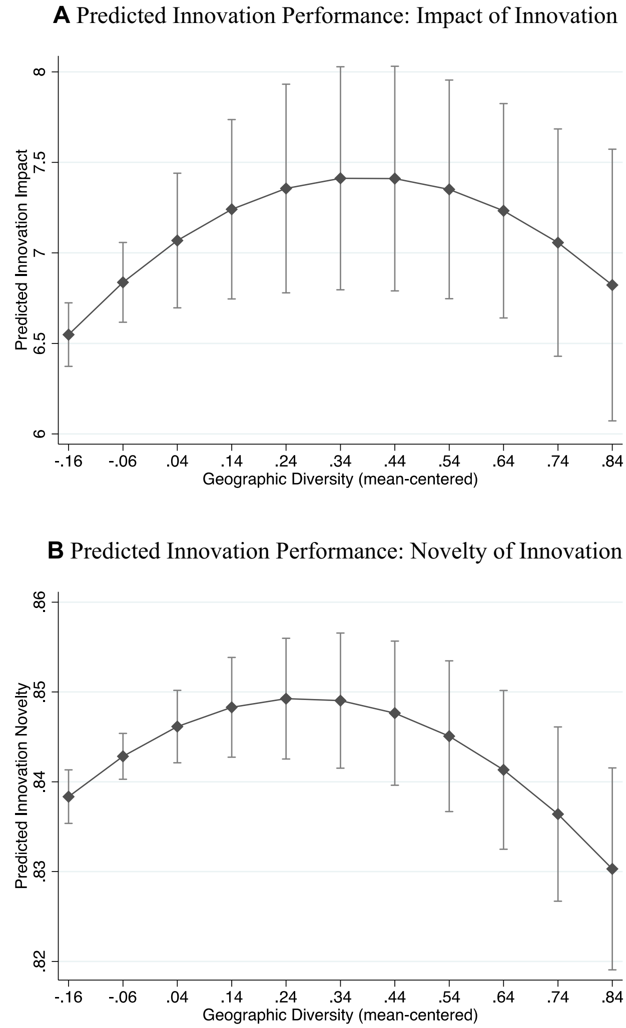

Figure 7 Estimated relationship between geographic diversity and innovation performance. *Note*: Vertical lines show the 95% confidence intervals.

Models 3 and 6 test Hypothesis 3, which proposes that repeated collaboration among inventors flattens the inverted U-shaped relationship between geographic diversity and innovation performance. In Model 3, the coefficient of *Geographic Diversity* × *Repeated Collaboration* is negative and highly

Table 4 Results of linear regression analyses

	DV: Impact of innovation			DV: Novelty of innovation		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Geographic diversity		2.251	2.162		0.032	0.034
		(0.935)	(0.921)		(0.012)	(0.012)
		[0.016]	[0.019]		[0.007]	[0.004]
Geographic diversity^2		− 2.907	− 2.993		− 0.059	− 0.061
		(1.380)	(1.376)		(0.016)	(0.016)
		[0.035]	[0.030]		[0.000]	[0.000]
Geographic diversity × Experience heterogeneity			2.699			0.054
			(0.870)			(0.015)
			[0.002]			[0.000]
Geographic diversity^2 × Experience heterogeneity			− 4.584			− 0.066
			(1.593)			(0.024)
			[0.004]			[0.006]
Geographic diversity × Repeated collaboration			− 0.816			− 0.009
			(0.191)			(0.003)
			[0.000]			[0.002]
Geographic diversity^2 × Repeated collaboration			1.020			0.012
			(0.326)			(0.005)
			[0.002]			[0.011]
Experience heterogeneity	0.050	0.053	0.567	0.001	0.001	0.011
	(0.048)	(0.048)	(0.202)	(0.001)	(0.001)	(0.004)
	[0.292]	[0.272]	[0.005]	[0.337]	[0.346]	[0.001]
Repeated collaboration	− 0.095	− 0.094	− 0.227	0.000	0.000	− 0.001
	(0.015)	(0.015)	(0.045)	(0.000)	(0.000)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.352]	[0.339]	[0.093]
Team Size	0.291	0.288	0.274	− 0.001	− 0.001	− 0.001
	(0.040)	(0.040)	(0.040)	(0.001)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.314]	[0.081]	[0.071]
Sum of experience	0.001	0.001	0.002	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
	[0.551]	[0.581]	[0.244]	[0.000]	[0.000]	[0.000]
Number of locations	0.229	− 0.211	− 0.198	0.001	− 0.001	− 0.001
	(0.133)	(0.230)	(0.230)	(0.002)	(0.004)	(0.004)
	[0.085]	[0.358]	[0.389]	[0.419]	[0.695]	[0.691]
Number of mobile inventors	0.056	0.061	0.123	0.001	0.001	0.001
	(0.100)	(0.099)	(0.098)	(0.001)	(0.001)	(0.001)
	[0.576]	[0.540]	[0.207]	[0.606]	[0.614]	[0.377]
Number of patents in regions	− 0.000	− 0.000	− 0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.018]	[0.023]	[0.027]	[0.967]	[0.841]	[0.796]
Linguistic distance	− 0.131	− 0.146	− 0.147	0.000	− 0.000	− 0.000
	(0.029)	(0.032)	(0.032)	(0.001)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.921]	[0.930]	[0.850]
Number of backward citations	0.018	0.018	0.020	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age of backward citations	− 0.044	− 0.044	− 0.044	0.002	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Self-citation ratio	− 0.442	− 0.446	− 0.457	− 0.049	− 0.049	− 0.049
	(0.204)	(0.203)	(0.202)	(0.004)	(0.004)	(0.004)
	[0.030]	[0.028]	[0.024]	[0.000]	[0.000]	[0.000]
Number of assignees	0.462	0.439	0.407	0.002	0.002	0.001
	(0.247)	(0.248)	(0.247)	(0.004)	(0.004)	(0.004)
	[0.062]	[0.076]	[0.100]	[0.653]	[0.719]	[0.786]

