ESSAYS ON INNOVATION AND RELATIONAL CAPITAL

by

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ABSTRACT

This dissertation is composed of three essays. Its central theme is a study of the antecedents to technological innovation. Essay One examines an important relationship that has been overlooked in the literature, i.e., the impact of prior alliance relationship between firms on their current innovation performance when they become competitors. I used a comprehensive longitudinal dataset that includes information on historical alliance activities and current innovation races between firms in the U.S. pharmaceutical industry, over two decades (1985-2004). I found that the impact of prior collaborations on current competitions is a function of both the type of prior alliance relationships between firms, and the number of prior allies of different types in the current competition.

Essay Two helps reconcile an ongoing debate in the literature regarding whether competition positively or negatively influences innovation. I used panel data containing innovation races from 1991 to 2004 in the U.S. pharmaceutical industry. I found that the degree of knowledge resource similarity (in both structure and amount) between the focal firm and its rivals is an important determinant of the balance between the positive and negative externalities of competition. The focal firm's innovation was likely to suffer from competition where rivals had relatively larger amounts of knowledge resources. Such negative effect, however, can be attenuated and the net effect may turn positive, as the knowledge structure similarity between the rivals and the firm increases.

While Essay One focuses on inter-firm relational capital, i.e., alliances, Essay Three focuses on the development of relational capital (i.e., trust) in the workplace, touching upon some of the fundamental conditions of innovation. I studied the antecedents to social trust in the workplace, a unique form of relational capital that draws an increasing research interest. Using two field studies conducted in Canada and China representing distinct cultures, I found that the diversity of one's social network in the community was positively associated with one's social trust in the workplace, in both societies, while the diversity of social network in the workplace was only positively associated with social trust in the workplace in China, and not in Canada.

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CO-AUTHORSHIP STATEMENT

The first two essays are co-authored with Ilan Vertinsky. I am the leading author in both essays, playing the major role in developing research ideas and frameworks, collecting and analyzing data, and preparing for manuscripts.

The third essay is co-authored with Ilan Vertinsky, Sandra Robinson and Oana Branzei. I am the first author, playing a leading role in developing research ideas and frameworks, analyzing a secondary dataset, and writing the manuscript.

INTRODUCTION

The central theme of this three-essay dissertation is a study of the antecedents to technological innovation. Essay One examines an important relationship that has been overlooked in the literature, i.e., the impact of prior alliance relationship between firms on their current innovation performance when they become competitors. Essay Two helps reconcile an ongoing debate in the literature regarding whether competition positively or negatively influences innovation (Cockburn & Henderson, 1994; Fleming, 2001; Henderson & Cockburn, 1996; Reinganum, 1989; Ziedonis, 2004); it suggests the impact is conditional on the knowledge resource similarity between competitors with respect to both knowledge amount and structure. Essay Three adds to the literature by shedding light on the mechanisms through which social capital is developed within organizations, which has been regarded as an important antecedent to innovation (Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998).

Specifically, Essay One begins with a review of recent research on strategic alliances which has elaborated upon the consequences of alliance experiences in future alliances (Gulati, 1995; Larson, 1992; Podolny, 1994; Goerzen, 2007). The review suggests, however, the focus of these studies is the impact of prior collaborations on future collaborations between firms, while overlooking the impact of prior collaborations on future competitions when former allies become competitors. While prior collaborations do facilitate information sharing that smoothes new collaborations, they can backfire in competition, because the knowledge acquired about a firm's needs, capabilities, managerial practices, and operating routines may be used against it by the former collaborators (Li, et al., 2008; Gulati, 1995).

The purpose of this essay is to investigate the impact of former collaborations on future competitions. Specifically, I study how prior alliances between firms influence their innovation performance when they compete to develop potentially substitutable new products. I used a comprehensive longitudinal data that includes information on historical alliance activities and current innovation races between firms in the U.S. pharmaceutical industry, over two decades (1985-2004). I found that the impact of prior collaborations on current competitions is a function of both the type of prior alliance relationships between firms, and the number of prior allies of different types in the current competition. The major findings include the following: (1) the number of prior strong allies (e.g., equity-based allies, R&D collaborators) is curvilinearlly related to a firm's innovation performance in a race, taking a U-shape, (2) the number of prior recurring weak allies (e.g., licensing, patenting or marketing agreement-based collaborators) is curvilinearlly related to the firm's innovation performance, but taking an inverted U-shape, and (3) the number of prior non-recurring weak allies is not related to the firm's innovation performance in a race.

Essay Two answers an important question that remains controversial in the literature: do competitors have a positive or negative influence on a firm's innovation (Cockburn & Henderson, 1994; Fleming, 2001; Henderson & Cockburn, 1996; Reinganum, 1989; Ziedonis, 2004)? Incorporating insights from the resource-based view (e.g., Barney, 1991) and the organizational learning theory (e.g., Cohen & Levinthal, 1990; Lane & Lubatkin, 1998), I developed a theoretical framework that sheds light on this question. I argue that the degree of knowledge resource similarity (in both structure and amount) between the focal firm and its rivals is an important determinant of the balance between the positive and negative externalities of competition. I tested my hypotheses using panel data containing innovation races from 1991 to 2004 in the U.S. pharmaceutical industry. I found that the focal firm's innovation was likely to suffer from competition where rivals had a relatively larger amount of knowledge resources. Such negative effect, however, can be attenuated and the net effect may turn positive, as the knowledge structure similarity between the rivals and the firm increases.

While Essay One focuses on inter-firm relational capital, i.e., alliances, Essay Three focuses on the development of relational capital in the workplace, touching upon some of the fundamental conditions of innovation (e.g., Nahapiet & Ghoshal, 1998). Relational capital, such as trust, is essential for innovation because it largely facilitates knowledge transfer across different units of an organization in order to create new knowledge (e.g., Tsai & Ghoshal, 1998). In Essay three, I studied the antecedents to trust in the workplace from the perspective of conservation of resources (COR) theory.

There has been an increasing interest in the COR theory over the past two decades (e.g., Hobfoll, 1988; 1989, 2001; Wright & Hobfoll, 2004). However, the majority of prior research has focused on explaining stress-related negative psychological states while overlooking the possible influence of resources on positive attitudes and behaviors (e.g., Grandey & Cropanzano, 1999; Ito & Brotheridge, 2003; Wright & Hobfoll, 2004). Additionally, prior research studying social resources, such as family, co-workers, and supervisors, typically viewed these resources as independent entities, ignoring the fact they, as a whole, compose one's social network (e.g., Cordes & Dougherty, 1993). The social network perspective towards resource accumulation, transfer, and utilization has not drawn sufficient attention. This study expands the boundary of extant COR research by examining the impact of social networks on the development of positive attitudes and behaviors, i.e., social trust in the workplace, a unique form of trust that draws an increasing research interest. Using two field studies conducted in two nations (Canada and China) representing distinct cultures, I found that the diversity of one's social network in the community was positively associated with one's social trust in the workplace, in both societies, while the diversity of social network in the workplace was only positively associated with social trust in the workplace in China, and not in Canada.

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ESSAY ONE: "Will you act like we have never kissed?" The Impact of Alliance History with Current Competitors on Innovation Races in the U.S. Pharmaceutical Industry (1985-2004)[1]

[1] Cui, H. & Vertinsky, I., 2010. "Will you act like we have never kissed?" The Impact of Alliance History with Current Competitors on Innovation Races in the U.S. Pharmaceutical Industry (1985-2004). A version of this paper is in preparation for submission.

INTRODUCTION

Over the past decades, there has been an increasing research interest in strategic alliances (e.g., Ahuja & Katila, 2001; Gulati, 1998; Mowery, Oxley, & Silverman, 1996; Lavie & Miller, 2008; Kale, Dyer, & Singh, 2002). Notably, researchers have examined the consequences of alliance experiences in future alliance activities, e.g., re-entering alliances with the same partner (Gulati, 1995; Podolny, 1994; Goerzen, 2007), enhanced capacity of managing new alliances (Gulati, Lavie, & Singh, 2009; Hoang & Rothaermel, 2005; Sampson, 2007), and partner selection in new alliance relationships (Li, et al, 2008). One of the core arguments of these studies is former alliance relationships can help develop mutual understanding and routines between firms which consequently facilitate or benefit their future alliances (Gulati, 1995; Larson, 1992; Podolny, 1994; Goerzen, 2007).

Previous research, however, has mainly focused on the impact of prior collaborations on future *collaborations* between firms, while overlooking the impact of prior collaborations on future *competitions*, when former allies become competitors. While prior collaborations do facilitate information sharing that smoothes new collaborations, it can backfire in competition: with first-hand knowledge of a firm in regard to its needs, capabilities, managerial practices, and operating routines, former collaborators can turn into possibly the most dangerous competitors (Li, et al., 2008; Gulati, 1995). They will be in a better position in competition, if they choose to take advantage of such knowledge (Arrow, 1974; Heiman & Nickerson, 2004; Heiman & Nickerson, 2002). Would former collaborators behave opportunistically, and what are the competitive landscapes in which a firm suffers or benefits from competing with its former collaborators?

The purpose of this paper is to address these issues. Specifically, I study how prior alliances between firms influence their innovation performance when they compete to develop potentially substitutable new products. I used a comprehensive longitudinal data that includes information on historical alliance activities and current innovation races between firms in the U.S. pharmaceutical industry, over two decades (1985-2004). I found that the impact of prior collaborations on current competitions is a function of not only the type of prior alliance relationships between firms, but the number of prior allies of different types in the current races, both of which construct the competitive landscape. The major findings include the following: (1) the number of prior strong allies (e.g., equity-based allies, R&D collaborators) is curvilinearlly related to a firm's innovation performance in a race, taking a U-shape, (2) the number of prior recurring weak allies (e.g., licensing, patenting or marketing agreement-based collaborators) is curvilinearlly related to the firm's innovation performance, but taking an inverted U-shape, and (3) the number of prior non-recurring weak allies is not related to the firm's innovation performance in a race.

The findings yield the following core contributions. First, by revealing the impact of prior alliances on future competitions, the findings suggest revisiting an implicit assumption made in many studies on inter-firm competition, i.e., competitors relate to a focal firm as if alliance histories between them did not matter. Refining extant research models by incorporating historical alliance relationships may reconcile some important debates regarding inter-firm competition, for example, whether competitors' innovations facilitate (Cockburn & Henderson, 1994; Henderson & Cockburn, 1996; Katila & Chen, 2008) or block a focal firm's innovation (Reinganum, 1989; Ziedonis, 2004). The findings suggest a contingent view that this relationship may depend on the type of prior inter-firm alliances between competitors and the focal firm and the number of former allies in current competition.

Secondly, this research makes a unique empirical contribution to the innovation literature. Most prior research regarding inter-firm competition in developing new products assumed that all innovation outputs (e.g., patents) aggregated at the organizational level are directly relevant to the development of a new product (e.g., Cockburn & Henderson, 1994; Henderson & Cockburn, 1996; Yang, Steensmam, & Phelps, 2009). I used a more fine-grained product-level data, focusing on intermediate innovations. These innovations are the critical new technologies that are actually used in developing a specific new product. It is these technologies that support the ingredients, functions, or the manufacturing processes of a new product (Mossinghoff, 2005). Due to the high technological and competitive value of these innovations (Lichtenberg & Philipson, 2002), using the refined data allows me to provide more precise insight into innovation races.

THEORETICAL BACKGROUND

Governance Structures of Strategic Alliances

Strategic alliances are governed through different structures, ranging from equity-based agreements (e.g., joint ventures) to contract-based partnerships (e.g., licensing agreements) (Roijakkers & Hagedoorn, 2006). According to the degree of resource commitment and frequency of interactions in alliances, researchers have classified alliance structures into two groups: strong alliances and weak alliances (Rowley, et al., 2000).

Strong alliances refer to the type of collaborative arrangements such as equity-based alliances, joint ventures and non-equity cooperative (R&D) ventures, which demand frequent interactions and considerable investment in partnerships, through which firms develop close collaborative relationship (Rowley, Behrens, & Krackhardt, 2000). The alliances not only facilitate the “student” firms in learning more complex knowledge, but also increase the “teacher” firms’ willingness to share organizationally embedded tacit know-how (Kogut, 1988; Kogut & Zander, 1992; Sampson, 2007; Williamson, 1991). In contrast, weak alliances refer to more arm’s length transactions such as marketing, licensing, and patenting agreements in which firms interact on the basis of instant value exchange (Rowley, Behrens, Krackhardt, 2000). The amount of knowledge to be learned in weak alliances is generally more limited and the technology to be transferred is more tightly “packaged” (Mowery, et al., 1996: 80).

The literatures on strategic alliances and organizational learning suggest that the two types of alliance structures may influence the post-alliance relationship between former allies along the following four dimensions, i.e., information asymmetry, relational capital, relative absorptive capacity, and novelty of knowledge spillovers. These dimensions collectively can help understand the influence of different types of former allies on firms' innovation performance, constructing the research framework of this paper.

Information Asymmetry and Relational Capital

An important stream of the literature on strategic alliance focuses on the impact of alliance relationships on levels of information asymmetry and relational capital between partners. Information asymmetry between firms serves as an informal method of protecting firms' interests (Li et al., 2008). Researchers have found firms intentionally use secrecy as an important instrument to defend against others' opportunistic behavior (Epstein, 2004; Katila, Rosenberger, & Eisenhardt, 2008). The literature on strategic alliance suggests that firms can know more about each other through collaborations, with respect to not only general and explicit information about the partners, but some of their proprietary information and tacit knowledge, such as technology capability, areas of deficiency, decision routines, and managerial practices (Balakrishnan & Koza, 1993; Li, Eden, Hitt, & Ireland, 2008). The extent of mutual understanding increases with the frequency and intensity of interactions, suggesting that information asymmetry between former allies decreases with the strength of their prior alliance relationship.

Reduced information asymmetry may increase the vulnerability of a firm in later competitions, because it increases the ability and incentive of those firms which have acquired some first-hand information of high competitive value to launch targeted attacks (Arrow, 1974; Heiman & Nickerson, 2002). The first-hand knowledge is valuable particularly because it could be used to infer the trajectory of prior allies in developing new technologies in later innovation races. The literature on learning implies that in technology innovation, firms are likely to follow some technology routes (i.e., learning paths) consistent with their knowledge development trajectory and existing technology capabilities (Axelrod, 1972; Fiske & Taylor, 1991). Firms' knowledge and capabilities develop from their historical R&D activities, alliance experiences, and competition in various product markets, etc. (Mowery, et al., 1996). As a typical feature of any type of learning, firms innovate by exhibiting a propensity to exploit or explore new knowledge that is adjacent to their existing knowledge domain (March, 1991). Because technology innovations are likely to be path-dependent, competitors familiar with a firm's knowledge assets are capable of predicting the firm's innovation pathways. They may take advantage of such information in their own innovation, by blocking the paths of the focal firm, forcing it to innovate at significantly higher cost or even withdraw from the innovation race altogether (e.g., Reinganum, 1989; Ziedonis, 2004).

The capacity and incentive to launch attacks, however, is constrained by the relational capital developed between firms in previous alliance relationships. Relational capital is an important intangible asset such as trust, reciprocity, informal obligation, and loyalty, which can be developed between partners in alliances (Gulati, 1995a; Gulati & Wang, 2003; Kogut, 1989; Park & Kim, 1997). An important function of relational capital is to prevent opportunistic behavior, reduce uncertainty, and increase the predictability in inter-firm interactions (Gulati et al., 2009; Gulati & Singh, 1998; Kale, Singh, & Perlmutter, 2000; Williamson, 1985). Consistent with the above mentioned observations, researchers have found firms have a tendency to repeatedly enter alliances with the same partners because the relational capital, cultivated in previous collaborations, may reduce transaction costs in new relationships (Dyer & Chu, 2003; Gulati, 1995a, 1995b; Podolny, 1994). An important implication is high levels of relational capital may prevent firms from launching detrimental attacks on former allies as such attacks could jeopardize the deliberately cultivated relationship and burn bridges to future collaborations.

Researchers also noted information symmetries and relational capital evolve at different speeds. Information asymmetry decreases rapidly through alliances, while relational capital develops more slowly, following a non-linear trajectory (Li et al., 2008). For example, the development of trust typically depends on both the quantity and the quality of interactions, the outcome of which is continuously evaluated by both sides, with respect to the predictability, reliability, and honesty of the other party (Gulati, 1995a; Lewicki & Bunker, 1996; Mayer, Davis, & Schoorman, 1995). Sometimes, it takes multiple, close collaborations before firms can make the leap of faith (Barney & Hansen, 1994). Since repeated interactions and intensive involvement in alliances cultivate mutual commitment and bonded relationships, it is suggested that the level of relational capital that could regulate new interactions between firms depends positively on the strength of their prior alliance relationships.

Overall, this stream of literature suggests while reduced information asymmetry increases a firm's vulnerability, the actual chances of being taken advantage of by its former allies may be constrained by the level of relational capital developed between the firm and its former allies.

Relative Absorptive Capacity and Novelty of Knowledge Spillovers

Several important studies regarding organizational learning have suggested that firms may learn and benefit from prior allies' knowledge spillovers in competition. The degree of benefit is determined by the other two important dimensions of post-alliance relationships, i.e., a firm's relative absorptive capacity and the novelty of its prior allies' knowledge spillovers.

Relative absorptive capacity refers to a firm's ability to recognize, value, and assimilate others' knowledge outputs at the learning-dyad level (Lane & Lubatkin, 1998). The literature on organizational learning has shown that the level of relative absorptive capacity is positively determined by the level of knowledge overlap between firms (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998). A core argument of the literature is knowledge overlap enables a firm to relate others' knowledge to its existing knowledge (Cohen & Levinthal, 1990), which permits the firm to learn external knowledge that is different from what it already knows (March, 1991). Viewing technology innovation as a learning process, researchers have found firms actively search the innovation outputs of others (Cohen & Levinthal, 1990; Daft & Weick, 1984), particularly when they are working on similar problems or in adjacent research areas (Henderson & Cockburn, 1996;

Katila & Chen, 2008). This is because the innovations of others can spillover valuable knowledge which may suggest new opportunities for combining existing knowledge (Fleming, 2001; Jaffe, 1986; Jaffe, Trajtenberg, & Fogarty, 2000). In innovation races, similarity in knowledge assets facilitates a firm to be more alert to others' technological development, enhances its ability to understand their innovation approaches and rationale, and enables it to absorb useful technological knowledge.

