경영학석사학위논문

Managing Technological Diversity

: The Role of Intra-unit Network Structure in Innovation

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ABSTRACT

Why do firms' R&D units differ in their abilities to exploit technological diversity? We argue that the differences can arise from the heterogeneity in their internal social network structures. We examine how knowledge distribution shaped by the two global properties of internal network structure – clustering and connectivity, each measured by clustering coefficient and average path length – differently moderate the inverted U-shaped relationship between technological diversity and innovation. An investigation of a 20-year panel of 27 pharmaceutical R&D units reveals the curvilinear relationship between technological diversity and innovation and the negative moderating role of intra-unit network structure on this relationship. By questioning the assumption of a strong correspondence between network structure and knowledge diversity, this study contributes to knowledge diversity and innovation literature and further provides implications to managers in designing informal structure of their R&D units.

Keywords: knowledge diversity, intra-unit networks, clustering, average path length, innovation.

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I. INTRODUCTION

How to manage a given set of diverse knowledge in an R&D unit is a critical issue for firms' innovation (Cohen & Levinthal, 1990; Nahapiet & Ghoshal, 1998). In the strategic management literature, extensive research addresses how firms can obtain competitive advantages through exploiting, recombining and extending their diverse knowledge resources (Cohen & Levinthal, 1990; Grant, 1996; Kogut & Zander, 1992). The particular capabilities of organizations for sharing and creating knowledge include the informal structuring through which individuals cooperate and expertise is communicated (Cohen & Levinthal, 1990; Hargadon & Sutton, 1997). How individuals are informally connected to each other affects the knowledge flow and distribution among unit members. Therefore, a surge of research points to the role of internal social network structure on innovative performance of an organization (Guler & Nerkar, 2012; Paruchuri, 2010; Singh, 2005).

Central to the research on the informal structure of knowledge workers is the assumption of a strong correspondence between network structure and knowledge diversity. Although knowledge diversity and network structure are intertwined, they are theoretically and empirically distinctive (Rodan & Galunic, 2004; Sosa, 2011; Tortoriello, McEvily & Krackhardt, 2015). Consider a pharmaceutical research center in Boston, Massachusetts that may have enjoyed knowledge spillover from collocated research institutes and have amassed affluent diverse knowledge, and a recently established research unit in Singapore that may have accumulated less diverse set of technological expertise. Given the level of technological diversity each laboratory has, the same social structure of their scientists may have different impacts on their innovative activities. To the degree that network structure is not strictly overlapping with knowledge diversity, there may be a variety of ways in which networks and knowledge are configured (Tortoriello, McEvily & Krackhardt, 2015). Building on this distinction, research on inter-organizational alliances (Ahuja, 2000) and managers' interpersonal networks (Rodan & Galunic, 2004) has shown that network structure and knowledge diversity are empirically disparate. Extending this line of research, we examine both independent and interactive effects of inventor collaborative network structure within R&D units and the level of technological diversity on innovation performance.

This paper aims to answer the following questions: Why do firms' R&D units differ in their abilities to exploit technological diversity? How does informal network structure facilitate their ability to make the most out of combination potential and how is it associated with the units' innovation performance? We answer these questions by investigating the interplay between social structure and knowledge diversity in the generation of innovation. Specifically, we examine the impact of two key large-scale network properties, *clustering* and *connectivity*, on the relationship between technological diversity and innovative outcome. The dense local clusters create common knowledge base and relational lock-ins (Burt, 2000), while high global connectivity (i.e., short average path length of intra-unit network) within a unit ensures rapid diffusion of information internally (Schilling & Phelps, 2007). Building on recombinatory innovation perspective and social network theory, we argue that these network compositions affect the level of knowledge distribution among members, moderating the members' knowledge exchange and combining process to generate innovation. We propose that the structure of the intra-unit network is likely to be an important determinant of a unit's diversity management capability, or its ability to generate novel and valuable recombination out of heterogeneous knowledge resources.

To test these arguments, we created a dataset from United States Patent and Trade Office (USPTO) patent database on globally distributed R&D units of five big pharmaceutical companies and constructed internal social networks out of patent co-authorship from 1991 to 2010. We focus specifically on patent collaboration ties between individual scientists in a single R&D unit, as prior research has shown that co-patenting networks provide a suitable proxy for informal conduits of information and resource exchange (e.g., Fleming, King & Juda, 2007; Guler & Nerkar, 2012; Paruchuri, 2010; Singh, 2005). We show that the relationship between technological diversity and innovative performance is curvilinear (i.e., inverted U-shaped) that the knowledge diversity boosts innovation only up to a point, and is moderated by internal social network structure that affects the curvature of the graph.

This research offers several important contributions for understanding innovation in intra-unit networks. First, we find empirical support for our argument that the inventor networks with clustered structure and short average path length each reduce marginal benefits and eases the burden of technological diversity. We also ascertain that this locally clustered structure amplifies overall innovative performance of a unit. Dispersed R&D units serve important roles in a firm's innovation, each assigned distinctive mission from its headquarter. Each unit has different technological expertise with the different level of knowledge accumulation, where some units are directed to broaden their technology portfolio by sourcing different local knowledge while others concentrate on a specific type of technological area. Depending on the breadth of their technological portfolio, units may design their informal network structure in order to reach full combination potential to boost innovation. Second, following recent studies in management literature that advanced a rigorous analytical formulation of network theory (e.g., Davis, Yoo &

Baker, 2003; Lee, Song & Yang, 2015; Schilling & Phelps, 2007), we further the current understanding of the role of internal network structure on organization innovation. Although recent studies have examined the structure of large-scale inter-firm networks and the consequences of these structures (Schilling & Phelps, 2007), little research has examined the large-scale intra-organizational networks. Moreover, while most studies of the intra-firm network structure have examined position of the members (Nerkar & Paruchuri, 2005; Paruchuri, 2010), our study focus on the whole network structure within an organizational boundary, which strengthens our understanding of intra-organizational network structure.

II. THEORY AND HYPOTHESES

2.1. Network Structure and Knowledge Creation

Not only does the level of technological knowledge matter, but so does its structure within the organization (Argyres & Silverman, 2004). Networks and network structures influence the range of information that may be exchanged and that becomes available for innovative combination (Nahapiet & Ghoshal, 1998). Ties provide the channels for information diffusion, and the overall configuration of these ties constitutes the pattern of resource flow and the level of knowledge distribution within a unit. Here, we consider the distribution of technological knowledge resources across the unit (the extent to which a certain knowledge is concentrated in a small number of members or distributed evenly among unit members) by taking intra-unit network into account.

First, we consider the process of knowledge creation. Nahapiet and Ghoshal (1998) have suggested that the knowledge is created through two generic processes: namely, *exchange* and *combination*. When technological knowledge is held by disparate parties, exchange of different knowledge enhances combination potential of innovation by increasing availability of knowledge elements reside in an organization to each individual. A unit needs a good 'shake' to create a novel perspective on its existing knowledge when its knowledge base comprises diverse technological domains (Kanter, 1988; Zhou & Li, 2012). Knowledge exchange provides such a shaking process, through which members can share and integrate broad knowledge across various fields in novel patterns to generate innovation (Zahra & George, 2002). When exchanges are made through connections, existing ideas are often combined with other ideas to appear new and creative as they change forms. Strategic management researchers have employed this notion to define innovation and explored how the innovation is created by integrating knowledge within, outside, and across firm boundaries (Hargadon & Sutton, 1997; Katila, 2002; Nerkar, 2003).