Table 4 (*Continued*)

	DV: Impact of innovation			DV: Novelty of innovation		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Number of claims	0.111	0.111	0.111	0.001	0.001	0.001
	(0.007)	(0.007)	(0.007)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
US Only	− 2.046	− 2.042	− 2.073	− 0.015	− 0.014	− 0.015
	(0.249)	(0.248)	(0.248)	(0.005)	(0.005)	(0.005)
	[0.000]	[0.000]	[0.000]	[0.007]	[0.009]	[0.007]
Firm size	− 0.028	− 0.028	− 0.028	− 0.001	− 0.001	− 0.001
	(0.006)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm age	0.595	0.594	0.624	− 0.004	− 0.004	− 0.004
	(0.040)	(0.040)	(0.041)	(0.001)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	25.658	26.635	26.770	0.907	0.920	0.923
	(15.575)	(17.583)	(17.565)	(0.014)	(0.015)	(0.015)
	[0.144]	[0.130]	[0.127]	[0.000]	[0.000]	[0.000]
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes
Class dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,988	59,988	59,988	51,705	51,705	51,705

Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

significant ($\beta = -0.816$, *p* value < 0.001), while the coefficient of *Geographic Diversity*^{2} × *Repeated Collaboration* is positive and highly significant ($\beta = 1.020$, *p* value = 0.002). The positive moderation of the quadratic term indicates that the relationship between geographic diversity and innovation impact weakens as the degree of repeated collaboration among inventors increases. That is, the slope of the inverted U-shaped curve of the relationship becomes *flatter* (Haans et al. 2016). Specifically, the marginal impact on innovation impact of the geographic diversity of an MNC research team at its minimum level (i.e., geographic diversity = 0) is estimated to decrease from 5.542 to 0.861 (less enhancing) when the level of repeated collaboration increases by one standard deviation around its mean value. On the other hand, the marginal impact of geographic diversity at its maximum level (i.e., geographic diversity = 1) is estimated to increase from − 4.522 to − 1.045 (less reducing) when the level of repeated collaboration increases by one standard deviation around its mean value.

In Model 6, the coefficient of *Geographic Diversity* × *Repeated Collaboration* is also negative and highly significant ($\beta = -0.009$, *p* value = 0.003), while the coefficient of *Geographic Diversity*^{2} × *Repeated Collaboration* is positive and highly significant ($\beta = 0.012$, *p* value = 0.013). In support of our Hypothesis 3, therefore, increasing the level of repeated collaboration mitigates both the positive and negative impacts of geographic diversity on both the impact and novelty of innovation performance. Specifically, the marginal impact on innovation impact of the geographic diversity of an MNC research team at its minimum level (i.e., geographic diversity = 0) is estimated to decrease from 0.078 to 0.028 (less enhancing) when the level of repeated collaboration increases by one standard deviation around its mean value. On the other hand, the marginal impact of geographic diversity at its maximum level (i.e., geographic diversity = 1) is estimated to increase from − 0.090 to − 0.045 (less reducing) when the level of repeated collaboration increases by one standard deviation around its mean value. These results imply that increasing the level of experience heterogeneity amplifies both positive and negative impacts of geographic diversity on innovation performance. Figure 8 illustrates the moderating effects of experience heterogeneity and repeated collaboration on the inverted U-shaped relationship between geographic diversity and innovation performance.