Researchers have found that the stronger the alliance relationship, the larger the post-alliance knowledge overlap, because stronger alliance relationships are featured by more chances and deeper levels of capability transfer, which permit sharing a significantly larger quantity and higher complexity of knowledge resources (Mowery et al., 1996, 1998). The suggestion is a firm's relative absorptive capacity, and particularly its ability to learn specifically from its former allies' innovations, is positive related to the strength of their prior alliance relationship.

The literature on learning also indicates that knowledge resource relatedness between firms is associated with their similarity in mental maps in creating new knowledge. When their knowledge overlap is extremely large, their mental maps tend to resemble each other (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998). As a result, they are less likely to suggest new directions of innovation to each other, but may inadvertently crowd the specific paths of technological innovation. The implication is while relative absorptive capacity increases with the degree of knowledge overlap, the amount of novel ideas suggested by former allies' innovation, i.e., novelty of former allies' knowledge spillovers, decreases with the degree of their knowledge overlap.

Two key implications are derived from the literature. First, when the degree of knowledge overlap is high the level of relative absorptive capacity between firms is also high. Second, however, the degree to which competitors' technology approaches are able to suggest new directions for innovation, different from the focal firm, is probably low, because they may have developed similar cognitive schemata and technology capabilities during relatively strong alliance relationships (Mowery, Oxley, & Silverman, 1996, 1998). The extent to which others' innovations benefit a firm is a function of both the firm's relative absorptive capacity to learn from the innovations (Lane & Lubatkin, 1998) and the value of the innovations as to how novel they are to the firm (March, 1991; Katila & Ahuja, 2002).

Overall, the literatures on strategic alliances and organizational learning suggest that the levels of post-alliance relational capital and relative absorptive capacity increase with the strength (e.g., intensity and frequency) of previous alliance relationships, while the levels of information asymmetry and novelty of others' knowledge spillovers decrease with it. Former allies of different governance structures and frequency of collaborations may exhibit distinct combinations of these four dimensions, and therefore have various impacts on the firm's innovation performance in competition.

Based on characteristics of alliances, with respect to the level of mutual commitment and chances of interactions (Gulati, 1995; Mowery, et al., 1996; Rowley, et al., 2000), I categorized prior alliance relationships into three groups: group one consists of former strong allies, group two consists of former weak allies with repeated collaborations, and group three consists of former weak allies with just one interaction. The strength of prior collaborative relationships decreases monotonically from group one to group three. I argue that participation of former allies in innovation races changes the landscape of the competition. Their impact on a firm's innovation performance displays a variety of patterns, reflecting the balance between both the positive (e.g., relative absorptive capacity, relational capital) and the negative (e.g., opportunism) effects imposed by former allies of different types and quantity in a race.

HYPOTHESES

Former Strong Allies and Innovation Races

Former strong allies, arguably, have the highest ability to block a firm in innovation races because they are the most familiar with the firm's areas of deficiency. On the other hand, the level of relational capital between the firm and its former strong allies may also be considerably high. In relational-oriented alliance activities, they may have cultivated a considerable degree of mutual commitment, which typically demands maintaining a good relationship. Sustainable relationships could breed future collaborations and benefit a wider range of interests, which may be more rewarding in the long run (Gulati, 1995). Therefore, although former strong allies are able to inflict more targeted damage upon the focal firm in the race, they also have the most incentive to maintain the relational capital. Overall, it is very unlikely that former strong allies will act opportunistically towards the focal firm in innovation races.

The organizational learning literature suggests that knowledge development paths shared among strong allies increase the degree of similarities in their knowledge resources (Axelrod, 1972; Fiske and Taylor, 1991; March, 1991). As a result, they have a high relative absorptive capacity to learn from each other's knowledge outputs in innovation races (Lane & Lubatkin, 1998). On the other hand, the degree of redundancy in their knowledge spillovers compared to the focal firm tends to be high too, which constrains the opportunities for the firm to combine existing knowledge in creative ways (March, 1991; Katila & Ahuja, 2002; Katila & Chen, 2008).

Although they may not be taken deliberately, innovations of former strong allies may inevitably crowd the technological paths of each other as they are likely to follow highly similar innovation approaches. The effect of crowding increases with the number of former allies in competition. When the number of former strong allies is small, the crowding effect is likely to dominate the relatively smaller positive spillover effect associated with the very limited supply of new technological opportunities suggested by their innovations. As a result, the net effect of competing with a small number of former strong allies is likely to be negative.

When there are a large number of former strong allies, more variations in their innovation models are likely to emerge. As the innovation models diversify, the marginal crowding effect is very likely to decline. The variations represent more distinctive technological solutions and diversified perspectives, which can inspire more ideas of recombining technologies to solve innovation problems (Flemming, 2000; Yang, et al., 2009). Due to its high relative absorptive capacity, the focal firm is able to identify, understand, and synthesize these ideas, thus generating novel solutions to its own innovations problems (March, 1991; Katila & Ahuja, 2002; Katila & Chen, 2008). As the number of former strong allies increases, the spillover effect continues to pick up and may possibly overcome the crowding effect that grows at a declining rate. Overall, the influence of former strong allies on a firm's innovation performance is likely to be negative when the number of these former allies is small, where creating distinctive innovations is difficult. The influence of former strong allies is likely to be positive when the number of these former allies is large, because knowledge spillovers become more diversified that provide richer innovation opportunities. Figure 1 illustrates the hypothesized relationship.

Hypothesis 1. The innovation performance of a firm is curvilinearly associated with the number of former strong allies in innovation races, taking a U-shape. The relationship is negative when the firm is competing with a small number of former strong allies, but it is positive when the firm is competing with a large number of former strong allies.

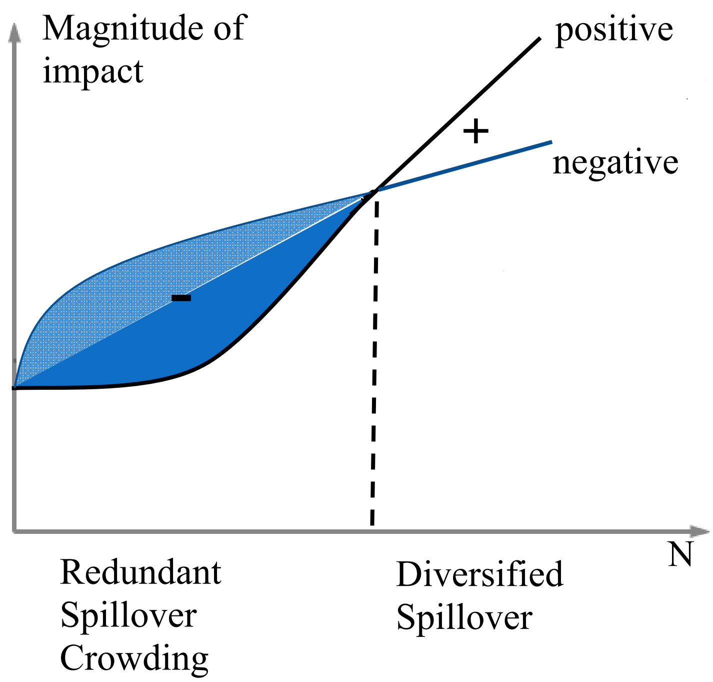

FIGURE 1 Number of Former Strong Allies in a Race and Firms' Innovation Performance

Former Repetitive Weak Allies and Innovation Races

Former, repetitive, weak allies are likely to have accumulated a significant amount of knowledge regarding a firm's technological assets and innovation routines through multiple transactions with it. Therefore, they have the ability to block the firm in innovation races more effectively than firms without such knowledge. However, as the focal firm is also familiar with the technology assets of these former allies, it can retaliate if attacked (Edwards, 1955). Furthermore, because of their recurring transactions, they may also want to avoid damaging their sustainable market-oriented collaborations (Podolny, 1994; Yamagishi & Yamagishi, 1994). Concerns regarding revenge and expectation of future collaborations may prevent former repetitive, weak allies from moving aggressively against each other, resulting in mutually forbearing relationships in races (Chen, 1996; Evans & Kessides, 1994; Gimeno, 1999). Overall, former, repetitive, weak allies are unlikely to act opportunistically against each other in a race.

Innovations developed by former, repetitive, weak allies can create a large number of technological opportunities that promote a firm's innovation. Due to the relatively low level of knowledge overlap between former, repetitive, weak allies and the firm, the technological approaches embedded in their innovations are likely to suggest novel directions for combining and developing technologies (March, 1991; Katila & Ahuja, 2002). The larger the number of former, repetitive, weak allies in a race, the greater the quantity of non-redundant technology approaches, which can inspire the firm and significantly benefit its innovation performance (Ahuja, 2000; Granovetter, 1973).

However, the innovation performance of the firm is unlikely to increase constantly with the number of these allies in the race. This is because the level of relative absorptive capacity of the firm is moderate, preventing it from absorbing all the valuable knowledge spillovers. It is moderate because the degree of knowledge overlap among weak allies is relatively small (Mowery et al., 1996). As the number of former, repetitive, weak allies increases in the race, the focal firm continues to benefit from their knowledge spillovers. The marginal value of additional spillovers on the firm's innovation performance, however, declines as the firm approaches the limit of its relative absorptive capacity until the capacity is saturated. On the other hand, as the number of former, repetitive, weak allies increases, the chances for them to identify and compete on same or closely related technological opportunities increases too. Such crowding of competitors in the same technological field elevates the financial and time cost of innovation, further dampening the benefits of knowledge spillovers for the focal firm. The increasing negative effect of crowding may eventually overcome the caped positive effect of absorbing spillovers. It is therefore likely that the net impact of former, repetitive, weak allies on the innovation performance of the focal firm is initially positive and increasing at a declining rate when the number of such former weak allies in the race is small, but declines and becomes negative when the number is large. Figure 2 illustrates the hypothesized relationship.

Hypothesis 2. The innovation performance of a firm is curvilinearly associated with the number of former, repetitive, weak allies in innovation races, taking an inverted U-shape. The relationship is positive when the firm is competing with a small number of former, repetitive, weak allies, but it is negative when the firm is competing with a large number of former, repetitive, weak allies.

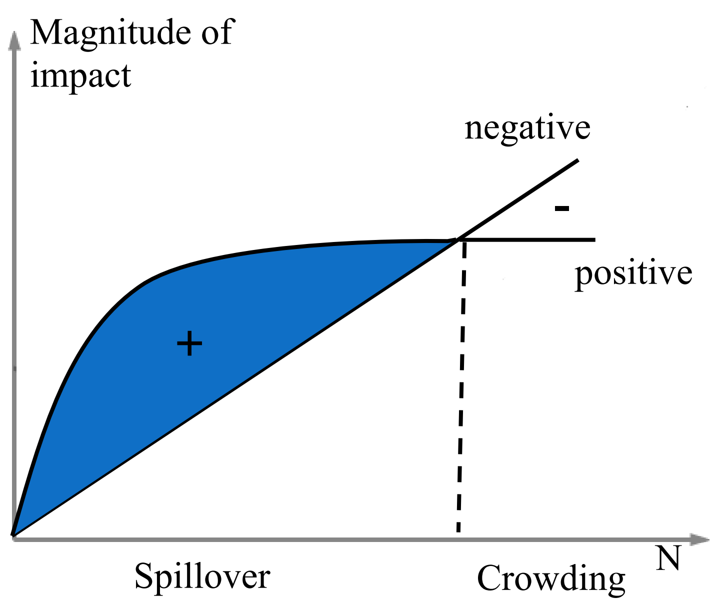

FIGURE 2 Number of Former Repetitive Weak Allies in a Race and Firms' Innovation Performance

The core argument regarding the positive effect of former, repetitive, weak allies is they provide novel innovation approaches, but such an effect levels off due to the moderate level of relative absorptive capacity of the firm. Following this logic, the positive impact quite likely could be enhanced if the former, repetitive, weak allies "showcase" their technology approaches by working on innovation problems closely relevant to those of the focal firm. The intuition is: if such former allies provide not only general "principles" of innovation, but actually demonstrate how to successfully implement the "principles" of innovation by solving a relevant problem, the positive impact is likely to be more significant.

This logic is supported by prior research on learning, suggesting that when solving new problems or learning something novel, a good initial strategy would be to imitate successful models (Levitt & March, 1988; Offerman & Sonnemans, 1998). Research on innovation also suggests that innovations of others can benefit a firm to a greater extent when others work on relevant innovation areas (Henderson & Cockburn, 1996; Katila & Chen, 2008). This method of "case teaching" enhances the absorptive capacity of the firm to learn novel approaches, enabling it to apply them in solving its own relevant problems. Therefore, I expect that a higher relevance level of the knowledge spillovers of former, repetitive, weak allies can enhance the positive effect that their novel technology approaches have on the firm's innovation.

On the other hand, relevance of competitors' innovations may also intensify the crowding effects in the same innovation areas. In innovation races, firms compete for technology resources and opportunities in order to solve innovation problems. Successful innovations developed by competitors, in the form of patents, claim a boundary of technological territory, as well as proprietary rights over a method of solving a particular type of innovation problems (Walker, 1995). Competitors' patenting, crowded in the same technology area of the firm, may impose "exhaustion externality" on the focal firm, forcing it to innovate around the rivals' "territory", and significantly increasing its research cost (e.g., Reinganum, 1989; Ziedonis, 2004). Therefore, high relevance of former, repetitive, weak allies' innovations may increase incidents of blocking of a firm's innovation paths.

Taken the two opposing effects of innovation relevance together, it is suggested that when innovations of former, repetitive, weak allies are highly relevant, a firm's innovation performance would increase sharply when the number of such competitors in a race is small, but decrease sharply when the number of such competitors is large. As the level of relevance decreases, this moderating effect would decrease, and the predicted inverted U-shape should become flatter.

Hypothesis 3. The relevance level of innovation outputs of former, repetitive, weak allies positively moderates the curvilinear relationship (taking an inverted U-shape) between the number of former, repetitive, weak allies and the firm's innovation performance in innovation races. The inverted U-shape will be sharpened as the level of relevance increases.

Former Non-repetitive Weak Allies and Innovation Races

Former, non-repetitive, weak allies accumulated some knowledge about a focal firm which increases their capacity to launch targeted attacks (Li, et al, 2009). In addition, the level of relational capital developed between these former allies and the firm is likely to be very low. This suggests that former, non-repetitive, weak allies are likely to block the focal firm aggressively in innovation races by taking advantage of their knowledge of the firm. While the number of blocking attempts may increases with the number of former, non-repetitive, weak allies in the innovation race, their marginal efficacy is likely to decline because of redundancies in targeting. Since attacks by such allies are not coordinated, duplications in efforts are likely to increase, the larger the number of independent attacks. Thus, such blocking effect increases with the number of these former allies in an innovation race, but at a declining rate.

The knowledge development paths of such former allies and the firm are more divergent, therefore their current level of knowledge asset overlap is much lower. Since a firm tends to pay attention to and favor innovation pathways of other firms to whom it is most similar (March 1988), the innovation models of weak non-repetitive former allies are unlikely to draw immediate attention of the firm or be valued higher than those of the other two groups of former allies. When the levels of attention and appreciation are low, their innovations are unlikely to benefit the focal firm's innovation. Insufficient influence of the spillover effect and a negative blocking effect increasing with the number of former, non-repetitive, weak allies lead to the following hypothesis. Figure 3 illustrates the hypothesized relationship.

Hypothesis 4. The innovation performance of a firm decreases with the number of former, non-repetitive, weak allies in innovation races, but at a declining rate.

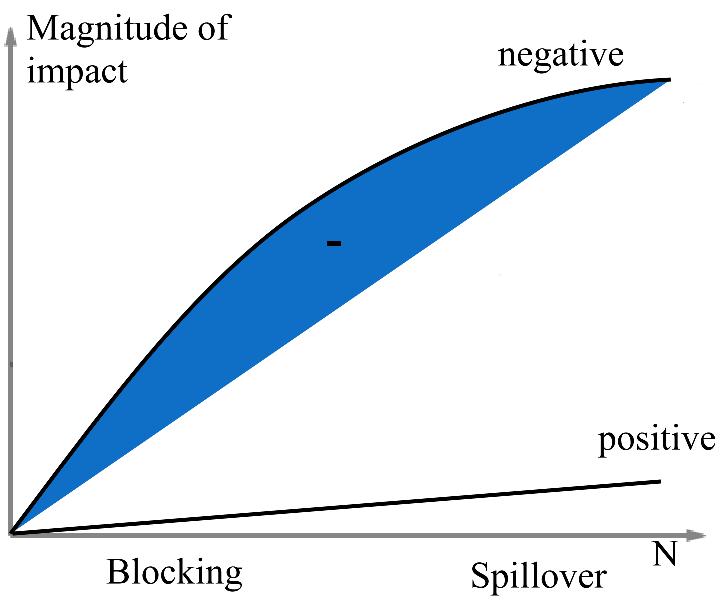

FIGURE 3 Number of Former Non-Repetitive Weak Allies in a Race and Firms' Innovation Performance

I expect the relevance of knowledge outputs of former, non-repetitive, weak allies is likely to sharpen the existing relationship between the number of these competitors and the firm's innovation performance, as was the case with former, repetitive, weak allies. When the number of these former allies is small, higher relevance of their knowledge spillovers may not cause a significant increase in a firm's innovations due to the small economies of scale of the spillovers; but the crowding effect inevitably increases as more competitors concentrate in a specific field. When the number is large, the positive spillover impact tends to be more pronounced, because of both the increased absorbability of innovation spillovers and the much larger economies of scale.

Hypothesis 5. The relevance level of innovation outputs of former, non-repetitive, weak allies positively moderates the relationship between the number of former, non-repetitive, weak allies and the firm's innovation performance in innovation races. When the number is small, the relevance level increases the negative blocking impact; when the number is large, the relevance level increases the positive spillover impact.

Table 1 summarizes the direct effects of prior allies on innovation races.