The structure of connections between members holding different knowledge elements affects them locating knowledge within a unit, sharing their knowledge, and responding to others' knowledge (Lewis, Lange & Gillis, 2005). Research has shown that intra-team shared task experiences and interactions are antecedents to the development of transactive memory systems (Austin, 2003; Lewis, 2003). Individual members who know “who knows what” tend to be inclined to share knowledge because they recognize its value to the whole task and know who can properly use it; however, if each team member is a deep specialist whose knowledge does not overlap with that of others, knowledge sharing is more likely to suffer (Cronin & Weingart, 2007).

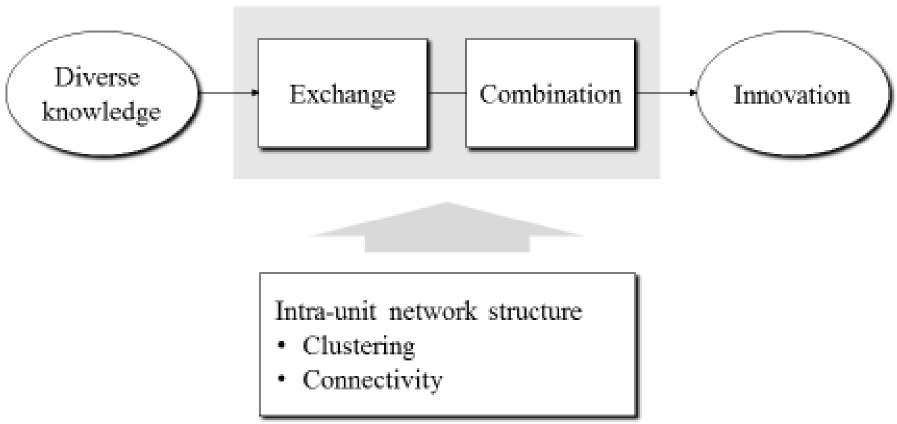
The network structure also influences members in choosing which information to share and pool by shaping familiarity and preference towards the source of information, and thereby willingness to dedicate time and effort to interact with members located in different parts of a research unit. Individuals have to devote effort communicating what they know to their counterparts (Reagans & McEvily, 2003), assimilating and transforming what they learn from other members. This type of cooperation is not likely to naturally occur among individuals in different parts of an organization. The information-pooling approach examines information exchange during team interactions, revealing that team members' preferences are shaped more by more frequently communicated information and that teams favor shared information over unshared information (Stasser, Stella, Hanna, & Colella, 1984). Thus, the distribution of knowledge resources within units shaped by the overall network configuration affects their willingness to share and pool information from different members (Gardner, Gino & Staat, 2012).

While some of prior work investigate both network structure and content, most of the empirical work is at ego level, examining the position of individuals or firms in their ego-networks (Mors, 2010; Sosa, 2011). Moreover, these studies examine the benefits that accrue to the firm or individuals that hold positions in ego networks, rather than to the overall organization. In this study, we intend to focus on the properties of whole network structure within a unit and their impacts on its innovation performance.

Recent studies advanced a rigorous analytical formulation of the whole network structure using two key attributes of the small-world effect: local *clustering* measured by clustering coefficient and global *connectivity* measured by average path length (Watts & Strogatz, 1998) (e.g., Davis et al., 2003, Rosenkopf & Schilling, 2007; Uzzi & Spiro, 2005). Many of these studies, however, focus on small-world structures within overall industries, regions, or fields, rather than on intra-organizational networks. We argue that these two structural characteristics of the intra-unit network will significantly influence the knowledge exchange and recombination process. We first examine how the level of technological diversity affects units' innovation performance, and then investigate how this effect is moderated by the two intra-unit network properties.

FIGURE 1

Conceptual framework



2.2. Technological diversity and innovation performance

Diverse technological knowledge that an R&D unit possesses is a critical input to the innovation process (Lahiri, 2010). Prior research has shown that greater innovation occurs when firms search for broader knowledge in a variety of technological domains (Ahuja & Katila, 2004; Ahuja & Lampert, 2001), as technologically diverse units will benefit from a variety of perspectives and therefore be able to make better collective decisions and produce more creative work. Hargadon and Sutton (1997) suggest that firms that connect different industries can share and integrate knowledge from those industries and therefore be innovative.

However, the knowledge diversity simultaneously raises impediments to successful knowledge exchange and recombination (Tushman, 1977). Integrating information is challenging particularly when individuals are exposed to too much heterogeneous information and knowledge (Bechky, 2003; Mors, 2010). Existing research suggests that diverse team take longer and encounter frequent difficulties in integrating their different knowledge stores to reach a solution because individuals in different knowledge domain might struggle to find a common ground to facilitate knowledge interaction (Argote, 1999; Carlile, 2004; Dougherty, 1992). Interactions might suffer due to the differences in languages and perspectives, lack of shared understandings (Bechky, 2003), and coordination problems (Mors, 2010). Assimilating and integrating highly diverse knowledge components can lead to information overload, confusion, and diseconomies of scale in innovation activities (Ahuja & Lampert, 2001; Phelps, 2010).

Recognizing these trade-offs, several research has shown that as technological knowledge become more diverse, it enhances innovation performance only up to a point beyond which excessive diversity reduces the chance of recombination into useful innovations (Fleming & Sorenson, 2001; Huang & Chen, 2010). Following this line of research, we posit our baseline hypothesis as follows:

> ***Hypothesis 1.*** *The level of technological diversity within a unit has an inverted U-shaped relationship with its innovation performance.*

2.3. Intra-unit Network Structures and Diversity Management

2.3.1. Clustering

Clustering in a network refers to the extent to which the network is consisted of cohesive relationships where collaborators of an actor are themselves connected as well. The emergence of interconnected subgroups, or network cliques, suggests that the network is being subdivided into distinct subnetworks or groups. Such networks provide members with the enforceability, trust, and knowledge-sharing benefits (Coleman, 1988). Local cohesion makes it easier for members to mobilize around new ideas, due in part to similarities in perspectives and interests (Obstfeld, 2005). At the same time, closed network may create relational lock-in that increases rigidity and decrease openness to external information (Gargiulo & Benassi, 2000).

We argue that the clustering may have a negative moderating effect on the relationship between technological diversity and innovative performance by reducing both benefits and costs from diverse knowledge base. Holding the level of global connectivity constant, the local clustering neighborhood may lead to a less pronounced positive relationship between technological diversity and innovativeness by lowering marginal benefits of knowledge diversity.

Clustering will lower the marginal benefits of knowledge diversity, as individuals tend to economize in search for the source of information by selecting those with whom they have some familiarity and stability. It is because the information about availability, reliability, and technological profiles of peer inventors is not perfectly distributed (Ahuja, Soda & Zaheer, 2012; Shore, Bernstein & Lazer, 2015). This idea is in line with recent research that has shown clustering unproductively biases individuals away from the exploration of new solutions and toward the exploitation of existing ones (Mason & Watts, 2012; Lazer & Friedman, 2007). The effects of local clustering in suppressing exploration may be due to the fact that an individual who copies a neighbor's solution is probably doing so because he or she expects the outcomes to be more "positive, proximate, and predictable" than the more "uncertain, distant, and often negative" returns of trying to solve the problem alone, or because the neighbor's choice of that answer seemingly provides social proof of its value (March 1991: 85). As novel exploratory solutions are uncertain in nature, it can be safe to adopt a solution on which other people seem to have already reached a consensus. Thus, being embedded in clustered networks may reduce 'openness to information and to alternative ways of doing things, producing forms of collective blindness' (Nahapiet & Ghoshal, 1998).