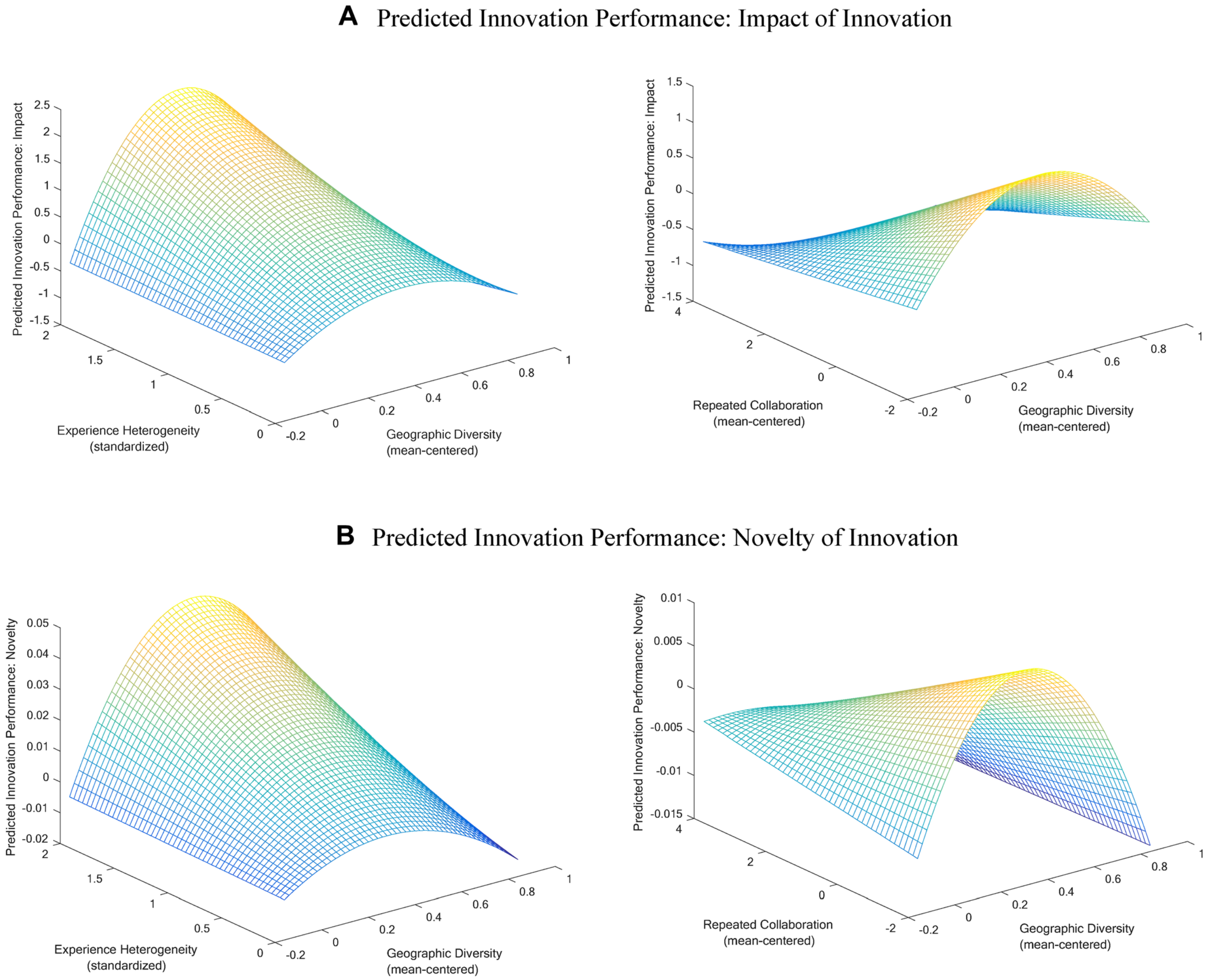

Figure 8 Estimated moderating effects of experience heterogeneity and repeated collaboration.

Robustness Checks

We performed a number of robustness checks. First, we conducted a sensitivity test with longer year windows than 5 years for our moderating variables. As we show in the Appendix, the results are robust across different time windows from 6 to 10 years. Second, considering that repeated collaboration may have a curvilinear impact on innovation performance, we re-ran the models including the squared term of repeated collaboration as a control and found qualitatively similar results. Third, we conducted negative binomial regressions for empirical specifications where the dependent variable is a count variable. The results shown in Table 5 are consistent with those of our OLS regression models. Fourth, to address the concern that citations made by patent examiners may not effectively reflect the impact of a patent (Alcácer & Gittelman, 2006; Criscuolo & Verspagen, 2008), we re-ran our regression analyses after excluding citations made by patent examiners with patents granted on or after 2001 for which we have full information on examiner-added citations. As we show in the Appendix, we found similar results. We also found consistent results after excluding self-citations. These suggest that our findings are not driven by citations made by examiners or those made by the same assignee firm that invented the cited patents. Fifth, to check if the first-time patenting inventor is driving all the variations and findings of our analysis, we re-examined the moderating impact of experience heterogeneity by excluding inventors who have not patented before the focal patent. The results shown in the Appendix remain robust,

Table 5 Results of negative binomial regression analyses

	DV: impact of innovation	
	Model 1	Model 2
Geographic Diversity	0.349 (0.071) [0.000]	0.356 (0.072) [0.000]
Geographic Diversity^2	− 0.436 (0.092) [0.000]	− 0.472 (0.094) [0.000]
Geographic Diversity × Experience Heterogeneity		0.329 (0.086) [0.000]
Geographic Diversity^2 × Experience Heterogeneity		− 0.521 (0.151) [0.000]
Geographic Diversity × Repeated Collaboration		− 0.067 (0.014) [0.000]
Geographic Diversity^2 × Repeated Collaboration		0.057 (0.025) [0.022]
Controls	Yes	Yes
Firm dummies	Yes	Yes
Class dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	59,988	59,988