TABLE 1 The Relationship between a Firm's Innovation Performance and the Number of Former Allies in Innovation Races

Types of Former Allies	**Reduced Information Asymmetry (ability to block)**	**Relational Capital (constraints on blocking attempts)**	**Relative Absorptive Capacity**	**Novelty of Knowledge Spillovers**	**Predicted Relationships (firm's innovation performance and the number of former allies in innovation races)**
Strong	High	High	High	Low	U-shape
Repetitive weak	High	High	Medium	High	Inverted U-shape
Non-Repetitive weak	Medium	Low	Low	High	Negative, but at a declining rate

METHODS

Empirical Setting, Data Sources, and Sample

I analyzed the influence of alliance history on innovation races in the U.S. pharmaceutical industry, over a period of 20 years, 1985 to 2004. This setting is particularly appropriate for several reasons. First, alliance activities have existed extensively in the pharmaceutical industry since the 1970's, covering a variety of collaborative activities, e.g., licensing, joint venture, marketing, establishing the industry as a reliable setting to study various types of alliance histories (Mowery, et al., 1996; Roijakkers & Hogedoorn, 2006). Secondly, the pharmaceutical industry is a suitable context within which to study innovation races. Researchers have noted this industry is technologically intensive (Roijakkers & Hogedoorn, 2006), and firms compete with each other aggressively in innovations in order to develop new products (Lichtenberg & Philipson, 2002).

I had two major tasks in data collection. The first was to identify competitors in innovation races, and the second was to identify prior alliance relationships between current competitors. I focused on races between firms producing brand-name drugs (as distinguished from firms specializing in producing generic drugs). I undertook three steps to identify competitors. First, I compiled a complete list of FDA-approved brand-name drugs and their producers as of September 2008, based on an official report, covering all FDA-approved drugs published by the FDA's Center for Drug Evaluation and Research, called "*Approved Drug Products with Therapeutic Equivalence Evaluations*". Secondly, I developed a list of the 30 most common diseases and conditions (e.g., depression, hypertension, inflammation, cancer, ADHD, etc.; see Appendix I). The areas were identified by interviewing professionals in the pharmaceutical industry, whose opinions were cross-validated by two additional sources: the PubMed database, which provides information on research and development moves made by different firms in various research areas, and leading drug information providers (e.g., Thomson Reuters-Micromedex).

Thirdly, to identify competitors in the above mentioned areas, I classified the FDA-approved brand-name drugs according to the diseases and conditions they treat, i.e., their indications. If drugs were classified into the same indication, e.g., anti-depressants, the producers were regarded as competing in these drugs, e.g., GlaxoSmithKline (producer of PAXIL), Noven Therapeutics LLC (producer of PEXEVA), and Pfizer Pharmaceuticals (producer of Zoloft) (Lichtenberg & Philipson, 2002). A medical professional conducted the first round of classification with the aid of the “Drugs-by-Condition” database provided by an independent and comprehensive drug information supplier (i.e., drugs.com). Information provided by this database is supplied by four leading drug information providers: Cerner Multum, Wolters Kluwer Health, Thomson Reuters-Micromedex, and the FDA. I then cross-validated the classification by checking each drug with AHFS Drug Information which is another database leading in the provision of drug classification information, published by the American Society of Health-System Pharmacists. The AHFS database confirmed the validity of my classification.

Based on the classification, I identified 260 firms working to develop 904 brand-name drugs. I further identified innovation races connected to these drugs. An innovation race refers to a competition between the firms developing potentially substitutable drugs. In a race, competitors make a series of important technological moves by patenting intermediate innovations (i.e., ingredient and process patents) that will be directly used in developing specific new drugs. I was able to explicitly link intermediate technology innovations and their corresponding new drugs, because pharmaceutical firms are required by the Drug Price Competition and Patent Term Restoration Act (1984 Amendments), commonly known as the Hatch-Waxman Act, to provide a complete list of patents which claim the signature functionalities and manufacturing processes of their new products (brand-name drugs) before the FDA approves their drugs (Mossinghoff, 2005). I also linked the intermediate patents to the NBER patent citation database of 2006 (Hall, Jaffe, & Trajtenberg, 2001) in order to collect patent-level information such as the exact year of a patent application. I therefore was able to identify innovation races of brand-name drugs and associated intermediate-innovation moves made by firms competing in proximate research programs, within any given year, from 1985 to 2004.

I then compiled a complete list of prior alliance relationships between the competitors, using three alliance information sources, SDC, ReCap, and Medtrack. Although there is a high overlap in the coverage of these databases, each provides some complementary information. The SDC data was historical and covered multiple industries, while MedTrack and ReCap had more recent data particularly concerning the pharmaceutical industry. The addition of data, collected in ReCap and Medtrack, to the dataset retrieved solely from SDC, allowed me to significantly increase my alliance observations by 28.2 percent. For the purpose of due diligence, I checked the differences between the datasets with two additional information sources, SEC 10-K reports and Lexis Nexis, where much of the alliance information was collected by the alliance data providers. The accountability of the combined alliance data was verified. Overall, I compiled possibly the most comprehensive alliance dataset for my research, including 875 observations of prior alliances between competitors.

I merged the data regarding innovation races and alliance histories, and retained the observations only if a firm raced with at least one former ally. My final data is a panel data, including 57 U.S. pharmaceutical firms involved in 830 rounds of innovation races, 30 research areas, over a period of twenty years (1985-2004). The unit of analysis is the racing round, which starts from time point *t-1,* when competitors make innovation moves, and proceeds to the next time point, *t* (one year lag), whether a firm makes its own innovation move or not.

Measures

Innovation performance measures a firm's performance in producing intermediate patents for a specific drug, in a given year (*t*). Because the innovation cycle in the pharmaceutical industry is by nature long (i.e., on average 8-10 years) (Achilladelis & Antonakis, 2001), intermediate patents embodying core technological breakthroughs of an innovation program are typically produced at a slow rate. My data show that in over 41.8 percent of my observations, firms produce intermediate patents for a specific drug at a rate of one per year, and in 48.6 percent of my observations, firms do not produce any intermediate patents for a drug in any given year. Given such characteristics, I measured the performance of producing intermediate patents using a dummy variable: the variable is assigned the value one if a firm produces an intermediate patent in an innovation race, in a year (*t*), and zero if it does not.

Number of former strong allies. Following Rowley, Behrens, and Krackhardt (2000), I identified former strong allies as those in the following alliance relationships: equity alliances, joint ventures, and non-equity cooperative (R&D) ventures. I counted the number of former strong allies of a firm, in a given year (*t-1*), in an innovation race.

Number of former, repetitive, weak allies. Following Rowley, Behrens, and Krackhardt (2000), I identified the following as weak alliances: marketing agreements, licensing agreements, and patenting agreements. A competitor is a prior, repetitive, weak ally if it has repetitively allied with a firm in weak alliances. I counted the number of former, repetitive, weak allies of a firm, in a given year (*t-1*), in an innovation race.

Number of former, non-repetitive, weak allies. A competitor is a former, non-repetitive, weak ally if a competitor has allied with a firm only once in a weak alliance. I counted the number of former, non-repetitive, weak allies of a firm, in a given year (*t-1*), in an innovation race.

Relevance of competitors' knowledge spillovers. Competitors' innovations in a race are more relevant to a firm's innovation if they are proximate to the firm's specific innovation areas. I distinguished between two types of innovations made by competitors: one is in the same technology class as the innovation of a firm; the other is in a different technology class. I counted the number of competitors' patents, produced in a race, in the same technology class as a focal firm in a given year (*t-1*). The larger the number, the more relevant competitors' knowledge spillovers are. I measured the relevance of knowledge spillovers of both former, repetitive, weak allies and former, non-repetitive, weak allies.

Control Variables.

Firm technology diversity. I controlled for the technological diversity of a firm at year *t-1*, because it may increase firms' ability to absorb external knowledge (Cohen & Levinthal 1990). Technological diversity was measured as Hall's (2002) adjusted Herfindahl index:

$$Firm\ \ techno\log ical\ \ diversity_{it-1} = \left[1 - \sum_{j=1}^{J} (\frac{N_{jit-1}}{N_{it-1}})^2\right] * \frac{N_{it-1}}{N_{it-1} - 1},$$

where N_{it-1} is the number of patents in firm *i*'s knowledge base at year *t-1*. N_{jit-1} is the number of patents in technology class *j* in firm *i*'s knowledge base at year *t-1*.

Firm innovation capability. Firms' overall innovation activities in all research areas as a whole reflect their innovation capabilities and may have an impact on their performance in a specific research program. Therefore, I controlled for innovation capability by measuring the number of patents produced by a firm at year *t-1*.

Technological opportunity. Research has shown external technological opportunities can significantly influence the likelihood of innovation (Klevorick, Levin, Nelson, & Winter, 1995). Following Yang, Steema, and Phelps (2009), I measured technological opportunities using the following formula:

$$Technological\ opportunity_{it-1} = \sum_{j=1}^{J} \left[Patents_{jt-1} * P_{jit-1} \right],$$

where $Patents_{jt-1}$ is the number of patents applied for in patent class *j* in year *t-1,* and P_{jit-1} is the proportion of firm *i*'s patents applied for in class *j* in year *t-1*. The number of patents granted in a patent class in a given year reflects the rate of technical change in that technology area (Patel & Pavitt, 1997). I used the natural logarithm of this value to reduce its skewness.

Knowledge spillovers. I controlled for the relevance of knowledge spillovers of former strong allies and other competitors with no prior alliance relationships. In addition, to control for any possible effect of less relevant knowledge spillovers, I also included the number of intermediate patents, not in the same technology class as a focal firm, produced by all types of competitors, in year *t-1*.

Research programs. The pace of innovation may also differ across therapeutic areas to which a research program belongs, due to different levels of technology complexity associated with each area. I therefore controlled for the unobserved fixed-effect of therapeutic areas of innovation programs (i.e., circulatory system, immune system, nervous system, digestive system, integumentary system, urinary system, lymphatic system, and others), using seven dummy variables.

Year. The likelihood of patenting may also be influenced by unobserved factors associated with the conditions of a specific year. Therefore, I included year dummies to control for the year-fixed effect.

Number of other competitors. Finally, I controlled for the number of other competitors in a race, in year *t-1*, which did not have any alliance relationships with a firm, as a reference group to the other three types of competitors.

Statistical Methods

I used logistic regression to test the likelihood that a firm can make an intermediate innovation in innovation races. To control for firm heterogeneity, I adopted the Generalized Estimating Equations (GEE) regression method. GEE accounts for autocorrelation caused by the repetitive measure of the same firm over multiple rounds of innovation races (Liang & Zeger, 1986). The standard errors that I report are the Huber/White robust estimator of variance which is insensitive to the choice of correlation structure in the GEE method.

Because the linear terms of variables are highly correlated with their higher-order terms, I followed Aiken and West (1991), and mean-centered all variables before creating interaction and quadratic terms. This procedure reduces the non-essential ill-conditioning between independent variables and their higher-order terms and facilitates a better interpretation of coefficients (Cohen, Cohen, West, & Aiken, 2003).

RESULTS

Table 2 reports descriptive statistics and correlations for the variables. Both dependent and independent variables show considerable variances, and the correlations between independent variables are low.

Table 3 reports the results of the GEE logistic regression analysis. Model 1 in Table 3 includes only the control variables, while Models 2 to 6 added independent variables. All independent variables were entered, both separately and simultaneously, in various orders, but the results were not affected by the choice of entry.

The results in Model 2 show, as predicted, the likelihood of developing an intermediate innovation is curvilinearly related to the number of former strong allies in a race. It decreases first with the number of former strong allies (b = -0.06, *n.s.*) but increases as the number of such former allies continues to increase (b = 0.01, $p < 0.05$) in a race. This U-shape relationship provides strong support for Hypothesis 1.

The results in Model 3 show the likelihood of developing intermediate innovations increases initially with the number of former, repetitive, weak allies (b = 0.48, $p < 0.01$), but decreases as the number of such competitors continues to increase in innovation races (b = -0.23, $p < 0.05$), forming an inverted U-shape. Thus, Hypothesis 2 regarding the role of prior, repetitive, weak allies in innovation races is strongly supported.

TABLE 2 Descriptive Statistics and Correlations

	Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Innovation Performance	0.51	0.50															
2	Firm Innovation Capability	75.92	78.84	0.01														
3	Technological Opportunity	2024.06	779.77	0.14	-0.22													
4	Firm Technology Diversity	0.69	0.19	0.03	0.42	-0.32												
5	Relevance of Knowledge Spillovers (other competitors)	1.07	3.32	0.04	0.09	0.00	0.04											
6	Relevance of Knowledge Spillovers (former strong allies)	0.11	0.54	0.01	0.04	0.13	0.01	0.27										
7	Relevance of Knowledge Spillovers (former, non-repetitive, weak allies)	0.06	0.44	0.05	0.04	0.08	0.05	0.25	0.13									
8	Relevance of Knowledge Spillovers (former, repetitive, weak allies)	0.02	0.20	0.02	0.07	0.06	0.02	0.40	0.09	0.10								
9	Indirectly Relevant Knowledge Spillovers (other competitors)	1.39	3.73	0.04	0.03	0.03	-0.01	0.53	0.13	0.21	0.09							
10	Indirectly Relevant Knowledge Spillovers (former strong allies)	0.09	0.44	0.04	0.04	0.15	-0.06	0.19	0.33	0.04	0.11	0.18						
11	Indirectly Relevant Knowledge Spillovers (former, non-repetitive, weak allies)	0.05	0.31	0.03	0.03	0.06	0.05	0.12	0.16	0.33	-0.02	0.20	0.05					
12	Indirectly Relevant Knowledge Spillovers (former, repetitive, weak allies)	0.02	0.18	-0.01	0.02	0.00	-0.02	0.06	-0.02	-0.01	-0.01	0.21	0.13	0.11				
13	Number of Other Competitors	4.15	2.97	0.01	-0.03	0.04	-0.06	0.32	0.05	0.11	0.12	0.35	0.04	0.04	0.1			
14	Number of Former, Non-Repetitive, Weak Allies	0.84	1.53	0.04	0.13	0.22	0.06	0.03	0.04	0.24	0.12	-0.03	0.03	0.10	0.00	0.07		
15	Number of Former, Repetitive, Weak Allies	0.24	0.60	0.05	0.28	0.20	0.07	0.09	0.01	0.14	0.25	0.06	0.04	0.04	0.16	0.06	0.39	
16	Number of Former Strong Allies	1.44	2.11	0.08	0.23	0.40	-0.02	0.02	0.26	0.07	0.08	-0.02	0.26	0.01	-0.02	-0.08	0.29	0.21

N = 830.

Contrary to my expectations, the likelihood of making intermediate innovations is not significantly related to the number of former, non-repetitive, weak allies in a race (Model 4). Thus, I did not find support for Hypothesis 4.

The results in Model 5 show the relevance of knowledge spillovers of former, repetitive, weak allies arguments, in the predicted direction, the curvilinear relationship between the number of former, repetitive, weak allies and the firm's innovation. The results in the full model (Model 6), where all theoretically important terms are included, show that the interaction coefficient of knowledge spillover relevance and the linear term of the number of former, repetitive, weak allies is positive (b = 28.64, p < 0.10); the interaction coefficient of knowledge spillover relevance and the quadratic term of the number of former, repetitive, weak allies is negative (b = -11.30, p < 0.10). To better interpret the interaction terms, I graphed the quadratic-by-linear effect following the procedure suggested by Cohen et al. (2003). Figure 4 shows that higher level of relevance of such competitors' innovations is associated with a sharper and greater positive impact and a sharper and bigger negative impact, regarding the number of former, repetitive, weak allies on a firm's innovation performance. As the level of relevance decreases, the inverted U-shape becomes flatter. Thus, Hypothesis 3 regarding the positive moderating effect of the relevance of knowledge spillovers of former, repetitive, weak allies is supported.