For the broader aggregate, such a configuration of connections may lead to isolation and strong identification with the focal clustered group may contribute to the fragmentation of broader whole (Adler & Kwon, 2002). This may create a situation where internal solidarity is likely to be detrimental to the members' integration into the broader whole, by splitting the organization into factions that seek their own special interests.

On the other hand, however, the burden on excessive technological diversity may become more manageable with increasing propensity of local clustering. Individuals face significant challenges interpreting and integrating too diverse information and knowledge. When the meaning of information is unclear or when exchanging parties differ in their prior knowledge, extensive interaction and relationship are crucial to innovation (Nahapiet & Ghoshal, 1998), implying the beneficial role of local clustering. There are several ways in which clustered networks may facilitate the assimilation and integration of diverse technological knowledge and, in turn, affect the individual's ability to create new knowledge.

First, cohesive or closed networks may promote extensive interactions and knowledge sharing among embedded colleagues who work in disparate areas of expertise (Coleman, 1988). Richer patterns of interaction with colleagues in different domains of knowledge increase the chances that an individual will become more accustomed to interpreting and transforming knowledge so that it can be understood and applied in new perspectives (Tortoriello, Reagans & McEvily, 2012). Second, closed network structure reduces absorptive capacity problems related to growing technological diversity by facilitating the development of shared languages, vocabulary, frames of thinking and common knowledge base (Carlie, 2004; Carlie & Rebentisch, 2003; Dougherty, 1992). Shared framework and common knowledge base foster effective assimilation among the members, since it is easier to absorb diverse knowledge and generate new ideas when knowledge exchanging parties share some common knowledge base (Cohen & Levinthal, 1990). Third, if an individual has colleagues who are connected to each other with common technological knowledge and cognitive frame, those colleagues may help the partner translate and integrate diverse information (Mors, 2010). As heterogeneity of knowledge increases, members may benefit from having indirect contacts who will help them interpret the diverse knowledge that they are exposed through that connection. Thus, the extent to which members within a unit are densely interconnected mitigates marginal costs of increasing knowledge heterogeneity.

In sum, local clustering in intra-unit network may both decrease benefits and costs arising from technological diversity within a unit, thereby flattening both the positive and negative slope of the inverted U-shaped graph described in Hypothesis 1. Hence, we predict the moderation effect of local clustering in intra-unit networks as follows:

> ***Hypothesis 2***. *The degree of clustering within a unit moderates the relationship between technological diversity and innovation performance in a way that the inverted U-shaped relationship will be flatter in units with high degree of clustering.*

2.3.2. Connectivity

Connectivity of a network is captured in the average path length connecting any two nodes within the network. Individuals in 'brokerage' roles (i.e., individuals who connect groups of individuals that would otherwise be disconnected) or hubs dramatically shorten the path length of a network. As the network becomes more "small-worldly," information and knowledge can diffuse more quickly (Watts, 1999). An individual that is connected to a large number of other members by a short average path can reach more information. Alternatively, as the average path length between any two nodes of a network diminishes, it is possible that information can become more democratized, resulting in a reduction in the informational advantage of any single player.

We argue that the connectivity of the whole network within a unit may have a negative moderating effect on the relationship between technological diversity and innovative performance by dampening both benefits and costs of increasing technological diversity. Holding the level of local clustering constant, intra-network with short average path length may lead to a less pronounced positive relationship between technological diversity and innovation by lowering marginal benefits of knowledge diversity.

Although it is easy to assume that the rapid diffusion of ideas will facilitate knowledge recombination by increasing the pool of ideas that individuals can access and utilize, this view does not take into consideration the heterogeneity of knowledge each individual possesses. In case of low technological diversity, decrease in the path length will lead to an increase in homogenization pressure. The knowledge landscape of direct contacts is rarely new to the inventors. Further, when ideas diffuse too quickly through a population, the result can be premature convergence around a popular set of ideas, deterring parallel problem solving within a unit.

On the other hand, when each individual possesses highly heterogeneous knowledge set, short average path length will lower the marginal costs and enhance the marginal benefits of knowledge heterogeneity. There are several ways in which networks with short average path length may facilitate the efficient assimilation of diverse technological knowledge and, in turn, enhance the individual's ability to create new knowledge. First, direct contact enables less distortion in understanding knowledge as inventors can reach others by short paths (Paruchuri & Awate, 2016). As information gets passed on across different individuals, there is likely to be some degree of imperfect transmission of the message about opportunities for knowledge use. When knowledge is passed on through long paths, it is likely to become distorted (Bartlett 1932), as people who exchange such information tend to misunderstand each other, forget details, filter or deliberately withhold aspects of what they know (Gilovich, 1991). Second, good ideas can be widely communicated in unit, thereby increasing efficiency of innovation process. Given the uncertainty of knowing which ideas will create meaningful innovation, the rapid and widespread diffusion may encourage low performers to adopt good ideas that flow through the network. Third, short path length increases availability of knowledge elements residing in an organization to each individual, enabling exchange of different knowledge. Connections between members enable them to successfully locate knowledge within a unit, share their knowledge, and respond to others' knowledge (Lewis et al., 2005). When an individual possesses an awareness of what her/his colleagues do and do not know, members develop a more accurate and complete understanding of what their coworkers need to move forward on a task (Moreland & Myaskovsky, 2000). Therefore, as members' social distance gets closer within the heterogeneous knowledge network, knowledge exchange is more likely to occur and availability and possibility for combination is also likely to increase.

In sum, short average path length may decrease both benefits and costs arising from technological diversity within a unit, thereby flattening both the positive and negative slope of the inverted U-shaped graph described in Hypothesis 1. Therefore, we predict the moderation effect of the level of connectivity in intra-unit networks as follows:

> ***Hypothesis 3**. The degree of connectivity within a unit moderates the relationship between technological diversity and innovation performance in a way that the inverted U-shaped relationship will be flatter in units with high degree of connectivity.*

III. DATA AND METHODS

3.1. Research Setting

Our research examines the context of pharmaceutical industry, for it provides an attractive setting to test our hypotheses for the following reasons. First, the pharmaceutical industry is where technological capabilities and research and development activities are important drivers of the industry. Second, innovation performance of individual units can be captured through patents which is a key appropriability regime in protecting newly developed technologies. Third, we need to observe the intra-unit networks of informal interactions and compare the multiple intra-unit network structures. Earlier work has suggested that we can infer the intra-organizational collaboration structure from the patterns of patent co-authorship among members within the same firm boundary. Patent co-authorship networks provide a suitable proxy for informal conduits of information and knowledge flow (Fleming, King & Juda, 2007; Guler & Nerkar, 2012; Singh, 2005).

We collected the patent data from USPTO patent database for 27 R&D units of the five largest firms in global pharmaceutical industry, Pfizer, Merck & co., Novartis, Abbott Laboratories and Roche, which own and operate 5-6 geographically dispersed R&D laboratories between 1991 and 2010. We selected only a limited number of firms to study because we investigated the intra-unit networks of each firm over a long observation period of 20 years. Further, given that the hypotheses are concerned about the impact of a unit's inventor collaboration network structure, we selected firms and their R&D units that have a history of research. We selected main research facilities that have actively filed patents for use in the analysis. The main sources of R&D unit locations information include annual Securities and Exchange Commission (SEC) filings for publicly traded companies (particularly Item 2, "Properties," found in 10-Ks) and company websites. For example, a 2000 Annual Report from Novartis states that "Our major research and development facilities are located in manufacturing/R&D complexes that we own containing multiple buildings in Groton, Connecticut; Sandwich, England and Nagoya, Japan." After identifying research locations for each firm, we used the addresses of patent authors to identify the actual R&D unit of patent invention (Jaffe & Trajtenberg, 2002). Patents that do not have at least one inventor located in the same state or country as the R&D units are excluded from calculating network variables. We took into consideration the selection of a limited number of firms and units by using firm and unit fixed effects in the analytical models, as explained in the model specification section.