Note: Standard errors in parentheses; *p* value (two-tailed) in squared brackets.

confirming that the findings hold not only for first-time inventors, but also for more experienced inventors. Sixth, due to the presence of extreme values for key variables (i.e., innovation impact and novelty, experience heterogeneity, repeated collaboration, sum of experience), we winsorized values for those variables beyond three standard deviations from the mean and re-ran our regression analyses. As shown in the Appendix, our main findings remain consistent in these models. Seventh, as shown in the Appendix, we additionally controlled for the possibility that citation patterns might differ across locations in which a patent was filed by including the location dummies of patent assignee firms in our regression models; the results remained consistent. Lastly, we conducted a three-level mixed effects regression analysis because patents (level 1) are nested in both technology classes (level 2) and in firms (level 3). In this analysis, constant terms were allowed to vary randomly across technologies and firms. Table 6 shows that our main findings are still consistent with these models.

DISCUSSION AND CONCLUSIONS

This study seeks to understand the roles of geographic diversity and team composition in cross-border R&D collaboration within MNCs. We theorize how geographic diversity affects innovation performance of MNC research teams and how experience heterogeneity and repeated collaboration moderate the relationship. Our empirical analysis of 59,998 U.S. patents of 25 global pharmaceutical firms confirms our predictions. We find that both impact and novelty of innovation of an MNC research team is maximized at a moderate level of geographic diversity. Importantly, MNC research teams made up of inventors with different levels of technical experience are more sensitive to the impacts of geographic diversity – both positive and negative – while teams made up of repeated collaborators are less sensitive to these impacts. The empirical findings are robust to a variety of estimation techniques, controls, and measures.

This research makes several important contributions to the literature in international business and innovation. First, our findings provide important insights for research on globalization of R&D

Table 6 Multi-level regression analyses

	DV: Impact of innovation		DV: Novelty of innovation	
	Model 1	Model 2	Model 3	Model 4
Geographic Diversity	1.824	1.693	0.032	0.034
	(0.741)	(0.749)	(0.012)	(0.012)
	[0.014]	[0.024]	[0.007]	[0.004]
Geographic Diversity^2	− 2.342	− 2.364	− 0.055	− 0.057
	(0.980)	(1.001)	(0.015)	(0.016)
	[0.017]	[0.018]	[0.000]	[0.000]
Geographic Diversity × Experience Heterogeneity		2.846		0.056
		(0.906)		(0.015)
		[0.002]		[0.000]
Geographic Diversity^2 × Experience Heterogeneity		− 4.808		− 0.070
		(1.699)		(0.028)
		[0.005]		[0.012]
Geographic Diversity × Repeated Collaboration		− 0.910		− 0.009
		(0.149)		(0.002)
		[0.000]		[0.000]
Geographic Diversity^2 × Repeated Collaboration		1.213		0.012
		(0.263)		(0.004)
		[0.000]		[0.002]
Random-effects parameters				
Technology Level	42.456	42.394	0.004	0.004
	(6.404)	(6.403)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]
Firm Level	35.600	35.688	0.002	0.002
	(2.575)	(2.578)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	59,988	59,988	51,705	51,705

Note: Standard errors in parentheses; *p* value (two-tailed) in squared brackets.

activities, which is an emerging topic in the evolution of global value chains (GVCs). In the past, studies on GVCs mainly focused on the offshoring of production (Ferdows, 1997; Lewin & Peeters, 2006; Kedia & Mukherjee, 2009; Schmeisser, 2013). Recently, offshoring of manufacturing activities of MNCs has been followed by offshoring of R&D activities in GVCs, while R&D and innovation have been traditionally among the least internationalized functions of the GVC (Belderbos, Sleuwaegen, Somers, & De Backer, 2016). More and more MNCs have organized innovation activities in their GVCs by setting up overseas R&D labs and establishing global R&D networks (Asakawa, Park, Song, & Kim, 2018; Cantwell, 2017; Castellani & Lavoratori, 2020). Accordingly, recent studies in international business have begun to investigate why MNCs geographically expand their R&D activities in their GVCs and how offshoring of R&D activities in GVCs affects the innovation performance of MNCs (Alcácer & Chung, 2007; Hsu, Lien, & Chen, 2015; Lahiri, 2010; Nieto & Rodriguez, 2011; Singh, 2008). According to our research, however, R&D globalization is more than just establishing many R&D labs around the world. Although some recent studies (e.g., Lahiri, 2010; Berry, 2014) examined the phenomena of cross-border R&D collaborations within MNCs per se, few studies examined how to manage cross-border R&D collaborations to enhance innovation performance of MNCs in GVCs (Kano, Tsang, & Yeung, 2020). Our study shows that innovation performance of MNCs could significantly differ depending on the extent of collaboration among the geographically dispersed R&D labs in their GVCs. That is, our research went one step further by suggesting the importance of intricate interactions among overseas R&D labs and their researchers in cross-border R&D collaboration within GVCs and the relationship of these interactions to key success factors of R&D globalization, which are salient in the evolution of GVCs of MNCs.