TABLE 3 GEE Logistic Analysis of Firms' Innovation Performance (N=830)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Independent						
Number of Former Strong Allies		-0.06 (0.04)	-0.07 (0.04)	-0.07 (0.04)	-0.07 (0.04)	-0.06 (0.04)
Number of Former Strong Allies (squared)		0.01 ** (0.01)	0.01 ** (0.01)	0.01 ** (0.01)	0.01 ** (0.01)	0.01 ** (0.01)
Number of Former, Repetitive, Weak Allies			0.48 *** (0.19)	0.49 *** (0.19)	0.51 *** (0.19)	1.07 *** (0.37)
Number of Former, Repetitive, Weak Allies (squared)			-0.23 ** (0.09)	-0.24 *** (0.09)	-0.24 *** (0.09)	-0.46 *** (0.16)
Number of Former, Non-Repetitive, Weak Allies				-0.04 (0.06)	-0.04 (0.06)	-0.09 (0.07)
Number of Former, Non-Repetitive, Weak Allies (squared)				0.01 (0.01)	0.01 (0.01)	0.02 (0.02)
Moderators						
Relevance of Knowledge Spillovers (former, repetitive, weak allies) * Number of Former, Repetitive, Weak Allies					0.79 (1.26)	28.64 * (16.13)
Relevance of Knowledge Spillovers (former, repetitive, weak allies) * Number of Former, Repetitive, Weak Allies (squared)					-0.27 (0.44)	-11.30 * (6.39)
Relevance of Knowledge Spillovers (former, non-repetitive, weak allies) * Number of Former, Non-Repetitive, Weak Allies						-0.95 * (0.56)
Relevance of Knowledge Spillovers (former, non-repetitive, weak allies) * Number of Former, Non-Repetitive, Weak Allies (squared)						0.28 * (0.16)

TABLE 3 GEE Logistic Analysis of Firms' Innovation Performance (Continued)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Controls						
Nervous System	0.14	0.14	0.16	0.17	0.17	0.14
	(0.23)	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)
Digestive System	0.25	0.26	0.23	0.24	0.24	0.21
	(0.31)	(0.32)	(0.31)	(0.31)	(0.31)	(0.31)
Circulatory System	0.01	0.01	0.01	0.02	0.02	-0.01
	(0.25)	(0.27)	(0.25)	(0.25)	(0.25)	(0.25)
Integumentary System	0.37	0.37	0.41 *	0.41 *	0.41 *	0.38 *
	(0.23)	(0.24)	(0.22)	(0.22)	(0.22)	(0.22)
Immune System	0.18	0.18	0.22	0.23	0.23	0.20
	(0.23)	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)
Lymphatic System	0.23	0.24	0.27	0.28	0.28	0.25
	(0.29)	(0.30)	(0.29)	(0.29)	(0.29)	(0.29)
Urinary System	-0.30	-0.33	-0.31	-0.30	-0.30	-0.32
	(0.44)	(0.47)	(0.45)	(0.44)	(0.44)	(0.44)
Relevance of Knowledge Spillovers (other competitors)	0.01	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Relevance of Knowledge Spillovers (former strong allies)	-0.17 *	-0.17	-0.15	-0.16	-0.15	-0.16
	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Relevance of Knowledge Spillovers (former, non-repetitive, weak allies)	0.13 (0.11)	0.14 (0.11)	0.14 (0.11)	0.15 (0.12)	0.16 (0.12)	0.54 (0.43)
Relevance of Knowledge Spillovers (former, repetitive, weak allies)	0.00 (0.25)	0.01 (0.25)	-0.10 (0.27)	-0.10 (0.27)	-0.61 (1.03)	-15.39 * (8.49)
Indirectly Relevant Knowledge Spillovers (other competitors)	0.01 (0.02)	0.01 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)
Indirectly Relevant Knowledge Spillovers (former strong allies)	0.04 (0.11)	0.02 (0.12)	0.02 (0.12)	0.02 (0.12)	0.03 (0.12)	0.03 (0.13)
Indirectly Relevant Knowledge Spillovers (former, non-repetitive, weak allies)	-0.08 (0.13)	-0.09 (0.13)	-0.10 (0.12)	-0.08 (0.12)	-0.09 (0.13)	-0.07 (0.13)
Indirectly Relevant Knowledge Spillovers (former, repetitive, weak allies)	-0.06 (0.25)	-0.04 (0.25)	-0.10 (0.24)	-0.10 (0.24)	-0.10 (0.24)	-0.10 (0.24)

TABLE 3 GEE Logistic Analysis of Firms' Innovation Performance (Continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Number of Other Competitors	0.00	0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Firm Innovation Capability	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm Technology Diversity	0.11	0.16	0.17	0.17	0.17	0.16
	(0.37)	(0.37)	(0.37)	(0.38)	(0.38)	(0.38)
Technological Opportunity	0.00 *	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	0.08	0.44	0.08	0.03	0.02	0.30
	(0.99)	(0.62)	(0.96)	(0.97)	(0.97)	(0.65)
Ward chi square	118.5 ***	119.34 ***	136.67 ***	159.87 ***	166.03 ***	182.31 ***
df	37	39	41	43	45	47

* p < 0.10; ** p < .05; *** p < .01. Two-tailed tests.
Robust standard errors are in parentheses.
All models include unreported temporal effects.

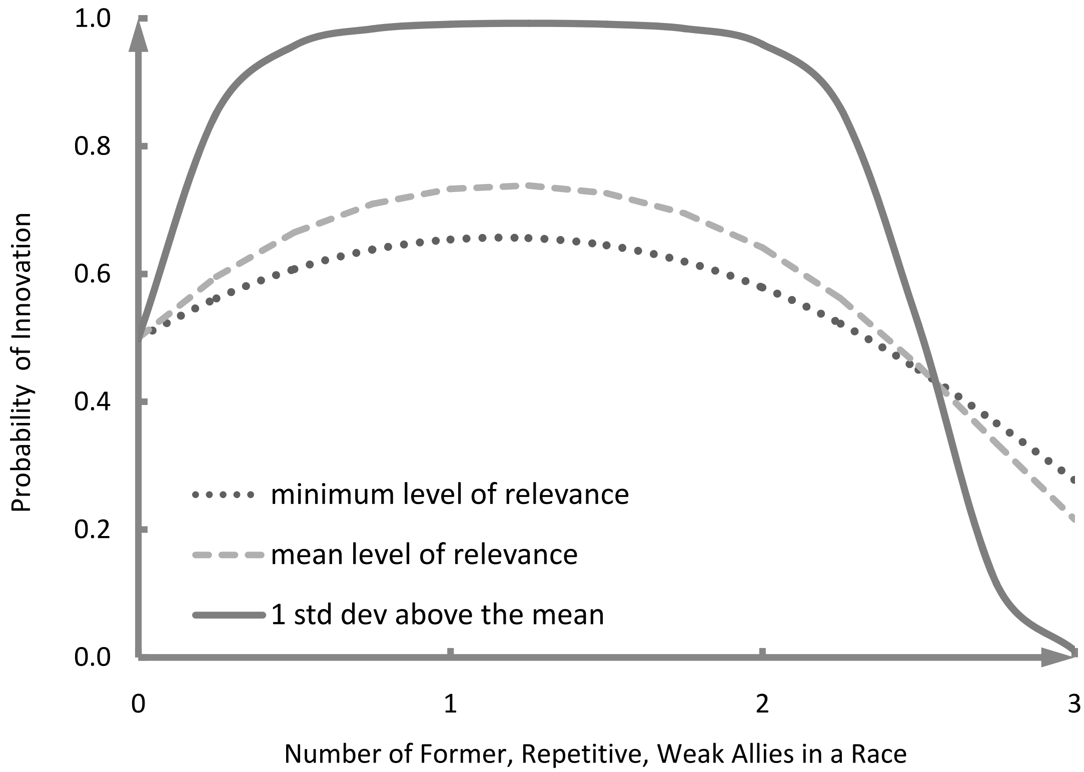

FIGURE 4 Interaction Effect of the Relevance of Knowledge Spillovers of Former, Repetitive, Weak Allies

The results in Model 6 also show that the relevance level of knowledge spillovers of former, non-repetitive, weak allies sharpens the predicted relationship between the number of such competitors and the rate of a firm's innovation. The interaction coefficient of knowledge spillover relevance and the linear term of the number of former, non-repetitive, weak allies is negative (b = -0.95, $p < 0.10$); the interaction coefficient of knowledge spillover relevance and the quadratic term of the number of these former allies is positive (b = 0.28, $p < 0.10$). I graphed the quadratic-by-linear effect in Figure 5, which shows that the higher level of relevance is associated with a sharper and more negative impact on a firm's innovation performance when the number of such former allies is small, and a sharper and more positive impact, when the number of such former allies is large. Thus, Hypothesis 5 regarding the moderating effect of the relevance of knowledge spillovers of former, non-repetitive, weak allies is supported.

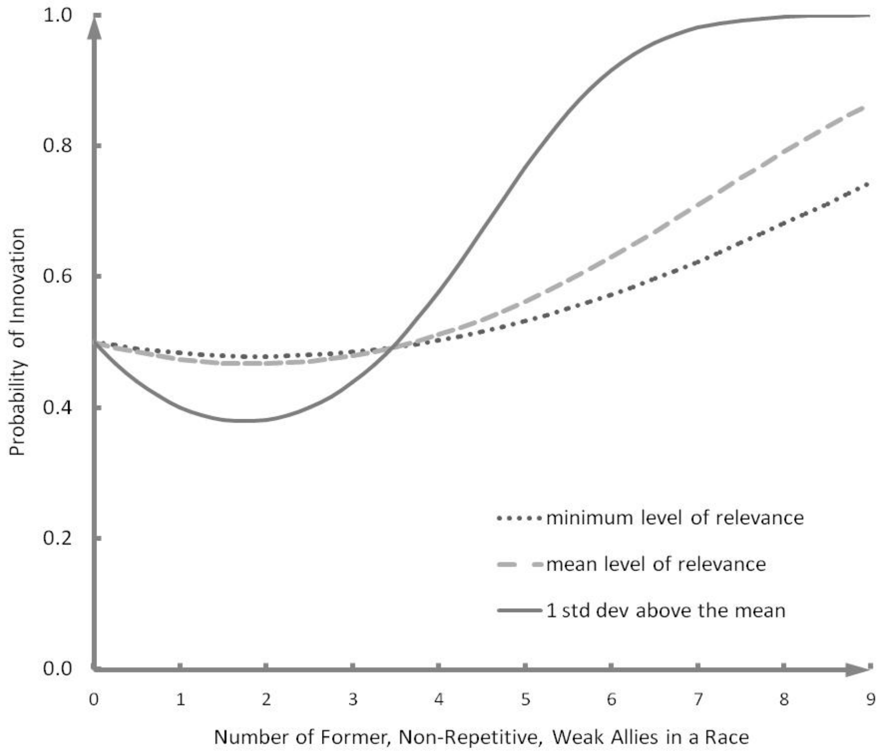

FIGURE 5 Interaction Effect of the Relevance of Knowledge Spillovers of Former, Non-Repetitive, Weak Allies

Robustness Checks

To check robustness, I ran additional analyses. First, to check whether repetitive and non-repetitive former strong allies differ in their effect, I separated former strong allies into two groups. The first group had repetitive alliance relationships with a focal firm and the second did not. Both groups showed the same pattern of influence on the likelihood of innovation of a firm, indicating that in the case of former strong allies, it is the quality of prior collaboration relationships (rather than the quantity) that matters.

Secondly, I added additional control variables such as firm size, financial performance (ROA), and R&D investment[2] for public firms in my sample, and ran the model with a smaller sample size (N = 560). No differences were found in the pattern of results between public and private firms.

Thirdly, I checked whether general competitors (i.e., those with no prior alliance relationships with a firm) have any potential non-linear impact on a firm's innovation performance. I ran the model with both the linear and the quadratic terms of the number of general competitors. The results showed that neither of the terms was significant, thus providing additional support to my core argument that alliance histories matter in inter-firm interactions and competitors having different collaboration histories with a focal firm have distinct impact on a firm's innovation.

Fourthly, I also examined whether current alliance relationships in other research programs caused any difference in my results. I ran models both including and excluding competitors who are also current allies. The results were not affected, indicating the impact of alliance history on innovation races holds, regardless of current alliance relationships.

Fifthly, I examined whether the selection of alliance histories of various lengths makes a difference in my results. I ran models by including only prior alliances established in the past five years proceeding to an innovation race; the results were not affected.

Lastly, I ran my model using various observation windows within the twenty years (1985-2004). The results were highly consistent, indicating my findings are not sensitive to time window selection.

[2] This additional information was collected from Compustat.

DISCUSSION

The results of my investigation support my overarching assertion that prior collaborations between firms influence their current competitions. I have posited that the strength of prior alliance relationships makes a difference in their impact on innovation races and that such difference depends on the competitive landscape as a whole (e.g., the number of former allies of different types). I found that competitors with a history of strong alliance relationship with a firm may reduce its innovation outputs when the number of such competitors in a race is small, but enhance the firm's innovation when their number is large. In contrast, competitors which have collaborated with the firm repetitively in weak alliances influence the firm's innovation in a reverse pattern: the firm's innovation performance increases with the number of such former allies in the race but then decreases as their number becomes larger. The influence of prior, repetitive, weak allies is stronger when their knowledge spillovers are highly relevant to the focal firm's areas of innovation, i.e., they innovate in the same technological class. The number of competitors which allied with a firm only once in weak relationships does not have significant impact on its innovation, but the impact of such competitors becomes more significant when the level of relevance of their knowledge spillovers is high: their impact is negative when their number in the race is small but is positive when their number is large. In addition, the number of competitors which did not ally with the firm in the past does not impact the firm's innovation in the race.

The findings have several important implications to the strategic alliance literature. First, while prior studies have addressed the impact of past alliance relationships on new *alliances* (e.g., Li, et al., 2008; Hoang & Rothaermel, 2005; Gulati, et al., 2009), my research extends prior studies by suggesting that past alliance relationships can influence future *competitions*. Specifically, alliance histories influence information asymmetry, relational capital, relative absorptive capacity, and novelty of innovation approaches between prior allies, all of which impact the result of their current competitions. My finding suggests that prior alliance relationships may backfire when former allies take advantage of what they have learned about the firm in order to block its innovation path. The negative effect is likely to be more salient when the firm is competing with a small number of former, non-repetitive, weak allies, especially when they are crowded in a narrow technological area. My findings also suggest that prior alliance relationship can benefit a firm by enhancing its relative absorptive capacity so that it can learn more from the innovation outputs of its prior allies. The positive effect is probably most salient when the firm is competing with a small number of former, repetitive, weak allies and a large number of former strong allies.

Second, my findings suggest revisiting some of the extant assumptions in the strategy literature by taking into consideration inter-firm alliance histories, which may yield new findings or interpretations that complement existing insights. For example, research regarding the effect of competitors' innovations on a focal firm's performance often ignored prior alliance relationship between current competitors (e.g., Cockburn & Henderson, 1994; Henderson & Cockburn, 1996; Katila & Chen, 2008; Yang et al., 2009), yielding inconsistent results and interpretations, leading to several important debates in the literature. While some researchers hold that competitors' innovation fosters a firm's innovation by spilling over knowledge (e.g., Henderson & Cockburn, 1996; Katila & Chen, 2008), other researchers emphasize that competitors' innovation prohibits a firm's innovation by strategically blocking it (e.g., Reinganum, 1989; Ziedonis, 2004). My findings may help reconcile such controversy by suggesting a contingent view: *ceteris paribus,* a firm's innovation performance in competition depends on the learning and competition conditions engendered by the number of different types of prior allies in current innovation race.

Last but not least, this research also makes a unique empirical contribution to the innovation literature. The majority of prior research regarding technology innovation has focused on all innovation outputs (e.g., patents) aggregated at the organizational level, assuming they are equally important innovation outputs of new product development programs (e.g., Cockburn & Henderson, 1994; Henderson & Cockburn, 1996; Yang, et al., 2009). I specifically focus on intermediate technology innovations, which are directly relevant to the development of new products and represent some of the core technology breakthroughs in an innovation program. I also distinguish between intermediate innovations produced by competitors that are directly relevant to the innovation areas of the focal firm from innovations not directly relevant. Fine-grained approach in studying key technological moves at research-program levels and investigating more precisely the innovation breakthroughs of research programs provide a fuller account of the contingent roles of alliance histories and the competitive context in shaping innovation races.

It is worth noting that the number of competitors with former non-repetitive, weak alliances is not significantly associated with a firm's innovation performance. Yet, the relationship between the number of such competitors and the firm's innovation is contingent on innovation relevance with respect to such former allies. This suggests that the innovations produced by former, non-repetitive, weak allies are generally too novel to be easily accessible to the focal firm, given its limited relative absorptive capacity, unless such knowledge is highly relevant to its innovation area. This highlights the importance of absorptive capacity, echoing the argument that appealing external technology opportunities only favor firms that are able to absorb them (Cohen & Levinthal, 1990, 1994).

Limitations

I examined innovation races between research programs developing new drugs that were eventually approved by the FDA. My sample does not include potentially competitive drug-development programs which failed in the middle of the research and development process. This is not an uncommon sampling method in this field of research because of the difficulty of linking intermediate innovations to a final product. For example, in literatures on innovation spillovers (e.g., Almeida, 1996; Jaffe, 1986; Jaffe et al., 2000; Katila & Chen, 2008) which have used patent citation data extensively, researchers have typically focused solely on successfully granted patents to measure knowledge spillovers, disregarding innovations that failed to be granted patents. While I appreciate merits of this widely adopted approach, I delved deeper to collect more historical data on potentially competing programs that did not result in any FDA approved drugs. I ran searches on multiple data sources, e.g., Health & Medicine Week, Pharma Business Week, etc, and consulted with industry professionals as to whether the additional programs that I found were actually competing with the programs in my data. With very limited additional data regarding the number of competitors and allies in some of the races, I re-ran my model, and the results were not affected. Econometrically, the effect of any other competing programs, not included in the races, may have been taken into consideration by controlling technology opportunities, which technically measure all technology programs which possibly influence the focal firm's innovation.

Conclusion

In this paper, I contribute to the literature by examining the role played by former allies in a firm's performance in innovation races. I have found competitors, with different alliance histories with a firm, have significantly different influences on its success in the races. My findings emphasize the importance of incorporating inter-firm alliance history into studies of inter-firm competitions.

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ESSAY TWO: The Impact of Knowledge Resource Similarity between Competitors on Innovation Performance: A Longitudinal Study of the U.S. Pharmaceutical Industry[3]

[3] Cui, H. & Vertinsky, I., 2010. The Impact of Knowledge Resource Similarity between Competitors on Innovation Performance: A Longitudinal Study of the U.S. Pharmaceutical Industry. A version of this paper is in preparation for submission.

INTRODUCTION

Over the past four decades, scholars have argued whether competition has a negative or positive net influence on firms' innovation. From the organizational learning perspective, researchers have contended that competition has a net positive effect on innovation. Empirically, they provided evidence demonstrating two important ways through which competition benefits a firm's innovation. First, a firm can benefit from competitors' innovation spillovers (i.e., positive externalities of their scientific discoveries) by mimetic learning, through which it directly copies their innovations or new products (e.g., Baldwin & Childs, 1969; Markides & Geroski, 2005). Second, the firm can also benefit from "inferential learning" (Katila & Chen, 2008) in which it observes rivals' R&D activities, deciphers the rationales of their innovation attempts (Katila & Ahuja, 2002; Miner & Mezias, 1996), understands what works and what does not, and relates rivals' experience and knowledge to its own innovation (Cockburn & Henderson, 1994; Fleming, 2001; Henderson & Cockburn, 1996). The implication is competitors' innovation spillovers may provide solutions to problems that the firm may not be able to solve on its own, or suggest technological opportunities of which the firm may not be aware.

The dark side of competition, however, is emphasized by researchers viewing the innovation process from the lens of competitive strategy. They argued that firms in competition often crowd in a knowledge space to draw opportunities (Katila et al., 2008). A large degree of overlap in their knowledge space is likely to deplete technological opportunities. This is because the best technological opportunities are normally exploited first, and the remaining opportunities are more difficult to find and often are less valuable (Podolny, Stuart, & Hannan, 1996; Swaminathan, 1996). Rather than suggesting more opportunities, rivals' successful innovations may result in exhaustion externalities (Reinganum, 1989). Particularly, in industries operating under rigorous intellectual property regimes, competitors typically innovate strategically by fencing their innovation outputs and related opportunities (e.g., through broad patents), forcing competitors to invent around the claimed proprietary domains, normally at a significantly high cost with much time delay, or even forcing them to withdraw from the technological area altogether (Ziedonis, 2004).