We measure the patent collaboration structure of the organizations for each of the years between 1991 and 2010 for each of 27 R&D units using this patent co-authorship data. We started sample from 1986 because we needed information prior to the start of the sample period for calculating technological diversity and for constructing inventor collaboration networks. We used patent filed dates instead of grant dates, because application dates better represent the timing of interactions among scientists (e.g., Sorenson & Stuart, 2000). The data comprises total 412 unit – year observations.

3.2. Dependent Variable

Following earlier research, we used the number of patents filed to the USPTO by a unit in year t to represent innovative performance of the unit, weighted by the number of citations received from the date the patent is granted. Patenting frequency is a widely adopted proxy for innovation performance, particularly in the research of knowledge-intensive industries (e.g., Ahuja & Katila, 2004). A firm with the higher number of patent application can be seen as the firm with more technological innovations. However, since patents can widely vary in their quality, simple patent counts may be an insufficient indicator of performance. To account for the heterogeneity in quality, we weighted each patent by the number of forward citations it received from future patents. Evidence shows that the number of forward citations of a patent is significantly associated with the social value of the underlying innovation (Trajtenberg, 1990).

3.3. Independent Variables

Technological diversity. Each patent provides information on the main three-digit technological domain to which the USPTO has assigned. We measured technological diversity of a unit by calculating the Herfindahl index of these primary technological classes of the unit's patents and subtracting the result from 1 so that units with diverse knowledge domains have higher values. A value of 0.05 indicates a low level of technological diversity (i.e., technological focus), and a value of 0.95 indicates a high level of technological diversity. We used a five-year moving window. For example, when the dependent variable is measured in 2000, the year *t*, we considered all patents filed by the sample unit during 1996-1999, ending in year ($t - 1$).

Clustering. We measured the level of clustering in a unit's inventor network by calculating clustering coefficient of each network. Considering patents and their inventors as an affiliation network, we constructed a single-mode network of inventor collaborations in UCINET 6 software (Borgatti, Everett & Freeman, 2002). Since we were interested in comparing the structural rather than the relational properties of the network, we only captured the presence of a tie among individuals rather than the strength of the tie. This network has inventors as nodes, and co-patenting activities as ties. We updated intra-unit network measures annually, as new ties are formed and old ties dissolve every year. Following prior work, we considered collaboration ties that are older than five years dissolved, employing a five-year moving window. For example, when the dependent variable is measured in 2000, year *t*, we considered all collaborative ties between inventors in each unit during 1996-1999, ending in year ($t - 1$), to construct intra-unit network. For each year between 1991 and 2010, we constructed a matrix of collaborative ties between scientists formed in the past five years. Using this martrices, we calculated clustering coefficient of the network following Watts and Strogatz (1998). Clustering coefficient is a measure of the level of clustering in the network, and when this measure is high, almost all actors in the network are embedded in closed local neighborhoods (Hanneman & Riddle, 2005). Specifically, we used the following formula to calculate clustering coefficient of the observed network for each unit *i* at time *t* in UCINET 6 software (Borgatti et al. 2002):

$$CC_{it}^{O} = \frac{3N_{\Delta}}{N_{\mathrm{V}}} = \frac{3\ \times (number\ of\ triangles)}{(number\ of\ connected\ triples)}$$

where a triangle is a closed triad and a triple is an open triad. As Schilling and Phelps (2007: 1118) pointed, “While network density captures the density of the entire network, the clustering coefficient captures the degree to which the overall network contains localized pockets of dense connectivity. A network can be globally sparse and still have a high clustering coefficient.”

Note that the inventors’ ties are derived from a single-mode projection of an affiliation network. As a result, some of the observed structure may be artificial as all inventors listed on the same patent automatically form ties to each other through the process of projection. To account for this artificial clustering, we scaled the clustering coefficient in the observed network (CC_{it}^{O}) by the clustering coefficient of a random network (CC_{it}^{R}) with an identical degree distribution, following the approach suggested by Newman, Strogatz and Watts (2001). Random graph clustering coefficient is calculated by the following formula,

$$CC_{it}^{R} = \frac{k}{N-1}$$

where N is the size of the network and k is the average degree (Watts & Strogatz, 1998). Thus, clustering coefficient ratio, calculated by dividing the measures of observed networks (CC_{it}^{O}) by the random network clustering coefficient with the same degree distribution (CC_{it}^{R}), is our clustering measure.

Connectivity. We measured the level of connectivity as the reciprocal of 'harmonic mean' geodesic distance between all pairs in a network, i.e., the average of the reciprocal path lengths (Newman, 2003) at time t. Geodesic distance between two nodes is the length of the shortest path between them and the average path length is the average geodesic distance to go from one node to another. We calculated the average path length of each intra-unit collaboration network and took the reciprocal of it. Because paths across disconnected components are undefined, we set the distance to infinity in case of no reachability so that it becomes zero when inverted.

Because the single-mode projection can result in artificially short path lengths, we scaled this measure by the expected path length of a random network (Newman, Strogatz & Watts, 2001), and constructed average path length ratio of a network. The average shortest path of a random graph of the same degree distribution is the ratio between the logarithm of the number of nodes and the logarithm of the average number of ties that nodes have. Specifically,

$$PL_{it}^{R} = \frac{\log(N)}{\log(k)}$$

where N is the size of the network and k is the average degree. Note that in case of a network where average degree k is less than 1, this value becomes negative. The average path length ratio is thus calculated by dividing the measures of observed networks (PL_{it}^{O}) by the random network average path length with the same degree distribution (PL_{it}^{R}). Our final measure of connectivity is the reciprocal of the average path length ratio so that units with high level of global connectivity have higher values.

3.4. Control Variables

Network size. A large-sized unit tends to have less clustering while a small-sized unit is more likely to be clustered. Moreover, the number of scientists in a unit is likely to be related to the unit's innovation potential – the more inventors in R&D activities, the more likely the unit has increased chances for knowledge creation. To account for the differences among networks with the varying number of actors, we controlled for the log number of nodes, or inventors, in each unit's network.

Between-unit collaboration. To control for the effect of external knowledge sourcing, we measured the number of co-patenting activities with other R&D units in the same firm, applying the same five-year window that we used to measure our independent variables. Since there is no data available for external collaborations across firm boundary, we could only control for between-unit collaboration inside a firm.

Unit age. We used unit age as a control for experience as an input into innovation. As a unit ages, it may have accumulated more diverse knowledge resources and experience, affecting subsequent innovative performance of the unit.

California/Massachusetts. Firms perform a part of their R&D activities in the places where inventors are able to source knowledge from multiple locales (Lahiri, 2010). To account for the possibility that firms with dispersed R&D units are influenced differently by knowledge spillover from external sources in the region of their research units, we controlled for the places where extensive collocation of pharmaceutical companies has been formed – namely, California and Massachusetts.

California's Silicon Valley and San Diego regions have been long known for their unique high-technology clusters (Saxenian, 1996). California has a volume of knowledge flow between firms, as it generally invalidates noncompete agreements. Further, the Boston area in Massachusetts is one of the largest concentrations of pharmaceutical and biotechnology firms in the world (Stuart & Sorenson, 2003). Boston has a rich population of public research organizations, including universities, independent research institutes and research hospitals. To account for the unique characteristics of these two states, we controlled for whether or not a firm's R&D unit was located in California or Massachusetts at time *t*.