The most significant contribution of this study is, arguably, its examination of the role of team composition as an instrument for managing cross-border R&D collaboration. Building an effective global team has been an important topic in the international business research (Govindarajan & Gupta, 2001). A large body of research has identified challenges in the management of such teams (Armstrong & Cole, 2002; Cramton, 2001) and explored various managerial instruments that address the associated challenges and enhance team performance (Boh, Ren, Kiesler & Bussjaeger, 2007; Jarvenpaa & Leidner, 1999; Montoya-Weiss et al., 2001; O'Leary & Mortensen, 2010; Sole & Edmondson, 2002). Cummings and Haas (2012), for instance, suggested that time allocation significantly shapes the performance of geographically dispersed teams. Our study extends this stream of research on global team management by shedding light on the role of team composition, which has been largely unaddressed to date. It is our hope that our findings will spur further international business research into the relationship between composition of cross-border collaboration and innovation performance.

Furthermore, the results of our research extend the literature on global innovation and knowledge management. Highlighting the importance of integrating heterogeneous knowledge, prior studies have explained *why* geographically dispersed collaboration takes place within a firm (Berry & Kaul, 2015; Foss & Pedersen, 2002; Frost, 2001; Gupta & Govindarajan, 2000; Lahiri, 2010). In our research, however, we focus on *how* to facilitate such important global innovation processes, which has important theoretical and practical implications. Hiring talent from dispersed locations to create a research team does not necessarily result in the desired outcomes. To borrow Grant's (1996: 380) words, "the critical source of competitive advantage is knowledge integration rather than knowledge itself." In order to realize the full potential of geographically dispersed collaboration, therefore, MNCs need to develop managerial processes to mitigate the challenges the team may face while still enjoying the benefits arising from geographic diversity. To this end, our research offers theoretical as well as practical insights as to how team composition affects innovation performance when R&D is performed by geographically dispersed teams.

From the results of this study, therefore, MNC managers can gain insights into how to compose global research teams to realize their full potential and maximize their innovation output. Our findings suggest that geographic diversity of a multinational research team initially is positively associated with innovation performance resulting from global R&D activities, but when geographical diversity exceeds a certain threshold level, a further increase in geographic diversity has a negative relationship with innovation performance. Moreover, our results using the Blau Index imply that when a team consists of members from two locations, a balance between the locations in terms of the number of members is advisable. When more than two locations are involved, however, having more inventors in some locations than in others is better. Given the level of geographic diversity, furthermore, managers can moderate its impact through team composition. When geographic diversity is relatively low, that is, when the positive benefits of geographic diversity outweigh its challenges, MNC research teams with different levels of technical experience and more fresh collaborators may improve performance by amplifying the benefits of sourcing diverse knowledge. On the other hand, for teams with high levels of geographic dispersion, minimal experience heterogeneity and more instances of past collaboration could result in better outcomes by facilitating the integration of diverse knowledge.

We acknowledge that our findings are subject to some limitations. First, we do not directly observe how teams actually work to produce their innovative outcomes. For instance, we were unable to measure and decompose how cross-border R&D teams actually *source* and *integrate* knowledge in our empirical analyses since we relied on secondary archival data, or patents. In this study, we examined how these sourcing and integration activities altogether led to the teams' innovation outputs after controlling for a variety of factors that could differ across teams and over time. We hope that other such mechanisms behind the innovation processes may be examined in future research on R&D collaboration of cross-border teams. Second, it is worth discussing the generalizability of our findings, because our research context is the pharmaceutical industry. In the literature on innovation, recombination of diverse knowledge has been identified as the essence of innovation regardless of the type of innovation (e.g., Fleming, 2001; Kogut & Zander, 1992; Schumpeter, 1934; Uzzi & Spiro, 2005). According to Teece (1996), however, *autonomous* innovations can be pursued more independently from other innovations, while *systemic* innovations require interrelated changes in other areas. Thus, although knowledge recombination is germane to all types of innovation, sourcing diverse knowledge and integrating the knowledge sourced may be more important in industries with systemic innovations than in industries with autonomous innovations. The pharmaceutical sector is said to be an industry primarily characterized by autonomous innovations. Provided that our theoretical arguments and empirical findings hold for an industry with autonomous innovations, we expect to find stronger moderating effects of team composition for industries in which systemic innovation is the norm. Lastly, we identify prior collaboration experience only from patents. Research suggests that academic publication may be an important source of collaboration (Magerman, Van Looy, & Debackere, 2015; Murray, 2002). Thus, this study might omit prior collaboration ties that produced academic publication but not patents. However, we expect that this will not pose a significant problem or cause measurement error because inventive collaborations tend to produce both patents and academic publications and, therefore, meaningful collaborations towards academic publication can still be captured by patents.