The empirical evidence concerning whether competitors' innovation enhances or inhibits a firm's innovation performance is inconsistent, suggesting that some important factors are likely missing from the analyses, factors that reflect the conditions under which positive or negative externalities from competitors dominate in the innovation race. The purpose of this paper is to reconcile the apparent inconsistency. Incorporating insights from the resource-based view and the organizational learning theory, I developed a theoretical framework that provides a contingent perspective on the relationship between competition and innovation. I argue that the net impact of competition on a firm's innovation depends on both the relative knowledge amount and knowledge structure of rivals compared with those of the focal firm.

Using a longitudinal dataset of innovation races where firms competed to develop potentially substitutable new products in the U.S. pharmaceutical industry, I found that, first, a firm's innovation performance was negatively impacted by the knowledge amount advantage that competitors have, i.e. rivals with a larger knowledge stock were likely to impede the firm's technological innovation. Second, the negative effect of competing with knowledge -abundant rivals was moderated by the knowledge structure similarity between the firm and its rivals, i.e.

the negative impact of such competitors on the innovation of the focal firm was reduced as similarity between the rivals and the focal firm increased until a point where the net effect became positive.

THEORETICAL BACKGROUND AND HYPOTHESES

Organizational knowledge resources have many manifestations, including explicit knowledge resources reflected in codified rules, manuals, and patents, and tacit knowledge resources embedded in implicit organizational routines and practices. In this paper, I focus on explicit technological knowledge resources developed in R&D intensive industries (e.g., pharmaceutical), which are often measured in the form of proprietary knowledge assets such as patents (Achilladelis & Antonakis, 2001; Mowery et al., 1996).

Knowledge Amount and Structure

Knowledge resources can be characterized along two dimensions: knowledge structure and size, both having a significant impact on innovation (Ahuja & Katila, 2001; Cohen & Levinthal, 1990; Chen, 1996; Lane & Lubatkin, 1998). With respect to technological knowledge, knowledge amount refers to the stock of technological assets that an organization possesses, indicating its capacity of absorbing external technological knowledge, as well as developing, accumulating and protecting proprietary technological innovations (Ahuja & Katila, 2001; Cohen & Levinthal, 1990). Knowledge structure refers to the various domains of technological knowledge that an organization possesses, indicating the specific configuration of technological areas on which the organization focuses. Reflecting an organization's overall "cognitive" schemata, knowledge structure determines the technological models and roadmaps that the organization is most likely to follow in innovation (Cohen & Levinthal, 1990; Fiske & Taylor, 1991; Higgins & Bargh, 1987; Lane & Lubatkin, 1998).

In a fierce competition where firms race to develop potentially substitutable new products, innovation performance is not solely determined by the size and structure of a firm's knowledge assets, but also by the relative knowledge stock of the firm in comparison with its rivals. Firms with relatively larger knowledge amount are more able to exploit external technological opportunities and influence others' pace of innovation in the race (Greve & Taylor, 2000; Zollo & Winter, 2002). Similarity in knowledge structure between competitors determines the extent to which they can communicate, understand, and likely benefit from each others' innovation spillovers (Lane & Lubatkin, 1998). The relative knowledge amount and knowledge structure similarity of competitors mold innovation dynamics in the race, and consequently influence firms' innovation performance.

Relative Knowledge Amounts of Competitors and the Firm

Having a larger stock of knowledge than rivals provides a firm with competitive advantage in innovation races. This is because a larger amount of knowledge capital normally reflects more intensive prior innovation activities, e.g., R&D investment and technological search (Cohen & Levinthal, 1990; March, 1991). The literature on organization learning suggests innovation is a problem-solving process, in which firms develop creative ways of recombining existing knowledge in order to generate new products (Clark, Chew, Fujimoto, Meyer, & Scherer, 1987; Dougherty & Hardy, 1996; Katila & Chen, 2008). As a learning process, innovation always involves trials and errors to solve problems (Gavetti & Levinthal, 2000). Intensive prior innovation activities help firms accumulate rich experiences and insights that are valuable in solving new innovation problems in particular technological areas (e.g., Cohen & Levinthal, 1990; Ellis, 1965; Harlow, 1959).

The resource-based view (RBV) suggests superiority in innovation experiences and insights can result in higher innovation performance in competition. The RBV contends that valuable, rare, imperfectly imitable, and non-substitutable resources are the sources of sustainable competitive advantage (Barney, 1991; Barney, Wright, & Ketchen Jr, 2001). Innovation experiences and insights, a form of intangible resources, are particularly difficult to be identified, understood, and replicated by others (Dierickx & Cool, 1989; Itami, 1987; Rumelt, 1984), and therefore are an important basis of competitive advantage (Hall, 1993; Lippman & Rumelt, 1982).

Firms with a relatively larger amount of knowledge are likely to have two types of advantages over competitors in innovation races. First, they will likely identify and utilize new innovation opportunities faster than other firms (Lieberman & Montgomery, 1988, 1998). This is because firms with richer innovation experiences and insights are more able to recognize what are the most rewarding pieces of information embedded in the fast and overwhelming changes of technologies (Cohen & Levinthal, 1990). Such capacity enables firms to identify innovation opportunities ahead of competitors. More intensive prior innovation activities also enable firms to foresee and meet the technological challenges presented by new opportunities by drawing upon a larger amount of experiences. Thus firms are more likely to be first to develop innovations (Cohen & Levinthal, 1990; Ellis, 1965; Katila & Chen, 2008). In contrast, the probability of other firms to benefit from the new technologies is largely reduced, as the technological opportunities are likely depleted by first movers (Podolny, et. al., 1996; Swaminathan, 1996).

Second, relatively larger amount of knowledge enables firms to innovate not only fast, but also strategically. With more intensive innovation experiences, firms are likely to develop a repertoire of routines that enable them to play more proactively and strategically by hampering rivals' innovation processes (Gavetti & Levinthal, 2000). They can leverage their first-mover status, claiming ownership of key technological areas and innovation processes, blocking technological routes that rivals may want to take to achieve their innovation targets (Greve & Taylor, 2000; Ziedonis, 2004; Zollo & Winter, 2002). This increases the difficulty and cost for the other firms to innovate, reducing threats of entry and imitation (Reinganum, 1989; Teece, 1998; Walker, 1995; Ziedonis, 2004). To sum up,

Hypothesis 1: The ratio of rivals' knowledge amount to that of a firm is negatively related to the firm's innovation performance.

Knowledge Structure Similarity between Competitors and the Firm

There are, however, some conditions that reduce the liability of (knowledge-stock) smallness. In innovation activities, firms inadvertently generate positive externalities to other firms in the form of knowledge spillovers and enjoy spillovers from others (Cockburn & Henderson, 1994; Henderson & Cockburn, 1996). There might be, however, an asymmetry between the amount of spillovers that firms contribute to and what they gain from others (Shaver & Flyer, 2000). The net balance of benefit and cost of knowledge spillover is determined by the relative knowledge stock size of firms (Baum & Haveman, 1997; Shaver & Flyer, 2000). Organizations with more abundant knowledge resources will likely spillover a significantly larger amount of knowledge than what they might absorb from others. In contrast, organizations with more modest knowledge resources tend to contribute less, and are likely to benefit more. The size of net benefit from the asymmetries of contributions and gains that knowledge-poor firms enjoy depends on their ability to absorb knowledge spillovers, despite being knowledge constrained. This ability to absorb is determined by the degree of knowledge structure similarity between the firm and the source of spillovers (Cohen & Levinthal, 1992; Lane & Lubatkin, 1998).

The literature on organizational learning has shown that the ability to learn from each other (i.e., relative absorptive capacity) is a function of the similarity of knowledge structure between the "student" and the "teacher" firms (Bower & Hilgard, 1981; Ellis, 1965; Estes, 1970; Lane & Lubatkin, 1998). This is primarily because similar knowledge structure enhances the "student" firm's ability to understand the assumptions and rationale that shape the "teacher's" knowledge development trajectory (Lane & Lubatkin, 1998; March, 1991). With such understanding, the "student" is more able to relate "teacher's" experiences regarding what works and what does not to its innovation activities (Katila & Chen, 2008; Lane & Lubatkin, 1998). As a result, the "student" firm is more able to develop appropriate approaches that most likely will lead to successful innovations (Katila & Chen, 2008; Lane & Lubatkin, 1998). The key implication is, in innovation races, knowledge-constrained firms can benefit from the knowledge spillovers of the knowledge-abundant firms, if their knowledge-structure is similar. The net benefit will likely increase with the knowledge structure similarity, ceteris paribus.

The RBV suggests knowledge structure is an important resource that molds a firm's technological development roadmaps (Levinthal & March, 1993; Rosenkopf & Nerkar, 2001; Toby & Podolny, 1996). A unique structure of knowledge can permit a firm to exploit external knowledge in a unique model that is unlikely to be directly relevant to that of other firms or be easily imitated (Barney, 1991; Chen, 1996), but may nevertheless inspire them with some new ideas for innovation (Ahuja & Katila, 2001; Katila & Ahuja, 2002; Katila & Chen, 2008). In contrast, a similar knowledge structure to rivals may increase the probability of understanding their innovation roadmaps and spillovers, as they are more relevant. Yet such knowledge may not vary significantly from what the firm already knows and thus is less valuable for its innovation (Cloodt, Hagedoorn, & Van Kranenburg, 2006; Lane & Lubatkin, 1998; March, 1991; Marianna, Michael, & Peter, 2009).

Two important implications are drawn from the RBV and literature on organizational learning. First, even though knowledge-constrained firms have little advantage with respect to innovate fast and strategically, they can benefit from the net inflow of spillovers if their knowledge structure is similar to that of the knowledge-abundant firms. As a result, the disadvantage associated with relatively smaller knowledge amount is mitigated. This suggests that the negative effect of competing with knowledge-abundant rivals can decrease as the level of knowledge structure similarity increases between a firm and its rivals.

Second, the inspirational value of competitors' innovations regarding how much they can suggest new innovation directions to the focal firm reflects a tradeoff between relevance and newness of rivals' innovations. While knowledge structure similarity increases the ability of the resource-constrained firms to absorb knowledge spillovers from the knowledge-abundant firms, the inspirational value of such spillovers tends to decline as the degree of knowledge structure similarity increases (Cloodt et al., 2006; Lane & Lubatkin, 1998; March, 1991; Marianna et al., 2009). Thus, although the negative impact of competing with knowledge-abundant rivals decreases with the level of knowledge structure similarity between a firm and its rivals, the marginal rate of reduction of the negative impact declines.

Hypothesis 2: The relationship between relative knowledge amount and a firm's innovation performance is moderated curvilinearly by knowledge-structure similarity between competitors and the firm. The negative effect decreases as the knowledge-structure similarity increases, but at a declining rate.

METHODS

Empirical Setting, Data Sources, and Sample

I tested my hypotheses in the U.S. pharmaceutical industry. The pharmaceutical industry is a suitable setting to study innovation races because this industry is characterized by intensive investment in technological innovation (Roijakkers & Hagedoorn, 2006) and aggressive inter-firm competition to develop potentially substitutable new products (Lichtenberg & Philipson, 2002).

I focused on competition between firms producing brand-name drugs (as distinguished from firms specializing in producing generic drugs). I undertook four steps to identify innovation races. An innovation race refers to a competition between firms developing potentially substitutable drugs. First, I compiled a complete list of FDA-approved brand-name drugs and their producers as of September 2008, based on an official report, covering all FDA-approved drugs published by the FDA's Center for Drug Evaluation and Research, called "Approved Drug Products with Therapeutic Equivalence Evaluations". Second, I developed a list of the 30 most common diseases and conditions (e.g., depression, hypertension, inflammation, cancer, ADHD, etc.; see Appendix I). The areas were identified by interviewing professionals in the pharmaceutical industry, whose opinions were cross-validated by two additional sources: the PubMed database, which provides information on research and development activities made by different firms in various research areas, and leading drug information providers (e.g., Thomson Reuters-Micromedex).

Third, to identify competitors in the above mentioned areas, I classified the FDA-approved brand-name drugs according to the diseases and conditions they treat, i.e., their indications. If drugs were classified into the same indication, e.g., anti-depressants, the producers were regarded as competing in these drugs, e.g., GlaxoSmithKline (producer of PAXIL), Noven Therapeutics LLC (producer of PEXEVA), and Pfizer Pharmaceuticals (producer of Zoloft) (Lichtenberg & Philipson, 2002). A medical professional conducted the first round of classification with the aid of the "Drugs-by-Condition" database provided by an independent and comprehensive drug information supplier (i.e., drugs.com). Information provided by this database is supplied by four leading drug information providers: Cerner Multum, Wolters Kluwer Health, Thomson Reuters-Micromedex, and the FDA. I then cross-validated the classification by checking each drug with AHFS Drug Information which is another database leading in the provision of drug classification information, published by the American Society of Health-System Pharmacists. The AHFS database confirmed the validity of my classification.

Fourth, I identified innovation races connected to these drugs. In a race, competitors make a series of important technological moves as to patenting intermediate innovations (i.e., ingredient and process patents) that will be directly used in developing specific new drugs. I was able to explicitly link intermediate technology innovations and their corresponding new drugs, because pharmaceutical firms are required by the Drug Price Competition and Patent Term Restoration Act (1984 Amendments), commonly known as the Hatch-Waxman Act, to provide a complete list of patents which claim the signature functionalities and manufacturing processes of their new products (brand-name drugs) before the FDA approves their drugs (Mossinghoff, 2005). I also linked the intermediate patents to the NBER patent citation database of 2006 (Hall et al., 2001) in order to collect patent-level information such as the exact year of a patent application and technological classes of a patent. I therefore was able to identify innovation races of brand-name drugs and associated intermediate-innovation moves made by firms competing in proximate research programs, within any given year, from 1991 to 2004. A panel data (N = 704) was compiled that included 217 firms competing in 32 research programs.

Measurement

Innovation performance measures a firm's performance in producing intermediate patents for a specific drug, in a given year (*t*). Because the innovation cycle in the pharmaceutical industry is by nature long (i.e., on average 8-10 years) (Achilladelis & Antonakis, 2001), intermediate patents embodying core technological breakthroughs of an innovation program are typically produced at a slow rate. My data show that in over 54.1 percent of my observations, firms produce intermediate patents for a specific drug at a rate of one per year, and in 30.8 percent of my observations, firms do not produce any intermediate patents for a drug in any given year. Given such characteristics, I measured the performance of producing intermediate patents using a dummy variable: the variable is assigned the value one if a firm produces an intermediate patent in an innovation race, in a year (t), and zero if it does not.

Competitors' relative amount of knowledge was measured by first calculating the number of patents that each firm obtained each year from 1986 to 2004. Then I calculated the accumulated number of patents that a firm developed over a five-year window, weighted by an annual depreciation rate of 20 percent (Henderson & Cockburn, 1996). The five-year window was chosen because knowledge depreciates quickly in high-technology firms, losing significant value within approximately five years (Argote, 1999). The size of competitors' knowledge was calculated by averaging the number of weighted patents that a firm's competitors accumulated over five years (t-5 to t-1). Competitors' relative amount of knowledge at year t-1 was measured as a ratio of the size of competitors' knowledge to that of the focal firm in the same period of time (t-5 to t-1). I calculated the natural logarithm of this value to reduce its skewness.

Knowledge structure similarity. To measure inter-firm knowledge-structure similarity, I developed for each firm a knowledge profile that included an exhaustive list of technology classes in which they patented from 1986 to 2004. Using a five-year moving window, I constructed a vector (D_i) that measured the distribution of the focal firm's patents across these classes. $D_i = (d_{i1} \ldots d_{ij})$, where d_{ij} represents the fraction of the focal firm i's patents that are in patent class j. I also constructed vectors (E_i) that measured the distribution of the focal firm's rivals' patents across these classes. $E_i = (e_{i1} \ldots e_{ij})$, where e_{ij} represents the fraction of rival i's patents that are in patent class j. This approach (e.g., Jaffe, 1986; Yang et al., 2009) assumes the distribution of a firm's patents across patent classes reflects the underlying structure of its technological knowledge. Finally, based on the profiles, I constructed a knowledge-similarity index, for the firm and each of its competitors each year, using the following formula (e.g., Jaffe, 1986; Yang et al., 2009). Competitors' knowledge-structure similarity was calculated as an average of the indices between a firm and all of its competitors at year *t-1*.

$$Knowledge\ structure\ similarity_{it-1} = \sum_{j=1}^{J} d_{ij}e_{ij} / [(\sum_{j=1}^{J} d_{ij}^2)^{1/2}(\sum_{j=1}^{J} e_{ij}^2)^{1/2}]$$

Control variables.

Firm technological diversity. I controlled for the technological diversity of a firm at year *t-1*, because it may increase firms' ability to absorb external knowledge (Cohen & Levinthal 1990). Technological diversity was measured as Hall's (2002) adjusted Herfindahl index:

$$Firm\ \ techno\log ical\ \ diversity_{it-1} = \left[1 - \sum_{j=1}^{J} (\frac{N_{jit-1}}{N_{it-1}})^2\right] * \frac{N_{it-1}}{N_{it-1} - 1},$$

where N_{it-1} is the number of patents in firm i's knowledge base at year *t-1*. N_{jit-1} is the number of patents in technology class j in firm i's knowledge base at year *t-1*.

Firm innovation capability. Firms' overall innovation activities in all research areas as a whole reflect their innovation capabilities and may have an impact on their performance in a specific research program. Therefore, I controlled for innovation capability by measuring the number of patents produced by a firm at year *t-1*.

Technological opportunity. Research has shown external technological opportunities can significantly influence the likelihood of innovation (Klevorick et al., 1995). Following Yang, Steema, and Phelps (2010), I measured technological opportunities using the following formula:

$$Techno\log ical\ \ opportunity_{it-1} = \sum_{j=1}^{J}\left[Patents_{jt-1} * P_{jit-1}\right],$$

where Patents$_{jt-1}$ is the number of patents applied for in patent class *j* in year *t-1*, and P_{jit-1} is the proportion of firm *i*'s patents applied for in class *j* in year *t-1*. The number of patents granted in a patent class in a given year reflects the rate of technical change in that technology area (Patel & Pavitt, 1997). I used the natural logarithm of this value to reduce its skewness.