The United States. It is likely that R&D centers located in other countries might file patents to their own countries' patent offices, not in the United States Patent and Trade Office. Furthermore, the U.S. patents in the USPTO patent database identify inventor locations by city and state name while the non-U.S. patents display locations by city and country name. Thus, if an R&D unit is located in the U.S., we identified its location by the state and otherwise we identified by the country name. To control for the possible different effects stemming from this incongruity in the geographical classification in inventors' addresses, we included U.S. dummy variables in our models.

Headquarter. We controlled for whether a unit is a global research headquarter of a firm. Multiunit firms' headquarters are usually rich in knowledge resources as they can somehow force or motivate subsidiaries to transfer knowledge to headquarters (Foss & Pedersen, 2002). We controlled this distinctive characteristic of the headquarters by applying dummy variables to the unit that belongs to or serves as a research headquarter.

Lagged dependent variable. To address the path-dependent nature of corporate innovation, we included lagged dependent variable.

3.5. Model Specification

We applied the Poisson quasi-maximum likelihood estimation to our regressions. The Poisson quasi-maximum likelihood estimators can be obtained by estimating an unconditional Poisson model with robust standard errors (Wooldridge, 1999; Cameron and Trivedi, 2005). Given that the dependent variable is in counts that have values of zero or above, we could fit the Poisson family distributions. The Poisson model assumes equidispersion, which is often violated in models of patent counts, leading academics to prefer the negative binomial model to deal with the overdispersion issue. However, the negative binomial model is only consistent if the conditional variance has a gamma distribution, while Poisson models are consistent with only mean correctly specified, even if overdispersion is present. The standard errors in the Poisson model can be corrected by applying robust standard errors (Wooldridge, 2002). Overall, the Poisson quasi-maximum likelihood model is more likely to result in lower significance levels than the negative binomial model. Thus, we regard the Poisson quasi-maximum likelihood model as preferable. However, we also run regressions using the negative binomial model as a robustness check. The results are qualitatively consistent with the Poisson quasi-maximum likelihood results.

Such research models also control for unit heterogeneity by estimating effects using within variation. Since all units of the same firm are related to each other and the selection of firms was not random, the observations across units are also not independent. To account for these concerns, we employed unit-level fixed effect models. Therefore, the results indicate the change in the dependent variable by the change in the level of independent variables for the same unit, and the comparison is for different values within the same unit, not across units. Further, we controlled for the factors specific to a particular year that might affect the patenting behavior by including year dummy variables. By including year dummy variables, we could also control for the truncation issue of patent citation, as our dependent variable is weighted by the number of forward citations. We also controlled for the effect of the parent firms on each unit by including firm dummy variables.

IV. RESULTS

The descriptive statistics and correlations for relevant variables are displayed in Table 1. Examining the correlation matrix, we note that correlations between the independent variables do not imply any overt concerns about multicollinearity, as we confirmed by the mean variance inflation factors of 2.37 excluding squared terms and interaction terms (Neter, Kutner, Nachtsheim & Wasserman, 1996).

Table 2 present the models of the innovation performance of the R&D units. The controls are highly consistent in sign and significance across the models. Most coefficients are in the expected directions.

Hypothesis 1 predicts that the technological diversity and innovative performance will have an inverted U-shaped relationship. Model 2 tests this hypothesis by introducing *Technological diversity* variable and its squared term. The results that the coefficient of the squared term (*Technological* Diversity)^2 is negative and significant ($\beta = -9.53, p < 0.05$) and the coefficient of the variable *Technological*

Diversity is positive and significant $(\beta = 10.89, p < 0.05)$ indicate that the knowledge diversity boost innovative performance only up to a point, beyond which excessive diversity deters recombination into useful innovations. These findings support Hypothesis 1.

TABLE 1

Descriptive Statistics and Correlations

Variables	1	2	3	4	5	6	7	8	9	10	11
1.Innovation performance	1.00										
2.Technological diversity	0.18	1.00									
3. Clustering	0.48	0.45	1.00								
4. Connectivity	-0.10	-0.39	-0.53	1.00							
5. Network size	0.38	0.18	0.76	-0.36	1.00						
6. Between-unit collaboration	0.26	0.23	0.69	-0.42	0.82	1.00					
7. Unit age	0.03	0.13	0.27	0.07	0.42	0.32	1.00				
8. Headquarter	0.31	0.18	0.43	-0.12	0.45	0.48	0.18	1.00			
9. Location – CA	-0.08	0.14	-0.09	-0.16	-0.13	-0.04	0.02	-0.21	1.00		
10. Location – MA	-0.09	-0.23	-0.14	0.04	-0.19	-0.00	-0.45	0.19	-0.08	1.00	
11. Location – U.S.	0.18	0.31	0.10	-0.15	0.08	0.15	-0.01	0.06	0.39	0.14	1.00
Mean	145.70	0.64	19.94	0.45	4.65	3.62	3.12	0.16	0.18	0.03	0.60
Std. dev.	259.49	0.19	16.42	0.20	1.00	1.18	0.41	0.37	0.39	0.16	0.49
Min.	0.00	0.23	1.69	-0.55	2.30	0.00	0.69	0.00	0.00	0.00	0.00
Max	2122	0.93	85.90	1.14	6.68	5.84	3.74	1.00	1.00	1.00	1.00

TABLE 2

Unconditional Fixed Effects Poisson Regression, 1991-2010

Variables	Model 1	Model 2	Model 3
Network size	0.59 **	0.58 **	0.72 **
	(0.24)	(0.22)	(0.23)
Prior between-unit collaboration	-0.02	0.01	-0.02
	(0.13)	(0.13)	(0.13)
Unit age	-0.75	-0.67	-0.99
	(1.23)	(1.15)	(1.28)
Location – California	2.36 **	2.55 **	2.55 **
	(0.46)	(0.43)	(0.43)
Location – Massachusetts	0.01	0.36	0.86
	(0.66)	(0.69)	(0.74)
Location – U.S.	0.36	0.43	0.32
	(0.47)	(0.49)	(0.54)
Headquarter	-0.28	-0.18	-0.21
	(0.31)	(0.34)	(0.34)
Lagged dependent variable	0.00 **	0.00 **	0.00 **
	(0.00)	(0.00)	(0.00)
Clustering	0.01 *	0.01 **	0.16 **
	(0.01)	(0.01)	(0.07)
Connectivity	0.25	-0.02	9.90 **
	(0.28)	(0.28)	(4.15)
Technological diversity		10.89**	31.1 **
		(2.85)	(10.2)
$(\text{Technological diversity})^2$		-9.53 **	-23.4**
		(2.39)	(7.76)
Clustering × Technological diversity			-0.42 **
			(0.21)
Clustering × $(\text{Technological diversity})^2$			0.28 *
			(0.15)
Connectivity × Technological diversity			-29.4 **
			(13.0)
Connectivity × $(\text{Technological diversity})^2$			20.5 **
			(9.70)
Constant	-1.26	-2.06	-8.53 *
	(2.33)	(2.53)	(4.44)
Unit fixed effects	*Yes*	*Yes*	*Yes*
Firm fixed effects	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*
Log Likelihood	-6775.8	-6452.76	-6296.26
N	412	412	412