Despite this limitation, we believe that this study contributes to a more nuanced understanding of how cross-border R&D performance may be enhanced in MNCs through team composition. This study suggests that MNCs should pay attention to technical and social relationships among researchers in sourcing and integrating location-specific knowledge and ultimately enhancing the performance of the cross-border R&D team.

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NOTES

[1]Our assumption is that each location provides distinctive knowledge resources. This argument is well supported by studies on knowledge-seeking foreign direct investments (Belderbos, Olffen, & Zou, 2011; Chung & Alcácer, 2002; Shan & Song, 1997). Literature on reverse innovation, in addition, suggests that firms in developed countries could benefit from knowledge embedded in underdeveloped countries (Ambos, Ambos, & Schlegelmilch, 2006; Frost & Zhou, 2005; Govindarajan & Ramamurti, 2011). Still, we acknowledge that some locations have much more location-specific knowledge than others (Turkina & Van Assche, 2018). In our empirical analyses, we rule out the confounding effects arising from differing levels of local knowledge by controlling for the abundance of regional knowledge resources.

[2]Language differences among geographically dispersed inventors can also cause coordination problems. Extant international business research pointed out that language differences present significant barriers to coordination of tasks in MNCs (Harzing & Feely, 2008; Luo & Shenkar, 2006; Tenzer, Pudelko, & Harzing, 2014). In this study, however, we assume that all inventors are fluent in a parent functional language and that problems due to language barriers are minimal. This potentially reasonable assumption may be justified by the fact that MNCs can effectively mitigate the coordination costs associated with language barriers through appropriate global language design (Luo & Shenkar, 2006). This is especially the case in our setting where highly educated researchers collaborate using a common language like English; thus, technical jargon and language barriers are not likely to pose difficulties in collaboration. Even when all team members are using the same language, however, spatial separation could still make it difficult for team members to collaborate. In developing our theory, we thus focus on the coordination problems caused by physical separation per se, such as time zone differences and lack of face-to-face interactions. Our interviews with executives at multinational pharmaceutical companies also confirm that the challenges arising from physical separation are critical to cross-border R&D collaborations. In the empirical analysis, we partial out the impact of language barriers by including a control variable: linguistic distance between inventors.

[3]he heterogeneity in *technical* experience examined herein differs from the heterogeneity in *functional* expertise of scientists and engineers that stems from different fields or specializations. In this section, we focus on the mixture of technically experienced and inexperienced researchers.

[4]According to the Vice President at GlaxoSmithKline (2), the company composes their teams in terms of experience: leaders are experienced individuals so that less experienced team members can learn from them.

[5]The Vice President at GlaxoSmithKline (1) pointed out in our interview that "if you have a high-performing team doing this over and over for a certain period of time, you [initially] gain [on productivity], but you lose on innovation after a while.".

[6]The USPTO defines an assignee as "the entity that is the recipient of a transfer of a patent application, patent, trademark application or trademark registration." While a patent can be assigned to an individual, our sample consists of patents assigned to the top 25 pharmaceutical *firms*. In total, 4% of patents in our sample are registered jointly by multiple assignees.

[7]The firm dummies are made by 46 pre-M&A firms (see Figure 7).

[8]Statistically, the value of our geographic diversity variable based on the Herfindahl Index represents the probability that two individuals are randomly chosen who are not collocated. The marginal effect of geographic diversity, therefore, can be interpreted as an increase in the outcome variable (impact and novelty) when inventors' location profiles change from full colocation (when our measure takes a value of 0) to full dispersion (when our measure takes a value of 1).

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APPENDIX 1

See Table 7.