Knowledge spillovers. Following Henderson and Cockburn (1996), I controlled for the number of patents produced by competitors in competing research programs, in year *t-1*, to account for possible spillover effect associated with rivals' innovations in proximate technological areas.

Research programs. The pace of innovation may also differ across therapeutic areas to which a research program belongs, due to different levels of technology complexity associated with each area. I therefore controlled for the unobserved fixed-effect of therapeutic areas of innovation programs (i.e., circulatory system, immune system, nervous system, digestive system, integumentary system, urinary system, lymphatic system, and others), using seven dummy variables.

Year. The likelihood of patenting may also be influenced by unobserved factors associated with the conditions of a specific year. Therefore, I included year dummies to control for the year-fixed effect.

Statistical Model

I used logistic regression to test the likelihood that a firm can make an intermediate innovation in innovation races. To control for firm heterogeneity, I adopted the Generalized Estimating Equations (GEE) regression method. GEE accounts for autocorrelation caused by the repetitive measure of the same firm over multiple rounds of innovation races (Liang & Zeger, 1986). The standard errors that I report are the Huber/White robust estimator of variance which is insensitive to the choice of correlation structure in the GEE method. To reduce the non-essential ill-conditioning between independent variables and their higher-order terms and facilitates a better interpretation of coefficients (Cohen et al., 2003), I standardized the variables before creating interaction and quadratic terms.

Results

Table 4 reports the means, standard deviations, and zero-order correlations of the variables. Both dependent and independent variables show considerable variances, and the correlations between independent variables are low.

The regression results are presented in Table 5. Model one includes the control variables. Model two tests Hypothesis one by including relative knowledge amount. I found that a firm's innovation performance in an innovation race was negatively related to competitors' knowledge amount relative to that of the firm ($\beta = -0.12$, $p \leq 0.02$), supporting Hypothesis one. Models three and four test the moderating effect of knowledge-structure similarity on the relationship between relative knowledge amount and the firm's innovation performance. The result showed that the negative effect was attenuated, and turned positive, as the knowledge structure similarity increased ($\beta = 3.14$, $p \leq 0.06$). However, the negative impact picked up again when the firm was extremely similar as its competitors in knowledge structure ($\beta = -1.79$, $p \leq 0.06$). Thus, Hypothesis two is supported. Figures 6 and 7 depict this moderating effect. Figure 6 shows that when rivals and the firm are dissimilar in knowledge structure (1 standard deviation below the mean), the negative effect of relative knowledge amount is the largest, yet the effect tends to decrease as knowledge structure similarity between rivals and the firm increases. Figure 7 illustrates the moderating effect from an alternative perspective. It shows that when the firm is competing with resource-abundant rivals, the negative effect on the firm's innovation performance tends to be reduced as the firm becomes similar in knowledge structure as the rivals. The negative effect can be overcome and the net effect becomes positive.

TABLE 4 Mean, Standard Deviation, and Correlations

		Mean	Std	1	2	3	4	5	6	7	8	9	10
1	Innovation Performance	0.54	0.50	1.00									
2	Nervous System	0.24	0.42	-0.04	1.00								
3	Immune System	0.14	0.35	-0.02	-0.23	1.00							
4	Digestive System	0.08	0.27	0.06	-0.17	-0.13	1.00						
5	Circulatory System	0.20	0.40	-0.04	-0.27	-0.21	-0.16	1.00					
6	Urinary System	0.03	0.16	-0.02	-0.06	-0.05	-0.04	-0.06	1.00				
7	Integumentary System	0.15	0.36	0.04	-0.25	-0.20	-0.14	-0.24	-0.06	1.00			
8	Lymphatic System	0.09	0.29	0.00	-0.16	-0.13	-0.09	-0.15	-0.04	-0.14	1.00		
9	Innovation Capability	2.39	6.73	-0.23	-0.02	-0.16	-0.04	0.05	-0.09	0.13	0.02	1.00	
10	Technological Opportunity	7.48	0.48	-0.03	-0.04	0.10	0.07	-0.16	0.04	0.07	-0.04	-0.10	1.00
11	Technological Diversity	0.68	0.18	-0.03	-0.07	-0.14	-0.07	0.06	-0.02	0.09	0.11	0.53	-0.38
12	Knowledge Spillovers	4.48	3.92	-0.02	-0.16	0.09	-0.05	-0.01	-0.10	0.20	0.10	-0.02	0.15
13	Concentration of Competitors	20.40	13.77	-0.02	-0.17	0.11	-0.08	0.01	-0.13	0.19	0.11	-0.02	0.15
14	Knowledge Structure Similarity	0.16	0.21	-0.17	-0.06	-0.05	-0.05	0.02	-0.09	0.19	-0.04	0.23	0.26
15	Knowledge Structure Sim (sq.)	0.07	0.18	-0.16	-0.07	-0.08	-0.04	0.03	-0.06	0.21	-0.06	0.24	0.21
16	Relative Knowledge Amount	-2.62	10.11	-0.01	-0.04	0.01	0.02	0.03	-0.12	0.06	0.06	-0.21	0.06
				11	**12**	**13**	**14**						
11	Technological. Diversity			1.00									
12	Knowledge Spillovers			-0.01	1.00								
13	Knowledge Structure Similarity			0.07	-0.05	1.00							
14	Knowledge Structure Sim (sq.)			0.06	-0.12	0.97	1.00						
15	Relative Knowledge Amount			-0.16	0.16	0.04	0.01						

N=704

TABLE 5 GEE Logistic Analysis of Firms' Innovation Performance (N=704)

Variables	Model 1		Model 2		Model 3		Model 4	
Independent								
Relative Knowledge Amount (competitors/focal)			-0.12	**	-0.34	**	-1.82	**
			(0.05)		(0.16)		(0.92)	
Moderators								
Relative Knowledge Amount * Knowledge Structure Similarity					0.19	*	3.14	*
					(0.12)		(1.66)	
Relative Knowledge Amount * Knowledge Structure Similarity (squared)							-1.79	*
							(0.96)	
Controls								
Nervous System	1.00	**	-0.57	***	-0.57	***	1.06	**
	(0.46)		(0.22)		(0.23)		(0.44)	
Digestive System	0.90	**	-0.68	***	-0.67	***	-0.92	**
	(0.47)		(023)		(0.24)		(0.45)	
Circulatory System	1.35	**	-0.21		-0.19		1.42	***
	(0.57)		(0.38)		(0.38)		(0.54)	
Integumentary System	1.10	**	-0.45	*	-0.44	*	1.18	***
	(0.48)		(0.25)		(0.26)		(0.48)	
Immune System	1.42	***	-1.74	***	-1.74		-1.53	***
	(0.49)		(0.56)		(0.56)		(0.48)	
Lymphatic System	1.11	**	-0.11		-0.11		-1.21	**
	(0.52)		(0.23)		(0.24)		(0.50)	
Urinary System	1.57	***	-0.43		-0.42		1.64	***
	(0.48)		(0.33)		(0.33)		(0.46)	
Firm Innovation Capability	-0.57	***	-0.60	***	-0.61	***	-0.63	***
	(0.08)		(0.08)		(0.08)		(0.08)	
Technological Opportunity	-0.42	***	-0.43	***	-0.44	***	-0.46	***
	(0.13)		(0.13)		(0.13)		(0.14)	
Firm Technology Diversity	0.19	**	0.19	**	0.18	**	0.15	*
	(0.09)		(0.09)		(0.09)		(0.09)	
Knowledge Spillovers	-0.06		-0.05		-0.05		-0.05	
	(0.06)		(0.06)		(0.06)		(0.06)	
Knowledge Structure Similarity	-0.34		-0.32		-0.30		-0.30	
	(0.32)		(0.32)		(0.32)		(0.31)	
Knowledge Structure Similarity (squared)	0.15		-0.13		0.12		0.12	
	(0.30)		(0.30)		(0.30)		(0.29)	

TABLE 5 GEE Logistic Analysis of Firms' Innovation Performance (Continued)

Variables	Model 1		Model 2		Model 3		Model 4	
Intercept	-1.45	***	0.10		0.09		-1.50	***
	(0.54)		(0.33)		(0.34)		(0.52)	
Ward chi square	115.91	***	122.16	***	130.65	***	133. 91	***
df	27		28		29		30	

* p < 0.10; ** p < .05; *** p < .01. Two-tailed tests.
Robust standard errors are in parentheses.
All models include unreported temporal effects.

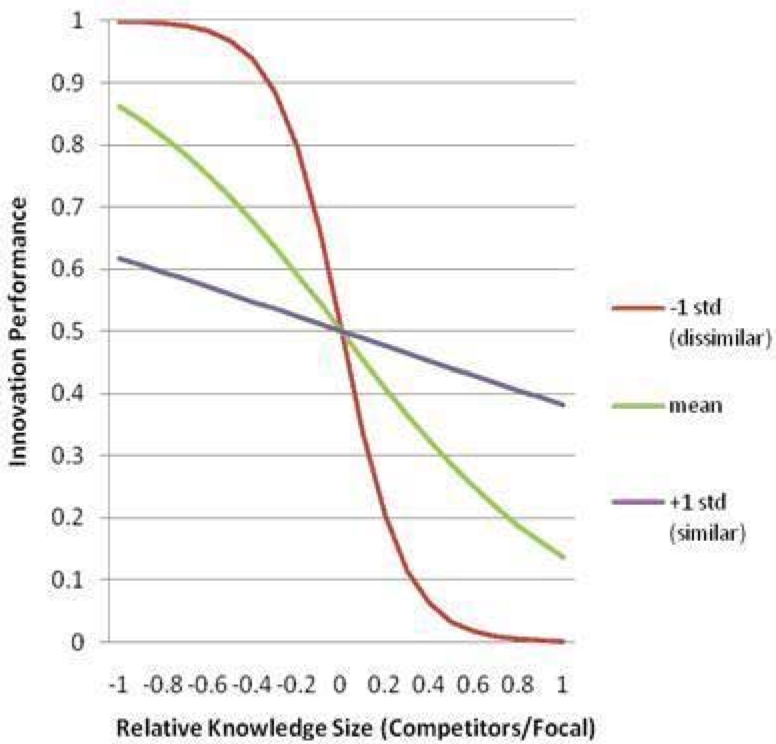

FIGURE 6 The Moderating Effect of Knowledge Structure Similarity-1

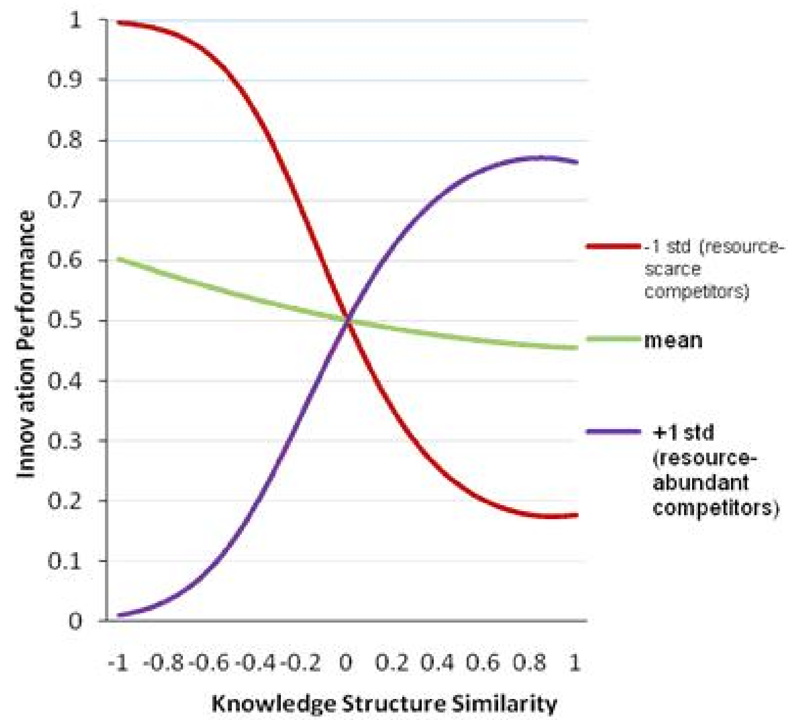

FIGURE 7 The Moderating Effect of Knowledge Structure Similarity-2

DISCUSSION

The results support the assertion that relative knowledge amount and knowledge structure similarity between a firm and its rivals influence the firm's innovation performance. I found that the relative stock of knowledge assets (i.e., competitors' knowledge amount over that of the firm) was negatively related to the firm's innovation performance. The negative relationship, however, is moderated by the knowledge structure similarity between the firm and its competitors. The negative impact is the largest when the firm is very dissimilar to its rivals in knowledge structure, a situation in which the firms is unlikely to understand rivals' innovation because they are following highly divergent technological models. The negative impact is reduced as the similarity of their knowledge structure increases, because the similarity increases relative absorptive capacity (Lane & Lubatkin, 1998) and enhances the firm's capacity to learn from and utilize the net inward flow of the rivals' innovation spillovers. The marginal moderating effect, however, declines from a certain point because increased similarity reduces the inspirational value of rivals' spillovers.

The findings have led to several important implications for the innovation and the strategy literatures. First, the findings provide a contingent perspective that helps reconcile the controversy over the impact of competition on a firm's innovation performance. The findings indicate that competition with rivals that are significantly larger in knowledge amount generally hampers the firms' innovation. The negative impact, however, is conditional on the knowledge structure similarity between rivals and the firm. Knowledge-constrained firms can turn their disadvantage into advantage by leveraging their knowledge structure similarity to the larger rivals. Such similarity allows absorbing knowledge spillovers effectively despite having fewer knowledge resources, permitting knowledge-constrained firms to exploit the advantage conferred by their asymmetry in contribution to the common pool of knowledge spillover, i.e. absorbing more from than contributing to the common knowledge pool (Shaver & Flyer, 2000; Baum & Haveman, 1997).

Second, the findings also shed light on some core issues in strategy with respect to sources of competitive advantage and choices regarding where and with whom to compete. The findings suggest that an important source of competitive advantages in innovation races is a relatively larger stock of knowledge assets. A generic innovation strategy for knowledge resource-constrained firms would be to avoid entering innovation races where dominant knowledge-abundant rivals are present or likely to join. This strategy can be refined by the second insight the findings suggest. Knowledge-constrained firms can exploit their similarity in knowledge structure to knowledge-richer firms in the race. By selecting carefully the races they enter and competing mainly with knowledge-richer rivals with similar knowledge structure, they can reduce or eliminate the liability of (knowledge-stock) smallness or even obtain a competitive advantage.

Limitations

This research is not without limitations. First, my sample includes both public and private firms. For private firms, I lack information on R&D investment and financial performance (e.g., ROA) which might account for innovation performance. Nonetheless, I controlled for firms' accumulated number of patents, a key factor that proxies, to a large extent, firms' unobserved idiosyncratic characteristics in producing patents (Rothaermel & Deeds, 2004). Second, I focused on the impact on a firm's innovation of rivals which race in the same research program as the focal firm. We do not know, however, whether and how the knowledge resources of other firms in technologically relevant (but not the same) research programs may have some impact on a firm's innovation. Although I have accounted for some of the effect by considering the influence of external technological opportunities suggested by all firms beyond the boundary of any specific innovation races, it might be rewarding to study such an effect in the future.

Conclusion

This study contributes to the literature by highlighting the role that relative knowledge amount and knowledge-structure similarity between competitors and a firm play in the firm's innovation performance. I found competitors' relative amount of knowledge impacts the firm's innovation negatively, while their knowledge-structure similarity with the firm moderates this relationship curvilinearly. These findings suggest that it is generally not beneficial for an organization to compete with rivals with more abundant knowledge resources, unless they are similar in knowledge structures with the firm. The marginal benefit associated with knowledge structure similarity, however, declines as the similarity increases.

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ESSAY THREE: Social Network Diversity in the Community and the Workplace and Employees' Trust: A Resource-Based Perspective[4]

[4] Cui, H., Vertinsky, I., Robinson, S, & Branzei, O., 2010. Social Network Diversity in the Community and the Workplace and Employees' Trust: A Conservation of Resources Perspective. A version of this paper is in preparation for submission.

INTRODUCTION

Over the past two decades, there has been an increasing interest in applying a resource-based perspective in the study of individuals' attitudes and behavior. The conservation of resources theory (COR), for example, represents such a perspective. The tenet of COR is individuals strive to obtain, retain, protect and foster what they prize and value, i.e., resources (Hobfoll, 1989, 2001; Wright & Hobfoll, 2004). The theory was developed in order to provide a new perspective to the stress process (Hobfoll, 1989), with a fundamental prediction concerning resource loss as an important reason for stress (Hobfoll, 1988, 1989, 2001). Over the years, researchers have applied such perspective to the study of job burnout (Wright & Hobfoll, 2004), emotional exhaustion (Ito & Brotheridge, 2003), work-family conflict (Grandey & Cropanzano, 1999), and interpretation of politics (Treadway et al., 2005).

In this paper we adopt the resource-based perspective to investigate social trust development as a result of acquisition of resources through interactions with others in social networks. We posit that social networks are an important type of resource; they are conducive to the development of social intelligence, a psychological resource which enhances one's positive attitudes and behaviors (e.g., social trust) in the workplace. Social trust which draws an increasing research interest, is a unique form of trust defined as impersonal or indirect trust that does not rest with knowledge regarding particular individuals, but is generalized to others in the social unit as a whole, reflecting one's willingness to be vulnerable to the others (Leana & Van Buren, 1999; cf: Putnam, 1993b; Rousseau, Sitkin, Burt, & Camerer, 1998).

Using two field studies conducted in two societies representing distinct national cultures, i.e., Canada and China, we find that while the diversity of one's social network in the community is positively associated with one's social trust in the workplace, in both societies, the diversity of one's social network in the workplace is only positively associated with social trust in the workplace in China, and not in Canada.