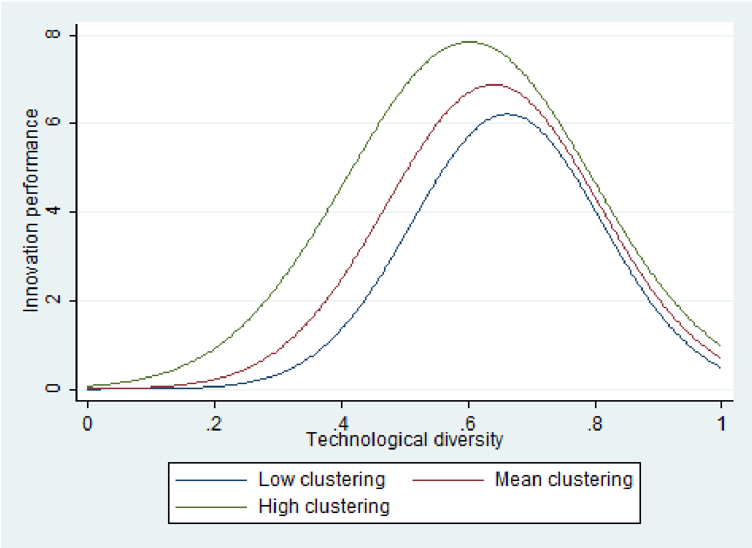
Robust standard errors are in parentheses. * $p < 0.1$ ** $p < 0.05$

The next hypotheses address the interdependent effects of the intra-unit inventor network structure and the technological diversity on innovation. Hypothesis 2 predicts a negative moderation effect of clustered network structure on the relationship between the technological diversity and innovation. The statistical findings in Model 3 show that the coefficient for *Clustering* × *Technological diversity* is negative and significant $(\beta = -0.42, p < 0.05)$, while the coefficient for *Clustering* × (*Technological diversity*)^2 is positive and significant $(\beta = 0.28, p < 0.1)$. This indicates to how greater the level of clustering within an internal network dampens both the positive and the negative effects of technological diversity to innovation, implying the flattening of the inverted U-shaped relationship by the clustered structure. The plot displayed in Figure 2 offers illustration of the interdependent effect of the intra-unit network clustering and the technological diversity on innovation over the range of one standard deviation above and below the mean value of clustering, all other things equal. At the same time, it shows the escalation of overall innovative performance with the greater clustering coefficient, suggesting the beneficial role of clustered network.

Hypothesis 3 predicts a negative moderation effect of the network connectivity on the relationship between the technological diversity and

FIGURE 2

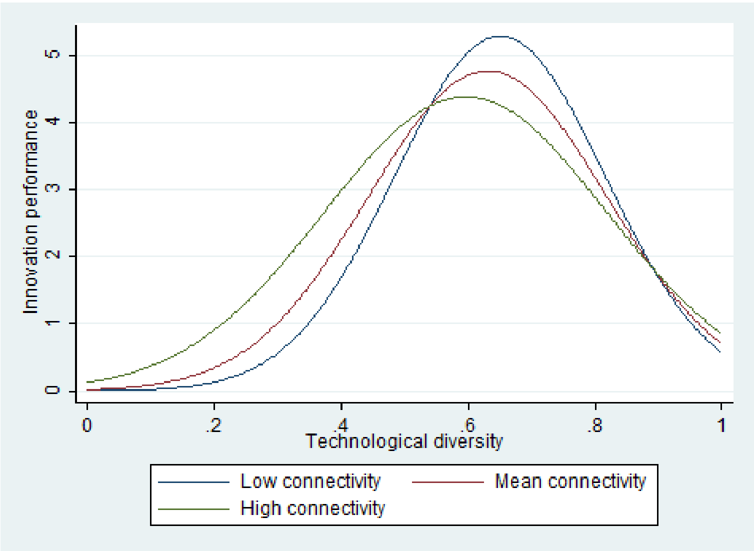
Moderation Effect Clustering



innovation. Model 3 shows the estimation results of the moderation effects of the intra-unit network connectivity. The statistical findings in Model 3 supports Hypothesis 3 by showing that the coefficient for *Connectivity* × *Technological diversity* is negative and significant $(\beta = -29.4, p < 0.05)$, while the coefficient for *Connectivity* × (*Technological diversity*)^2 is positive and significant $(\beta = 20.5, p < 0.05)$. This indicates to how shorter the average path length within an internal network decreases both the positive and negative effects of technological diversity to innovation, implying the flattening of the inverted U-shaped relationship by efficient network structure. The plot displayed in Figure 3 offers illustration of the interdependent effect of the network path length and the technological diversity on innovation over the range of one standard deviation above and below the mean value of clustering, all other things equal.

FIGURE 3

Moderation effect of Connectivity



V. DISCUSSION AND CONCLUSION

5.1. Contributions to Literature

In this paper, we intend to dichotomize the effects of technological diversity and network structure on the unit's innovation performance. We examined the curvilinear relationship between the technological diversity and innovation. Based on the baseline hypothesis, we tested the effects of our two main moderators – the clustering and the connectivity of intra-unit networks. The results statistically validate that in the case of low to moderate level of technological diversity, networks with high clustering and short average path length each decrease marginal increasing rate. However, when the level of technological diversity becomes excessive, both structures decrease marginal costs of managing diverse knowledge domains within a unit. Our findings support our central claim that the network structure influences the diversity managing capability, which in turn affects innovation process.

This study has important contributions for research. First, our study adds richness to the existent management literature by suggesting the role of informal social network structure in managing technological diversity. Prior studies in the literature suggest two possible alternatives of firm's technological diversity strategy, specialization and diversification. Recognizing that both specialization and diversification can be firms' strategic choices (Porter, 1980), we suggest that shaping informal social network structure can be one way to achieve their strategic objectives, especially innovation.

Second, this study addresses important limitations of research on intra-organizational networks and innovation. The literature has largely ignored the potential influence of different network contents, particularly the technological diversity that actors within the network hold. By considering the degree of technological diversity and knowledge distribution among actors, we examined the influence of the composition and structure of a unit's internal network on innovation, filling the void in intra-organizational network literature. The empirical results suggest that the distinction between the two is critical to understand the process of innovation.

Depending on the content and level of technological diversity that the network structure contains, a group with closed and exclusive social structure may become insular and blinded, or alternatively, may utilize its internal social capital to help its members assimilate heterogeneous knowledge and enhance innovative outcomes. Thus, our theoretical approach offers a more comprehensive understanding on the role of informal structure to the current stream of innovation literature.

Third, this study contributes to the application of social network theory to management literature. Building on network theory, we employed the two analytically rigorous measures for the network's global properties – clustering coefficient and average path length – and the concept of 'small-worldliness' to understand the structural effects of technological knowledge and knowledge distribution on innovative performance. In contrast to recent research that has analyzed small-world systems at a macro-social level (e.g., Davis et al. 2003; Rosenkopf & Schilling, 2007; Schilling & Phelps, 2007), our study focused on intra-unit networks adopting micro-level analysis.

5.2. Implications to Managers

We believe that our theoretical framework and empirical results have important practical implications for managers as well. Firms are likely to be divergent in their numbers, locations and designated roles of their R&D units. Lahiri (2010) points out that firms with increasing technological diversity are likely to limit different technological domains of expertise to individual R&D units, thereby decreasing the intra-unit diversity. This is because firms incur higher costs in duplicating every element of their diverse technological resources at all of their dispersed R&D locations. In managerial perspective, the question for the dispersed R&D units is whether they can benefit more from having their technologically diverse knowledge concentrated in each small number of their members, or if widely distributed diverse knowledge (holding constant the amount of diversity) is more beneficial for maximizing knowledge integration and innovation. We answered to this question by suggesting the role of intra-unit network structure, which amplifies the benefit of diversity and lightens the burden of coordinating and integrating excessive technological diversity. Our research suggests to managers that strategically shaping informal structure within a unit and aiming for a moderate level of knowledge diversity may be the most desirable approach to attaining knowledge creation.