Table 7 Sensitivity tests with different year windows

	DV: Impact of innovation					DV: Novelty of innovation				
	6 years	7 years	8 years	9 years	10 years	6 years	7 years	8 years	9 years	10 years
Geographic Diversity	2.161	2.139	2.111	2.098	2.076	0.034	0.034	0.034	0.033	0.033
	(0.921)	(0.921)	(0.920)	(0.920)	(0.920)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
	[0.019]	[0.020]	[0.022]	[0.023]	[0.024]	[0.004]	[0.005]	[0.005]	[0.006]	[0.007]
Geographic Diversity^2	− 3.002	− 2.926	− 2.904	− 2.893	− 2.893	− 0.060	− 0.061	− 0.060	− 0.059	− 0.058
	(1.376)	(1.372)	(1.369)	(1.368)	(1.368)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
	[0.029]	[0.033]	[0.034]	[0.034]	[0.035]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Geographic Diversity	2.591	2.601	2.476	2.353	2.317	0.051	0.048	0.042	0.033	0.027
× Experience	(0.904)	(0.960)	(0.948)	(0.919)	(0.908)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Heterogeneity	[0.004]	[0.007]	[0.009]	[0.010]	[0.011]	[0.000]	[0.001]	[0.007]	[0.037]	[0.085]
Geographic Diversity^2	− 4.496	− 4.256	− 4.172	− 4.118	− 4.253	− 0.061	− 0.059	− 0.048	− 0.034	− 0.025
× Experience	(1.625)	(1.664)	(1.644)	(1.605)	(1.596)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)
Heterogeneity	[0.006]	[0.011]	[0.011]	[0.010]	[0.008]	[0.011]	[0.015]	[0.050]	[0.173]	[0.318]
Geographic Diversity	− 0.706	− 0.695	− 0.678	− 0.667	− 0.673	− 0.008	− 0.007	− 0.006	− 0.005	− 0.005
× Repeated Collaboration	(0.201)	(0.191)	(0.182)	(0.174)	(0.169)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.007]	[0.010]	[0.023]	[0.048]	[0.054]
Geographic Diversity^2	0.850	0.858	0.840	0.835	0.855	0.011	0.010	0.008	0.007	0.006
× Repeated Collaboration	(0.339)	(0.320)	(0.305)	(0.293)	(0.283)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
	[0.012]	[0.007]	[0.006]	[0.004]	[0.003]	[0.022]	[0.029]	[0.053]	[0.099]	[0.112]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,988	59,988	59,988	59,988	59,988	51,705	51,705	51,705	51,705	51,705

This appendix table shows our main results in Table 4 with different time windows for our moderating variables: Experience Heterogeneity and Repeated Collaboration. To be specific, we used longer year windows (than 5 years) when measuring inventors' past technical experience and prior collaboration. The results are robust across different time windows from 6 to 10 years.

Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

APPENDIX 2

See Table 8.

Table 8 Regression analyses after excluding examiners' citations

	DV: Impact of innovation		DV: Novelty of innovation	
	Model 1	Model 2	Model 3	Model 4
Geographic Diversity	3.490	3.537	0.030	0.029
	(1.466)	(1.436)	(0.016)	(0.016)
	[0.017]	[0.014]	[0.050]	[0.066]
Geographic Diversity^2	− 3.687	− 3.872	− 0.063	− 0.061
	(2.323)	(2.305)	(0.021)	(0.021)
	[0.113]	[0.093]	[0.003]	[0.004]
Geographic Diversity × Experience Heterogeneity		3.305		0.024
		(1.366)		(0.018)
		[0.016]		[0.192]
Geographic Diversity^2 × Experience Heterogeneity		− 5.512		− 0.030
		(2.542)		(0.029)
		[0.030]		[0.305]
Geographic Diversity × Repeated Collaboration		− 0.782		− 0.011
		(0.243)		(0.003)
		[0.001]		[0.001]
Geographic Diversity^2 × Repeated Collaboration		0.725		0.014
		(0.423)		(0.005)
		[0.086]		[0.008]
Controls	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes
Class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	26,554	26,554	20,252	20,252

This appendix table shows our main results in Table 4 without counting patent citations made by patent examiners when constructing our dependent variables: Impact of Innovation and Novelty of Innovation. This approach addresses the concern that citations made by patent examiners may not effectively reflect the direct impact of a patent (Alcacer & Gittelman, 2006; Criscuolo & Verspagen, 2008). Since the information on examiner-added citations are available beginning in 2001, the sample size reduces to 44% of full sample. We find similar results, suggesting that our findings are not driven by citations made by examiners.

Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

APPENDIX 3

See Table 9.

Table 9 Regression analyses after excluding self-citations

	DV: Impact of innovation		DV: Novelty of innovation	
	Model 1	Model 2	Model 3	Model 4
Geographic Diversity	2.075	2.018	0.033	0.033
	(0.902)	(0.886)	(0.010)	(0.010)
	[0.021]	[0.023]	[0.001]	[0.001]
Geographic Diversity^2	− 2.789	− 2.890	− 0.052	− 0.052
	(1.326)	(1.314)	(0.014)	(0.014)
	[0.036]	[0.028]	[0.000]	[0.000]
Geographic Diversity		2.510		0.043
× Experience Heterogeneity		(0.720)		(0.012)
		[0.000]		[0.000]
Geographic Diversity^2		− 4.201		− 0.055
× Experience Heterogeneity		(1.344)		(0.020)
		[0.002]		[0.006]
Geographic Diversity		− 0.710		− 0.009
× Repeated Collaboration		(0.174)		(0.003)
		[0.000]		[0.001]
Geographic Diversity^2		0.870		0.014
× Repeated Collaboration		(0.295)		(0.004)
		[0.003]		[0.001]
Controls	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes
Class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	59,988	59,988	47,288	47,288

This appendix table shows our main results in Table 4 without counting patent citations made by the same assignee firm of the focal patent. This approach addresses the concern that backward or forward citations between the patents of the same assignee firm may not effectively reflect the impact or novelty of the focal patent. The results remain robust, suggesting that our findings are not driven by citation linkages made by the same assignee firms.

Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

APPENDIX 4

See Table 10.