THEORETICAL BACKGROUND

COR theorists posit four principal resource categories including "objects, personal characteristics, conditions, or energies that are valued in their own right, or that are valued because they act as conduits to the achievement or protection of valued resources" (Hobfoll, 2001, p. 339). Examples of resources include home and vehicle (objects); marriage, self-esteem, mastery (personal characteristics); tenure and seniority (conditions); and stocks, time, and credit (energies) (Hobfoll, 1989; Treadway et al., 2005). In his comprehensive list of resources, Hobfoll (1998) also included "involvement in organizations with others who have similar interests", suggesting inter-personal networks are a type of resource.

Other abundant research also suggests social networks are an important external resource. Social networks consist of ties with family, relatives, friends, colleagues, etc. (Carlson & Perrewe, 1999). Researchers studying work-family relationships have shown that the ties provide both work and non-work related social support (Wellman & Wortley, 1990) such as instrument aid, emotional concerns, or appraisal, which affects the entire stress process (e.g., Carlson & Perrewe, 1999; House, 1981; Uehara, 1990; Wellman & Wortley, 1990). Classic network literature also asserts that social networks carry and transfer important resources such as explicit information and tacit knowledge (Burt, 1992; Granovetter, 1973). Such resources not only facilitate interpersonal learning, but play an important role in one's career path by influencing job search, negotiation, promotion, etc. (e.g., Seibert, 2001; Seidel, Polzer, & Stewart, 2000).

Diversified Social Networks

Notably, researchers have argued that diversified social networks, in which individuals interact with various types of people, can help individuals develop social intelligence, a specific type of psychological resource that enhances one's confidence in social interactions. Social intelligence is a set of cognitive resources which enable individuals to be sensitive to subtle social cues, to identify others' intentions (Marlowe, 1986), to respond appropriately and promptly with a repertoire of strategies (Argyle, 1969; Yamagishi & Yamagishi, 1994), and to improvise when they perceive the strategies are unlikely to work (Ferris, Witt, & Hochwarter, 2001).

Prior research has shown social intelligence is acquired primarily through interpersonal interactions within social networks, by means of trial and error (Argyle, 1969; Hargie, Saunders, & Dickson, 1994; Kelly, 1982; Michelson et al., 1983; Tsang & Pearson, 2001). During interactions with a particular party, individuals learn to correctly detect and interpret non-verbal and verbal social cues, to empathize with this party and synchronize their reactions with it. Furthermore, they also learn to develop routines of responses to this particular party (Argyle, 1969; Hargie et al., 1994). The set of routines and social savvies are the principal ingredients of social intelligence.

Diverse social networks provide abundant opportunities through which individuals learn to cope with different types of people (Argyle & Henderson, 1985). They can apply, refine, and generalize their social savvies obtained in various social encounters, and develop a repertoire of strategies for common social interactions (Argyle, 1969). People with social experiences in diverse social networks are likely to develop high social intelligence, which enables them to more effectively control the course of social interactions by means of persuading others or influencing their responses (Argyle, 1969; Meichenbaum, Butler, & Gruson, 1981). The key implication is social intelligence can increase people's confidence in coping with unfamiliar social situations because they are experienced and capable of handling various types of social interactions (Argyle, 1969).

Social Trust

Researchers argued trust can be classified into two types: dyadic and impersonal trust (Leana & Van Buren, 1999). Dyadic trust (e.g., identification-based or instrumental trust) is directed towards particular others, e.g., someone you have known for years, while impersonal trust (e.g., social trust) relates to people at large. An example of social trust would be to trust someone transferred from another department whom you have not previously known, or another example would be to trust new colleagues in a cross-functional team.

Dyadic trust is developed based on knowledge regarding particular others' trustworthiness (Leana & Van Buren, 1999), which could be evaluated through repeated interactions with them, derived from their social identities (e.g., ethnicity), or provided by third-parties or certifications (e.g., a professional designation) (Lewicki & Bunker, 1996; McAllister, 1995; Rousseau, Sitkin, Burt, & Camerer, 1998). In contrast, social trust, directed towards other people in a social unit as a whole, does not rest on knowledge about any particular individual, but on the confidence of handling social situations (Leana & Van Buren, 1999). While it is less surprising that one would trust others based upon one's knowledge of them, it is theoretically more interesting as to whether trust can be developed without knowing others in a social unit sufficiently in order to make a judgment regarding their trustworthiness. While the majority of prior research has focused on the development of dyadic trust, antecedents to the latter type of trust, i.e., social trust in the workplace, are relatively unknown.

The personality-based perspective towards trust asserts that individuals' dispositions determine the propensity to trust can engender a trusting inclination, and therefore is likely to sustain social trust in the workplace (Rotter, 1971, 1980). From the resource-based perspective, this paper complements such an assertion. It suggests the propensity to trust, a trait, represents a type of resource that is innate or primarily developed from adolescence experiences (Caspi, 2000). It is stable across time and situations once it is imprinted (Lewis, 1999, 2001; Mayer, Davis, & Schoorman, 1995; McCrae & Costa, 1994), and therefore may account for the baseline of social trust in a social unit. Individuals' social network diversity represents another type of resource, social and interpersonal skills, which are acquired primarily through learning experiences in various social contexts in adulthood (Putnam, 1993a; Roberts, Robins, Trzesniewski, & Caspi, 2003; Yamagishi & Yamagishi, 1994). This resource adds to the baseline of social trust in the workplace.

Overall, prior research suggests the gaining of psychological resources, i.e., social intelligence through interpersonal interactions in diversified social networks, increases one's confidence in handling the unknown, including potentially untrustworthy social actors (Argyle, 1969), and thus may enable individuals to maintain a high level of social trust in the workplace (Lewis & Weigert, 1985). We focus on two types of social networks, one formed in the community and the other in the workplace.

HYPOTHESES

An important aspect of one's social network is developed in the community. Prior research has shown the community, composed of a wide range of organizations such as alumni, professional, religious, and sports-related voluntary associations, is an important venue in which individuals learn to interact with others (Brehm & Rahn, 1997; Putnam, 1993b; Stolle, 1998). In various types of voluntary associations, individuals learn to cope with people in a variety of social situations including both casual social contacts (e.g., conversation, networking, and friendship building) and formal business interactions (e.g., presentations, teamwork, and competition) (Letki, 2004; Putnam, 1993b). As a result of diverse social interactions, individuals are likely to develop a high level of general social intelligence that deals with common social situations.

The literature regarding the transfer of psychological resources between work and non-work situations (e.g., Staines, 1980) suggests individuals can transfer, whether intentionally or unintentionally, such general social intelligence to similar informal or formal social situations in the workplace (Argyle & Henderson, 1985). This suggests the more diverse individuals' social interaction networks in the community, the more confident they are to cope with similar social situations in the workplace, and therefore the more comfortable they will be in maintaining a high level of trust in others.

Hypothesis 1. An employee's social network diversity in the community is positively related to his/her social trust in the workplace.

Another important segment of one's social network is formed in the workplace. Interpersonal relationships in the workplace contain some unique features not necessarily shared by those in one's community life (Argyle & Henderson, 1985). For example, work relationships are characterized by the dominance of organizational role-based interactions, salient divisions of labor due to specializations of jobs, task-related demands for collaborations, and territorial and interest conflict stemming from the positions in organizations (Brown, Lawrence, & Robinson, 2005; Neuberger, 1996).

Researchers argued, because of such differences, vocational or professional social intelligence is needed to cope with a wide range of work-specific social situations such as job interviews, task coordination, performance feedback, promotion, etc. (Argyle, 1969;

Fontana, 1994; Tsang & Pearson, 2001). This type of social savvy primarily consists of organization-specific tacit knowledge regarding not only other people's patterns of behaviors and underlying values in role-based relationships, but also the implicit rules, taboos, informal organizations, and office politics that are embedded fairly deep in the social networks (Krackhardt & Hanson, 1993; Treadway et al., 2005).

Being connected to diverse organizational members provides the opportunity to acquire such tacit knowledge. People representing different membership groups provide information and perspectives that help individuals obtain a deeper understanding of various social situations in the organization, regarding the intentions and behaviors of others serving different roles and affiliated with various relationship circles, as well as the appropriate thoughts and behaviors that individuals are expected of in different social encounters. With a comprehensive understanding of the ecology of social relationships and a mastery of explicit and implicit norms in the organization, individuals become socially intelligent with respect to predicting correctly others' intentions and handling skillfully unknown social interactions in this specific context. Consequently, people with diverse social networks in the workplace are more confident in social situations and willing to afford a high level of trust even without sufficient knowledge of particular others' trustworthiness in the workplace.

Hypothesis 2. An employee's social network diversity in the workplace is positively related to his/her social trust in the workplace.

METHOD

Sample

We tested our hypotheses in two field studies. The first study was conducted in Vancouver, Canada, 2004. To investigate whether the findings were culturally bound, a second study was conducted in Shanghai, China.

In Vancouver, 125 organizations were randomly selected that were affiliated with the British Columbia Chapter of the American Marketing Association to participate in a survey. Fifty-seven organizations agreed to participate (response rate = 45.6%). A total of 300 individuals were randomly selected from these organizations; at least five respondents per organization were sought. These individuals were invited by phone calls and emails to participate in an online survey, and they were followed up by calls and emails twice or more. Two hundred and nine valid questionnaires were returned (response rate = 69.7%). The number of respondents per organization ranges from one to nine. After omitting organizations with an inadequate number of observations, i.e., less than three respondents (e.g., Zhang, Hempel, Han, & Tjosvold, 2007), the sample was reduced to 178 individuals in 42 organizations; on average, the number of respondents per organization was 4.2.

Eighty-seven percent of the organizations were for-profit. Eighty-eight percent were small-to-medium sized. Industries and the number of organizations each were as follows: health care, 7; financial services, 6; consulting and accounting, 5; sales, 5; social services, 4; food, 3; manufacturing, 3; hotel/tourism, 2; real estate, 2; logistics, 2; telecommunication, 1; education, 1; hairdressing, 1.

Nearly half (41%) of the respondents were males. Distribution of age was as follows: less than 20 years old, 6.6%; between 21 and 30, 33.7%; between 31 and 40, 25.9%; between 41 and 50, 21.9%; above 50, 11.6%. Distribution of educational backgrounds was as follows: no college education, 1.8%; some college education, 40.6%; bachelors' degrees, 39.4%; and graduate degrees, 18.2%. Occupations and the percentages of respondents in those occupations were as follows: administrative/clerical personnel, 22%; supervisors, 18%; customer service personnel, 14%; sales personnel, 13%; financial planners, 5%; accountants, 5%; production workers, 5%; consultants, 3%; fitness coach, 3%; analysts, 2%; teachers, 2%; HR specialists, 2%; scientists and engineers, 2%; technicians, 2%; hairdressers, 2%; and R&D staff, 1%.

For the survey in Shanghai, the original questionnaire was first converted from English to its Chinese version through translation and back-translation. Both versions of the translation were cross-checked by two bilingual management researchers. To avoid misunderstanding, the Chinese version was pre-tested before it was finalized. In the pre-test, strong resistance from the respondents was found to answering questions about trust, because they viewed such information as sensitive. To assure survey quality and increase the response rate, data were collected using personal networks. Our collaborator, a professor in a major university in Shanghai, helped assemble a list of organizations based on the affiliations of her MBA and EMBA students. She then asked the students to help persuade their affiliated organizations (N = 57) to participate in a survey; all of these organizations participated. The collaborator visited each organization, randomly selected at least five members per organization, solicited them to participate in a paper-based survey, and made follow-up phone calls to increase the response rate. Three hundred and fifty questionnaires were sent out, and 203 valid questionnaires were returned (response rate = 58%). After excluding organizations with less than three respondents, the sample included 169 respondents in 38 organizations. The number of respondents ranges from three to ten, i.e., an average 4.4 respondents per organization.

Ninety-two percent of these organizations were in the for-profit sector, and 86% were small-to-medium sized. Industries and the number of organizations in each were as follows: manufacturing, 8; sales, 4; social services, 3; automobile maintenance services, 3; consulting services, 3; financial services, 3; food, 3; construction, 3; IT, 2; research, 2; tourism, 1; real estate, 1; logistics, 1; filming, 1.

Regarding the characteristics of the individual respondents, 61% were males; 6.6% were less than 20 years old, 57.3% between 21 and 30, 27.3% between 31 and 40, 4.8% between 41 and 50, and 2.2% above 50; 13.4% had no post-secondary education, 31.8% had some college education, 43% had a bachelors' degree, and 11.8% had a graduate degree. Occupations and the percentages of respondents in each of them were as follows: administrative/clerical personnel, 16%; production workers, 15%; engineers, 13%; sales personnel, 12%; supervisors, 12%; consultants, 7%; accountants, 6%; customer service personnel, 6%; photographers, 3%; brokers, 3%; bankers, 2%; analysts, 2%; R&D staff, 2%; and HR specialists, 1%.

Measures

Diversity of social networks in the community. Following prior research measuring social networks in the community (Brehm & Rahn, 1997; Claibourn & Martin, 2000; Letki, 2004; Pickup, Sayers, Knopff, & Archer, 2004; Stolle, 1998), we focused on individuals' social networks developed in voluntary associations.

Diversity of social networks in various voluntary associations should capture not only the scope of different voluntary associations in which an individual participate, but also the distribution (i.e., reverse of concentration) of his/her social ties across these associations. We therefore used an entropy-based index to measure the diversity of social networks in the community, following prior research (e.g., Acar & Sankaran, 1999; Cummings, 2004; Raghunathan, 1995; Wiersema & Bantel, 1992). Entropy is calculated as a weighted average of the proportion of ties in each of the voluntary associations. The respondents were asked to indicate their memberships within the past 12 months in a wide range of voluntary associations, including professional, alumni, political, religious, ethnic, charity, activist, social, sports, and other associations (Brehm & Rahn, 1997; Stolle & Rochon, 2001). They were also asked to specify the number of ties they made in each association. Then, we calculated the entropy-index using the following formula:

$$Entropy = \sum_{i}^{n} \left[P_i * \ln(1/P_i) \right],$$

where P_i is the proportion of ties in association *i,* and *n* is the total number of voluntary associations

Diversity of social networks in the workplace. Following Stolle (1998), four questions were asked about the respondents' social network diversity within the workplace in terms of the percentage of time at work they spent interacting with employees of different race, gender, age cohort, and functional background. Factor analysis of these four percentages indicated one latent factor, labeled as the diversity of social networks in the workplace (Cronbach's α = 0.76). We then used the sum of these percentages to measure this construct.

Social trust in the workplace. Social trust in the workplace was measured based on the six-item scale developed by Yamagishi and Yamagishi (1994) which measured social trust in the community, on a seven-point Likert scale (1 = "strongly disagree", 4 = "neither disagree nor agree", and 7 = "strongly agree"). The scale was modified to suit the organizational context (Cronbach's α = 0.74). Sample items include: "I trust a typical employee in this organization" and "it is best not to share concerns or complaints with coworkers because they will probably use this information to harm you" (reverse coded). A complete list of the items is included in the appendix.

Individual-level control variables. First, we controlled for individuals' propensity to trust (Rotter, 1967), using a measurement developed by Huff and Kelley (2003), on a seven-point Likert scale (1 = "strongly disagree", 4 = "neither disagree nor agree", and 7 = "strongly agree") (Cronbach's α = 0.80). An example item is, "I believe that people usually keep their promises." Second, we controlled for individuals' demographical characteristics, such as age and gender (0 = "female"; 1 = "male") since people of different age and gender may exhibit different views towards the trustworthiness of others (Putnam, 1995; Uslaner, 2004). Third, we controlled for employees' socio-economic status in terms of post-secondary education (0 = "no"; 1 = "1 year"; 2 = "2 years"; 3 = "3 years"; 4 = "Bachelors degree"; 5 = "Masters degree"; 6 = "Ph.D.") (e.g., Letki, 2004), monthly income (e.g., Brehm & Rahn, 1997), and job levels (1 = "manager"; 0 = "non-manager") (e.g., Stolle, 1998) because high status may encourage individuals to trust more. Fourth, we also included one's total number of interpersonal ties in voluntary associations and in the workplace respectively, as a control for potential influence of network intensity on the development of social trust in the workplace. Finally, we controlled for the number of hours spent at work, per week, as a reflection of employees' workload intensity, which may influence their attitudes towards each other (Cordes & Dougherty, 1993).

Organizational-level control variables. We controlled for organizational size (e.g., Dutta & Crossan, 2005) because a large number of colleagues may inhibit the development of trust towards them as a whole (e.g., Stolle, 1998). We also controlled for whether an organization belongs to a for-profit or non-for-profit sector (0 = "non-for-profit"; 1 = "for-profit") since the ethical climate in non-for-profit organizations normally reflects higher benevolence factors than that in for-profit ones (Brower & Shrader, 2000).

Such climate difference may result in differing trusting attitudes and behaviors among employees in the two sectors (Kasper-Fuehrer & Ashkanasy, 2001). Last but not least, we controlled for perceived trustworthiness in organizational treatment of employees. According to the research on institutional trust, such perception may influence individuals' willingness to trust in the workplace (Zucker, 1986). This variable was measured using the six-item scale developed by Caldwell and Clapham (2003) (Cronbach's α = 0.85). This scale emphasizes particularly organizations' being honest with employees, a decisive factor for employees to infer whether the organization is trustworthy (Butler, 1991; Larzelere & Huston, 1980; Mayer et al., 1995; Mishra, 1996). Responses were made with a seven-point Likert scale (1 = "strongly disagree", 4 = "neither disagree nor agree", and 7 = "strongly agree"). An example item is, "the organization honors its commitments". Because it is an organizational characteristic, we constructed an organizational level measurement of this variable. This variable was assigned a value, which equals the average of the responses from subjects belonging to the same organization, excluding the response from the individual whose level of social trust is being predicted (e.g., Robinson & O'Leary-Kelly, 1998).

To ensure that aggregation of data from individual members to create organizational level data was appropriate, we first calculated within-group agreement statistics (r_{wg}'s). The results indicated that respondents exhibited a very high level of agreement on this aggregated variable, with a median of 0.90, exceeding the acceptable level of 0.70 (Janz, Colquitt, & Noe, 1997).