5.3. Limitations and Suggestions to Future Research

Several limitations of this work should be noted. The first concerns the use of patent data to measure the informal interactions among members and subsequent innovative performance. Although patents are reasonably good indicators of innovative performance and co-patenting activities are widely employed as a proxy for the communication and interactions among inventors in the management literature, they may not be a perfect measurement of the informal structure and innovation. A more thorough solution may be possible with supplementary data, such as qualitative in-depth interviews or surveys to capture the causal processes and mechanisms that we hypothesized.

Another limitation of this study lies in the fact that although we emphasized the benefits of clustered and small-world networks, we did not consider their long-term costs. Research suggests that clustered and connected networks reduces the diversity of information available in a network over time (Lazer & Friedman, 2007). Dense links provide redundant paths to the same knowledge sources and small-world networks enhance rapid diffusion of information. Soon everyone in the network comes to have the same knowledge (Burt, 1992). However, we did not take into account this direct effect of network structures on knowledge diversity.

Finally, the restriction of the sample to only pharmaceutical industry cast some limitations to generalizing the results of our study, suggesting the need for conducting the study in other industries. Additionally, the relevance and utility of the patent-based measures of innovation and network variables are likely to be limited to the industries in which patents are meaningful to firms' businesses. In addition to the industry sector examined in this study, further studies could be conducted on the other knowledge-intensive industries, including high-tech industries or professional service industries.

Our study, which highlights the importance and relevance of distinguishing the role of knowledge diversity and network structure, builds groundwork for the development of future research. We suggest that future studies may examine the effects of intra-organizational networks in relation to the formal structure and how they can jointly or differently affect diversity managing capabilities. Formal organizational structure as well as informal communication pattern are the two crucial mechanisms that reinforce interactions and activities within the organization. By examining these effects, such research may have implications for both organization literature and managers.

We also suggest that it may be important to investigate the evolution of intra-unit network structure in conjunction with the changes in knowledge diversity. One suggestion for future research is to examine the diverging role of intra-organizational network structure to diversity management depending on the age of an organization. Understanding the dynamics of small-world structures can offer valuable insight into the different opportunities and constraints these structures offer at variable levels of their evolutionary progression.

Another future extension can be made by studying network structural effects in relation to the impact of the influx of information and knowledge from external sources. For example, by adopting multilevel approach, one can examine the impact of both intra-organizational network structures and inter-organizational network structures such as alliance networks on innovative performance.

REFERENCES

Adler, P. S., & Kwon, S. W. 2002. Social capital: Prospects for a new concept. ***Academy of Management Review***, 27(1): 17-40.

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. ***Administrative Science Quarterly***, 45(3): 425-455.

Ahuja, G., & Katila, R. 2004. Where do resources come from? The role of idiosyncratic situations. ***Strategic Management Journal***, 25(8-9): 887-907.

Ahuja, G., & Lampert, C. M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. ***Strategic Management Journal***, *22*(6-7): 521-543.

Ahuja, G., Soda, G., & Zaheer, A. 2012. The genesis and dynamics of organizational networks. ***Organization Science***, *23*(2): 434-448.

Argote, L. 1999. *Organizational learning: creating, retaining and transferring knowledge*. Kluwer Academic Publisher, Norwell, MA.

Austin, J. R. 2003. Transactive memory in organizational groups: the effects of content, consensus, specialization, and accuracy on group performance. ***Journal of Applied Psychology***, *88*(5): 866.

Bartlett, F. C. 1932. *Remembering: An experimental and social study.* Cambridge: Cambridge University.

Bechky, B. A. 2003. Sharing meaning across occupational communities: The transformation of understanding on a production floor. ***Organization Science***, 14(3), 312-330.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. 2002. *Ucinet for Windows: Software for social network analysis*. Harvard, MA: Analytic Technologies.

Burt, R. S. 1992. ***Structural holes***. Cambridge, MA: Harvard University Press.

Burt, R. S. 2000. The network structure of social capital. ***Research in Organizational Behavior***, 22: 345-423.

Cameron, A. C., & Trivedi, P. K. 2005. *Microeconometrics: methods and applications.* Cambridge university press, Cambridge, England.

Carlile, P. R. 2004. Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. ***Organization Science***, 15(5): 555-568.

Carlile, P. R., & Rebentisch, E. S. 2003. Into the black box: The knowledge transformation cycle. ***Management Science***, 49(9): 1180-1195.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: a new perspective on learning and innovation. ***Administrative Science Quarterly***, 35(1): 128-152.

Coleman, J. S. 1988. Social capital in the creation of human capital. ***American Journal of Sociology***, 94: S95-S120.

Cronin, M. A., & Weingart, L. R. 2007. Representational gaps, information processing, and conflict in functionally diverse teams. ***Academy of Management Review***, 32(3): 761-773.

Davis, G. F., Yoo, M., & Baker, W. E. 2003. The small world of the American corporate elite, 1982-2001. ***Strategic Organization***, 1(3): 301-326.

Dougherty, D. 1992. Interpretive barriers to successful product innovation in large firms. ***Organization Science***, 3(2): 179-202.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. ***Research Policy***, 30(7): 1019-1039.

Fleming, L., King III, C., & Juda, A. I. 2007. Small worlds and regional innovation. ***Organization Science***, 18(6): 938-954.

Foss, N. J., & Pedersen, T. 2002. Transferring knowledge in MNCs: The role of sources of subsidiary knowledge and organizational context. ***Journal of International Management***, 8(1): 49-67.

Gardner, H. K., Gino, F., & Staats, B. R. 2012. Dynamically integrating knowledge in teams: Transforming resources into performance. ***Academy of Management Journal***, 55(4): 998-1022.

Gargiulo, M., & Benassi, M. 2000. Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital. ***Organization Science***, 11(2): 183-196.

Gilovich, T. 1991. *How we know what isn't so: The Fallibility of Human Reason in Everyday Life.* New York. The Free Press.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. ***Strategic Management Journal***, 17(S2): 109-122.

Guler, I., & Nerkar, A. 2012. The impact of global and local cohesion on innovation in the pharmaceutical industry. ***Strategic Management Journal***, 33(5): 535-549.

Hanneman, R.A., & Riddle, M. 2005. *Introduction to social network methods*: University of California Riverside, CA (published in digital form at http://faculty.ucr.edu/~hanneman/).

Hargadon, A., & Sutton, R. I. 1997. Technology brokering and innovation in a product development firm. ***Administrative science quarterly***, 42(4): 716-749.

Huang, Y. F., & Chen, C. J. 2010. The impact of technological diversity and organizational slack on innovation. ***Technovation***, 30(7): 420-428.

Jaffe, A. B., & Trajtenberg, M. 2002. *Patents, citations, and innovations: A window on the knowledge economy*. MIT press.

Kanter, R. M. 1988. Three tiers for innovation research. ***Communication Research***, 15(5): 509-523.

Katila, R. 2002. New product search over time: past ideas in their prime? ***Academy of Management Journal***, 45(5): 995-1010.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. ***Organization Science***, 3(3): 383-397.

Lahiri, N. 2010. Geographic distribution of R&D activity: how does it affect innovation quality? ***Academy of Management Journal***, 53(5): 1194-1209.

Lazer, D., & Friedman, A. 2007. The network structure of exploration and exploitation. ***Administrative Science Quarterly***, 52(4): 667-694.

Lee, J., Song, J., & Yang, J. S. 2015. Network structure effects on incumbency advantage. ***Strategic Management Journal***, *Early view*, doi: 10.1002/smj.2405

Lewis, K. 2003. Measuring transactive memory systems in the field: scale development and validation. ***Journal of Applied Psychology***, 88(4): 587-604.