Table 10 Regression analyses without inventors with no patents

	DV: Impact of innovation		DV: Novelty of innovation	
	Model 1	Model 2	Model 3	Model 4
Geographic Diversity	2.236	2.353	0.024	0.028
	(0.916)	(0.919)	(0.013)	(0.013)
	[0.015]	[0.010]	[0.058]	[0.029]
Geographic Diversity^2	− 3.404	− 3.640	− 0.051	− 0.055
	(1.364)	(1.394)	(0.017)	(0.017)
	[0.013]	[0.009]	[0.003]	[0.001]
Geographic Diversity		2.014		0.039
× Experience Heterogeneity		(0.915)		(0.011)
		[0.028]		[0.000]
Geographic Diversity^2		− 3.783		− 0.053
× Experience Heterogeneity		(1.915)		(0.020)
		[0.048]		[0.008]
Geographic Diversity		− 0.743		− 0.007
× Repeated Collaboration		(0.181)		(0.003)
		[0.000]		[0.015]
Geographic Diversity^2		0.955		0.009
× Repeated Collaboration		(0.309)		(0.005)
		[0.002]		[0.049]
Controls	Yes	Yes	Yes	Yes
Firm Dummies	Yes	Yes	Yes	Yes
Class Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	48,771	48,771	42,104	42,104

This appendix table shows our main results in Table 4 without inventors who have not patented before filing the focal patent. This approach addresses the concern that these first-time patenting inventors are driving all the variations and findings of our analysis. We re-examined the moderating impact of experience heterogeneity by excluding such first-time inventors. The results remain robust, confirming that the findings hold not only for first-time inventors, but also for more experienced inventors.

Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

APPENDIX 5

See Table 11.

Table 11 Regression analyses after winsorizing extreme values

	DV: Impact of innovation		DV: Novelty of innovation	
	Model 1	Model 2	Model 3	Model 4
Geographic Diversity	1.094 (0.461) [0.018]	1.235 (0.469) [0.009]	0.032 (0.012) [0.006]	0.036 (0.012) [0.003]
Geographic Diversity^2	− 1.178 (0.621) [0.058]	− 1.756 (0.653) [0.007]	− 0.059 (0.016) [0.000]	− 0.062 (0.016) [0.000]
Geographic Diversity × Experience Heterogeneity		2.833 (0.894) [0.002]		0.052 (0.018) [0.004]
Geographic Diversity^2 × Experience Heterogeneity		− 5.887 (1.685) [0.000]		− 0.069 (0.034) [0.045]
Geographic Diversity × Repeated Collaboration		− 0.445 (0.118) [0.000]		− 0.007 (0.003) [0.019]
Geographic Diversity^2 × Repeated Collaboration		0.463 (0.202) [0.022]		0.009 (0.005) [0.096]
Controls	Yes	Yes	Yes	Yes
Firm Dummies	Yes	Yes	Yes	Yes
Class Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	59,988	59,988	51,705	51,705

This appendix table shows our main results in Table 4 after winsorizing extreme values. This approach addresses the concern that the presence of extreme values for our key variables (i.e., innovation impact and novelty, experience heterogeneity, repeated collaboration, and sum of experience) may violate the assumption in the ordinary linear regression (OLS) and spuriously drive the results. As such, we winsorized values for those variables beyond three standard deviations from the mean and re-ran our regression analyses. Our main findings remain consistent in these models.
Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

APPENDIX 6

See Table 12.

Table 12 Regression with assignee location fixed effects

	DV: Impact of innovation		DV: Novelty of innovation	
	Model 1	Model 2	Model 3	Model 4
Geographic Diversity	2.267	2.174	0.026	0.028
	(0.937)	(0.923)	(0.012)	(0.012)
	[0.016]	[0.019]	[0.028]	[0.017]
Geographic Diversity^2	− 2.936	− 3.007	− 0.056	− 0.058
	(1.381)	(1.377)	(0.015)	(0.016)
	[0.034]	[0.029]	[0.000]	[0.000]
Geographic Diversity × Experience Heterogeneity		2.721		0.054
		(0.871)		(0.015)
		[0.002]		[0.000]
Geographic Diversity^2 × Experience Heterogeneity		− 4.600		− 0.067
		(1.591)		(0.024)
		[0.004]		[0.005]
Geographic Diversity × Repeated Collaboration		− 0.818		− 0.009
		(0.191)		(0.003)
		[0.000]		[0.003]
Geographic Diversity^2 × Repeated Collaboration		1.055		0.012
		(0.325)		(0.005)
		[0.001]		[0.012]
Controls	Yes	Yes	Yes	Yes
Assignee Location Dummies	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes
Class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	59,988	59,988	51,705	51,705

This appendix table shows our main results in Table 4 with additional fixed effects for assignee firm locations ("Assignee Location Dummies"). This approach addresses the concern that citation patterns might differ across locations in which a patent was filed. Our results are robust to the inclusion of location dummies for patent assignee firms' locations.

Note: Robust standard errors in parentheses; *p* value (two-tailed) in squared brackets.

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