Lewis, K., Lange, D., & Gillis, L. 2005. Transactive memory systems, learning, and learning transfer. ***Organization Science***, 16(6): 581-598.

March, J. G. 1991. Exploration and exploitation in organizational learning. ***Organization Science***, *2*(1), 71-87.

Mason, W., & Watts, D. J. 2012. Collaborative learning in networks. ***Proceedings of the National Academy of Sciences***, 109(3): 764-769.

Moreland, R. L., & Myaskovsky, L. 2000. Exploring the performance benefits of group training: Transactive memory or improved communication? ***Organizational Behavior and Human Decision Processes***, 82(1): 117-133.

Mors, M. L. 2010. Innovation in a global consulting firm: When the problem is too much diversity. ***Strategic Management Journal***, 31(8): 841-872.

Nahapiet, J., & Ghoshal, S. 1998. Social capital, intellectual capital, and the organizational advantage. ***Academy of Management Review***, 23(2): 242-266.

Nerkar, A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. ***Management Science***, 49(2): 211-229.

Nerkar, A., & Paruchuri, S. 2005. Evolution of R&D capabilities: The role of knowledge networks within a firm. ***Management Science***, 51(5): 771-785.

Neter, J., Kutner, M. H., Nachtsheim, C. J. & Wasserman, W. 1996. *Applied linear statistical models* (Vol. 4). Chicago: Irwin.

Newman, M. E. 2003. The structure and function of complex networks. ***SIAM review***, 45(2): 167-256.

Newman, M. E., Strogatz, S. H., & Watts, D. J. 2001. Random graphs with arbitrary degree distributions and their applications. ***Physical review E***, 64(2), 026118-026134.

Obstfeld, D. 2005. Social networks, the tertius iungens orientation, and involvement in innovation. ***Administrative Science Quarterly***, 50(1): 100-130.

Paruchuri, S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. ***Organization Science***, 21(1): 63-80.

Paruchuri, S., & Awate, S. 2016. Organizational knowledge networks and local search: The role of intra-organizational inventor networks. ***Strategic Management Journal**, Early view, doi: 10.1002/smj.2516.*

Phelps, C. C. 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. ***Academy of Management Journal***, 53(4): 890-913.

Porter, M. E. 1980. *Competitive Strategy: Techniques for Analyzing Industries and Competitors.* New York: Free Press. (Republished with a new introduction, 1998.)

Reagans, R., & McEvily, B. 2003. Network structure and knowledge transfer: The effects of cohesion and range. ***Administrative Science Quarterly***, 48(2): 240-267.

Rodan, S., & Galunic, D. C. 2004. More than network structure: how knowledge heterogeneity influences managerial performance and innovativeness. ***Strategic Management Journal***, 25: 541-556.

Rosenkopf, L., & Schilling, M. A. 2007. Comparing alliance network structure across industries: observations and explanations. ***Strategic Entrepreneurship Journal***, 1(3-4): 191-209.

Saxenian, A. 1996. Beyond boundaries: Open labor markets and learning in Silicon Valley. In M. B. Arthur and D. M. Rousseau (eds), *The Boundaryless Career: A New Employment Principle for a New Organizational Era*. New York: Oxford University Press, pp. 23-39.

Schilling, M. A., & Phelps, C. C. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. ***Management Science***, 53(7): 1113-1126.

Shore, J., Bernstein, E., & Lazer, D. 2015. Facts and Figuring: An Experimental Investigation of Network Structure and Performance in Information and Solution Spaces. ***Organization Science***. Advance online publication. doi:10.1287/orsc.2015.0980

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. ***Management Science***, 51(5): 756-770.

Sorensen, J. B., & Stuart, T. E. 2000. Aging, obsolescence, and organizational innovation. ***Administrative Science Quarterly***, 45(1): 81-112.

Sosa, M. E. 2011. Where do creative interactions come from? The role of tie content and social networks. ***Organization Science***, 22(1): 1-21.

Stasser, G., Stella, N., Hanna, C., & Colella, A. 1984. The majority effect in jury deliberations: Number of supporters versus number of supporting arguments. ***Law & Psychology Review***, 8: 115-127.

Stuart, T. E., & Sorenson, O. 2003. Liquidity events and the geographic distribution of entrepreneurial activity. ***Administrative Science Quarterly***, 48(2): 175-201.

Trajtenberg, M. 1990. A penny for your quotes: patent citations and the value of innovations. ***The Rand Journal of Economics***, 21(1): 172-187.

Tortoriello, M., McEvily, B., & Krackhardt, D. 2015. Being a catalyst of innovation: The role of knowledge diversity and network closure. ***Organization Science***, 26(2): 423-438.

Tortoriello, M., Reagans, R., & McEvily, B. 2012. Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the transfer of knowledge between organizational units. ***Organization Science***, 23(4): 1024-1039.

Tushman, M. L. 1977. Special boundary roles in the innovation process. ***Administrative Science Quarterly***, 22: 587-605.

Uzzi, B., & Spiro, J. 2005. Collaboration and creativity: The small world problem. ***American Journal of Sociology***, 111(2): 447-504.

Watts, D. J. 1999. *Small worlds: the dynamics of networks between order and randomness*. Princeton university press.

Watts, D. J., & Strogatz, S. H. 1998. Collective dynamics of 'small-world' networks. ***Nature***, 393(6684): 440-442.

Wooldridge, J. M. 1999. Distribution-free estimation of some nonlinear panel data models. ***Journal of Econometrics***, 90(1): 77-97.

Wooldridge, J. M. 2002. *Econometric analysis of cross section and panel data.* Massachusetts Institute of Technology, Cambridge, MA.

Zahra, S. A., & George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. ***Academy of Management Review***, 27(2): 185-203.

Zhou, K. Z., & Li, C. B. 2012. How knowledge affects radical innovation: Knowledge base, market knowledge acquisition, and internal knowledge sharing. ***Strategic Management Journal***, 33(9): 1090-1102.

국문초록

기술적 다양성의 활용에 관한 연구
: 조직 내 네트워크 구조가 혁신에 미치는 영향

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왜 기업의 R&D 조직마다 기술적 다양성의 활용 역량에 차이가 발생하는가? 본 연구는 이 차이가 조직 내 기술자들이 형성하고 있는 네트워크 구조에 기인한 것이라 주장한다. 네트워크 구조의 두 가지 속성 – 집단화 계수와 경로 거리 – 에 의해 달라지는 조직 내 지식 자원의 분포가 기술적 다양성과 혁신 간의 역 U자형 관계를 어떻게 조절하는지 살펴본다. 5개 글로벌 제약기업의 27개 R&D 연구센터를 대상으로 1991년부터 2010년까지 20년 간의 패널 자료를 분석함으로써 본 연구는 기술적 다양성과 혁신 간의 역 U자형 관계가 있음을 밝히고, 기술자 네트워크가 집단화된 조직, 경로 거리가 짧은 조직일수록 이 관계가 완만해짐을 밝힌다. 기존의 연구들이 가정하고 있는 네트워크 구조와 지식 다양성 간의 상관관계에 강한 의문을 제기함으로써, 본 연구는 지식 다양성과 혁신에 관한 연구에 이론적으로 기여할 뿐만 아니라 기업 내 R&D 연구소의 조직 구조 디자인에 실천적인 시사점을 제공할 것으로 기대한다.

주요어: 지식 다양성, 조직 내부 네트워크, 집단화 계수, 경로 거리, 혁신

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