To further justify the aggregation, we also calculated the value of intra-class correlation coefficients, ICC[1] and ICC[2]. ICC[1] measures the extent to which individual-level variability on a measure can be explained by higher-level units (Sun, Aryee, & Law, 2007). The value of ICC[1] is based on ANOVA (Bliese, 2000). ICC[2] estimates the reliability of group means. In this study, the group effect, or the F-value of the ANOVA for perceived organizational trustworthiness was 6.21 ($p \leq 0.01$). Using the Spearman-Brown formula, we derived the ICC[2] for this variable (0.78), exceeding the 0.6 criteria suggested by Glick (1985). Taken together, the r_{wg}, ICC[1] and ICC[2] justified the aggregation of perceived trustworthiness in organizational treatment of employees to the organizational level.

Common Method Variance

Single-sourced survey may have the problem of common method bias. This is severe when all variables are measuring perceptions on similar scales (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To minimize common method bias, the measurements of the key variables were largely diversified using subjective, objective and aggregated constructs (Podsakoff et al., 2003). While the dependent variable, social trust in the workplace, was a measure of subjective judgment constructed on a 1-7 Likert scale, the independent variables, diversity of social networks in the community and in the workplace, were measured using objective numbers (, which are less likely to be biased. The first independent variable, diversity of social networks in the community was an entropy index, constructed based on the number of people with whom an individual interacted in voluntary associations. The second independent variable, diversity of social networks in the workplace was constructed based on the fractions of time that one actually spent with various types of colleagues.

ANALYSIS AND RESULTS

Tables 6 and 7 report the means, standard deviations, and zero-order correlations of the variables in the two studies. The correlation results are generally consistent with those hypothesized. The Canadian data show that individuals' social trust in the workplace is positively correlated with their social network diversity in the community ($r = 0.15$, $p \leq 0.05$) and in the workplace ($r = 0.20$, $p \leq 0.01$). The Chinese data also show positive correlations between individuals' social trust in the workplace and their social network diversity in the workplace ($r = 0.20$, $p \leq 0.01$).

TABLE 6 Descriptive Statistics and Zero-Order Correlations (Canada)

	Variables	Mean	s. d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Propensity to trust	4.56	0.97														
2	Gender	0.40	0.49	-0.01													
3	Age	36.11	10.67	0.13	-0.03												
4	Education	3.32	1.36	-0.12	0.16	0.19											
5	Income	5.08	2.70	-0.04	0.01	0.36	0.21										
6	Work hours	43.75	9.02	0.10	0.17	0.04	0.03	0.28									
7	Number of ties (workplace)	70.48	91.08	-0.15	0.01	-0.03	-0.06	-0.02	-0.15								
8	Number of ties (community)	7.95	18.27	-0.02	0.02	-0.07	-0.02	0.00	-0.04	0.10							
9	Job level (manager = 1)	0.42	0.39	0.14	0.05	0.22	0.07	0.15	0.13	-0.04	-0.04						
10	Industrial sector (for-profit = 1)	0.82	0.49	-0.06	0.08	-0.05	-0.08	0.03	0.00	-0.10	-0.11	0.00					
11	Organizational size	4.58	2.31	0.10	0.11	0.11	0.16	0.04	0.11	0.02	0.03	0.17	-0.33				
12	Social network diversity (community)	0.24	0.39	0.07	-0.02	0.07	0.17	0.14	0.03	-0.09	0.36	0.04	-0.06	0.00			
13	Social network diversity (workplace)	48.44	24.07	0.16	0.02	0.05	-0.04	0.05	0.18	0.05	0.05	0.05	-0.07	-0.03	-0.1		
14	Perceived trustworthiness in org. treatment of employees	4.27	0.74	0.05	-0.02	-0.05	-0.17	-0.09	0.02	-0.04	0.03	-0. 13	0.29	-0.49	0.00	0.13	
15	Social trust in the workplace	4.32	0.90	0.43	-0.02	0.02	-0.14	-0.06	0.05	-0.15	-0.03	-0.05	0.02	-0.07	0.15	0.20	0.23

Correlations are significant at 0.1 level if they are over $|0.11|$, significant at 0.05 level if they are over $|0.14|$, significant at 0.01 level if they are over $|0.17|$.

TABLE 7 Descriptive Statistics and Zero-Order Correlations (China)

	Variables	Mean	s. d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Propensity to trust	4.23	1.06														
2	Gender	0.60	0.49	0.03													
3	Age	30.42	8.09	0.24	0.05												
4	Education	2.97	1.58	-0.13	0.05	-0.15											
5	Income	4.03	2.28	0.01	0.13	0.13	0.28										
6	Work hours	48.18	14.68	0.23	0.14	-0.03	-0.29	0.28									
7	Number of ties (workplace)	48.98	104.59	0.02	-0.06	0.05	-0.23	-0.09	0.17								
8	Number of ties (community)	3.26	9.36	0.01	0.06	-0.10	-0.03	-0.07	-0.02	0.06							
9	Job level (manager = 1)	0.31	0.46	0.09	0.06	0.22	0.01	0.28	0.07	0.07	0.08						
10	Industrial sector (for-profit = 1)	0.91	0.29	-0.13	-0.12	-0.07	0.11	-0.06	-0.33	0.00	-0.04	0.14					
11	Organizational size	5.01	2.05	-0.06	0.02	0.10	0.19	-0.06	-0.18	0.01	-0.07	0.04	0.21				
12	Social network diversity (community)	0.10	0.26	-0.07	0.05	-0.04	0.00	-0.02	0.01	-0.06	0.44	0.18	0.00	-0.05			
13	Social network diversity (workplace)	36.12	13.14	0.16	0.02	0.05	-0.04	0.04	0.18	0.05	0.05	0.05	-0.03	-0.07	-0.10		
14	Perceived trustworthiness in org. treatment of employees	4.27	0.74	0.21	0.07	0.08	-0.27	-0.11	0.40	0.16	0.05	0.16	-0.08	-0.26	0.02	0.00	
15	Social trust in the workplace	3.67	0.86	0.44	0.05	0.06	-0.03	0.01	0.11	-0.06	0.10	0.12	-0.05	0.01	0.11	0.20	0.22

Correlations are significant at 0.1 level if they are over $|0.12|$, significant at 0.05 level if they are over $|0.14|$, significant at 0.01 level if they are over $|0.18|$.

We tested our hypotheses using the Canadian data first, adopting OLS regression analysis in a hierarchal procedure. The results were presented in columns 2 to 4 of Table 8. We found that, on top of the effect that the propensity to trust had on social trust, employees' social network diversity in the community was positively associated with their social trust in the workplace (β = 0.20, $p \leq 0.05$), supporting Hypothesis 1. Employees' social network diversity in the workplace, however, was not significantly related to their social trust in the workplace (β = -0.03, *n.s.*), thus not supporting Hypothesis 2.

We then re-tested our hypotheses using the Chinese data. We found that social trust in the workplace was positively associated with employees' social network diversity in the community (β = 0.25, $p \leq 0.01$). Thus, Hypotheses 1 was supported. We also found social network diversity in the workplace was also significantly associated with social trust in the workplace (β = 0.21, $p \leq 0.01$), supporting Hypothesis 2. The results were presented in column 7 of Table 8.

We conducted several robustness checks to validate the findings. First, because error terms of observations belonging to the same organization might be correlated, the assumption of independent errors in OLS regression is at risks of being violated, resulting in biased estimation of standard errors. In such situation, it is normally recommended to correct for the autocorrelation caused by the cluster sampling. Thus, we controlled for the clustering effect in the OLS regression, using STATA 9.0, a procedure that is core to cross-level data analysis methods. Regression results based on robust standard errors (after correction) were reported in columns 5 (for the Canadian sample) and 8 (for the Chinese sample) of Table 8. They were highly consistent with the OLS regression estimates, indicating that the findings were robust to the clustering effect.

Second, due to the cross-sectional design of this study, there is a potential problem of reverse causality, e.g., social trust in the workplace might also have some influence on social network diversity in the community. If this is true, then a key assumption of OLS regression concerning that independent variables are not correlated with the error terms, is violated To test the robustness of the results to that possibility, we followed a standard econometric procedure, employing a two-stage least square (2SLS) model[5], in which we used an instrument variable (i.e., the total number of voluntary associations that an individual participated in the past 12 months) for social network diversity (Heckman, 1979). The results were very robust. We also applied the Wu-Hausman F test, which examines whether the coefficients under the 2SLS estimates differ from the OLS estimates. The Wu-Hausman test could not reject the null hypothesis that the two sets of estimates were the same (e.g., *F (1, 163) = 2.50*, *n.s. for the Canadian sample*), meaning that we can rely on the OLS estimates. The results were presented in columns 6 (for the Canadian sample) and 9 (for the Chinese sample) of Table 8.

[5] The method of two-stage least square (2SLS) is used to estimate causal relationships when controlled experiments are not feasible. It allows consistent estimation when the explanatory variables are correlated with the error terms, which may occur when the dependent variable causes at least one of the of independent variables (i.e., reverse causality). In this situation, ordinary linear regression (OLS) generally produces biased and inconsistent estimates. If an *instrument* variable is available, consistent estimates may still be obtained. An instrument is a variable that does not itself belong in the explanatory equation; it is correlated with the endogenous explanatory variables, but uncorrelated with error terms. The 2SLS model involves two stages. In the first stage, endogenerous variables are regressed on all exogenerous variables including the instrument variable. The predicted values of endogenous variables from the regressions are obtained. In the second stage, the regression of interest is estimated as usual, except that the endogenous variables are replaced with the predicted values from the first stage model.

TABLE 8 Regression Analyses of Social Trust in the Workplace

Variables	Canada					China		
	Controls	**H1**	**H2**	**Clustering**	**2SLS**	**OLS**	**Clustering**	**2SLS**
Independent variables								
Social network diversity (community)		0.20 ***	0.20**	0.19 **	0.30***	0.25***	0.25**	0.26 *
Social network diversity (workplace)			-0.03	-0.05	-0.04	0 .21***	0.21**	0.21 ***
Control variables								
Gender	-0.03	-0.04	-0.04	-0.04	-0.04	0.04	0.04	0.04
Age	0.03	0.02	0.01	-0.01	-0.01	-0.06	-0.06	-0.06
Education	-0.06	-0.09	-0.09	-0.07	-0.08	0.07	0.07	0.07
Income	-0.04	-0.05	-0.05	-0.04	-0.04	-0.03	-0.03	-0.03
Work hours	0.09	0.09	0.09	0.07	0.07	0.05	0.05	0.05
Number of ties (workplace)	-0.03	-0.00	-0.00	-0.00	0.01	-0.11	-0.11*	-0.11
Number of ties (community)	0.01	-0.08	-0.07	-0.08	-0.13	-0.17*	-0.17 **	-0.17
Job level (manager = 1)	-0.08	-0.08	-0.08	-0.06	-0.07	0.06	0.06	0.06
Industrial sector (for-profit = 1)	0.06*	0.08	0.09	0.07	0.08	0.20**	0.20 **	0.20 **
Organizational size	-0.08	-0.06	-0.06	0.02	0.03	-0.04	-0.04	-0.04
Perceived trustworthiness in org. treatment of employees	0.17**	0.17 **	0.18**	0.19 *	0.19**	0.16**	0.16 *	0.16 **
Propensity to trust	0.44***	0.44***	0.43***	0.42 ***	0.42 ***	0.42***	0.42***	0.42 ***

TABLE 8 Regression Analyses of Social Trust in the Workplace (Continued)

	Canada					China		
	Controls	H1	H2	Clustering	2SLS	OLS	Clustering	2SLS
R^2	0.24	0.27	0.27	0.32	0.31	0.32	0.32	0.37
Adj. R^2	0.19	0.22	0.21	0.26		0.26	0.26	
F value	4.76***	5.06 ***	4.66***	7.01 ***	5.56 ***	5.18***	8.57***	6.17 ***

* p ≤ 0.1; ** p ≤ 0.05; *** p ≤ 0.01

DISCUSSION

From the resource-based perspective, we developed and tested hypotheses depicting the relationship between diversified social networks and social trust in the workplace. We found the diversity of individuals' social networks in the community was positively associated with their social trust in the workplace; the results were consistent in two different national cultures. Social network diversity within the workplace was associated with social trust in the workplace, only in the Chinese sample.

Building upon prior research regarding work-life relationships and classic literature on social networks, we argue social networks are important resources which provide valuable information, knowledge, and social support (e.g., Calson & Perrewe, 1999; House, 1981; Wellman & Wortley, 1996; Uehara, 1990; Seidel, et al., 2000). Furthermore, we conceptually distinguish between two types of social networks, i.e., networks in the community and in the workplace, arguing diverse networks are conducive to the development of important psychological resources, i.e., general and workplace-specific social intelligence.

The empirical results suggest that while general social intelligence, developed in the community, is transferable to social situations in the workplace, regardless of national cultural contexts, professional social intelligence, developed in the workplace, affects individuals' social trust only in a collectivistic society. The findings suggest the utilization of workplace-social-network resources, in regard to social trust development, is likely to be culturally bound. This result is consistent with research findings regarding national cultures: in collectivistic societies such as China, individuals tend to categorize others into distinct relationship circles and cope with different circles employing different rules (Farh, Earley, & Lin, 1997; Yang, 1993), while in individualistic societies such as Canada, people are more likely to treat others using universal rules (Waterman, 1988). It is therefore not surprising that general social intelligence developed in the community is likely to be dominant in determining Canadians' social trust in the workplace. In contrast, Chinese social trust in the workplace may rely on both their workplace-specific and general social intelligence, because the workplace may be viewed as a distinct relationship circle, owing to its unique features of interpersonal relationship not shared by the community (e.g., Argyle & Henderson, 1985; Hargie et al., 1994).

It is worth noting the number of ties with others in the community and the workplace, (one of the control variables), is not significantly associated with individuals' social trust in the workplace. The only exception is the number of ties in the community is marginally negatively associated with social trust in the workplace in the Chinese sample. This implies that while diverse social networks broaden one's relational space and enhance one's capacity in dealing with a wide range of others, intense interactions with any particular group of people may narrow one's opportunities to learn social skills and therefore decrease one's confidence in coping with others in general. Overall, the findings support our argument regarding the role of social network diversity in the development of social trust in the workplace.

This research establishes the linkage between resources and positive attitude and behavior, i.e., social trust in the workplace, complementing extant studies from the resource-based perspective which concentrate on the relationship between resources and stress-related negative psychological states, e.g., job burnout, emotional exhaustion, work-family conflict, etc (Wright & Hobfoll, 2004; Ito, et al., 2003; Grandey & Cropanzano, 1999). The results show diverse social networks account for a significant proportion of the variance of social trust in the workplace, on top of what is explained by the propensity to trust. Thus, our findings suggest both types of resources can significantly affect social trust development in the workplace. An important implication is people's trust is, to some extent, resource based: it is founded upon both the trait-related resource which represents the dispositional account for trust, and the interpersonal-experience-related resource which represents the social-intelligence account for trust.

Limitations

This research is not without limitations. First, we are aware that in order to draw conclusions regarding causality, experiments or longitudinal studies would be a better research design than a cross-sectional one. We have ruled out the possibility of inverse causality using rigorous econometric techniques; we also demonstrated the validity of the findings employing field studies in two societies representing distinct national cultures. Nonetheless, future studies extending this research may benefit from adopting experimental or longitudinal design in order to further minimize such possibility.

Another possible limitation concerns the measure of individuals' social networks which reflect their interpersonal experiences in voluntary associations. This measure does not account for the possible loss through depreciation of social skills/knowledge over time (e.g., Arthur & Huntley, 2005). Researchers studying organizational learning and knowledge found experience-based knowledge depreciates rather rapidly (Argote, Beckman, & Epple, 1990; Epple, Argote, & Devadas, 1991). If social interactions in one voluntary association take place much earlier than those in other voluntary associations, the former social experiences may not be as fresh as those obtained later and thus may contribute less to current overall social intelligence. Effects of this potential limitation on the results may be minimal because individuals' voluntary association activities within a relatively short window of time (i.e., the past 12 months) were asked. Longer windows would have required the inclusion of a time-lag variable in order to adjust for the depreciation in the effects of social experiences at the time of the survey.

Managerial Implications

This research highlights the importance of employees' diverse social networks in providing resources for trust. Those who socialize in a variety of associations in the community are likely to trust others to a greater extent in the workplace. The important take-away message is that employees' out-of-workplace social activities can benefit organizations' internal social relationships, because the more diverse the social activities in which they are involved "outside" the workplace, the more trusting they are likely to be "inside" the workplace. Additionally, in collectivistic societies, the creation of opportunities for more diverse social interactions among employees is likely to contribute to their social trust development in the workplace.

Conclusion

From the resource-based perspective, this study highlights the importance of social network resources in social trust development in the workplace. We found employees' social trust in the workplace is positively related to their social network diversity in the community and in the workplace (in the Chinese study only). This finding suggests the mechanism through which social network resources in the community are accumulated and transferred to the workplace is culturally universal. The mechanism through which social network resources in the workplace are utilized varies across cultures: such resources play a larger role in collectivistic than in individualistic societies. An important implication is organizations should facilitate their employees' participation in diverse organizations in the community in order to promote their trusting attitude and behavior in the workplace.

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CONCLUSION

The first essay focuses on the impact of prior strategic alliances between firms on their current innovation performance when they become direct competitors developing potentially substitutable new products. Using a longitudinal dataset depicting strategic alliances and innovation races in the U.S. pharmaceutical industry, I found that such impact depended on the type of prior strategic alliances and the number of different types of prior allies in the current competition. Specifically, prior alliance relationships can negatively impact a firm's innovation performance when the firm competes with a small number of former strong allies or a large number of former repetitive weak allies. A negative impact on innovation performance was also found when the firm competed with a small number of former non-repetitive weak allies that innovated in the same technological areas as the firm. Prior strategic alliances can also promote the firm's innovation performance, when it competes with a large number of former strong allies or a small number of former repetitive weak allies. A positive effect on innovation performance was also found when the firm competed with a large number of former non-repetitive weak allies that innovated in the same technological areas.

The second essay focuses on the controversy regarding whether competition has a net positive or negative impact on a firm's innovation performance (Cockburn & Henderson, 1994; Fleming, 2001; Henderson & Cockburn, 1996; Reinganum, 1989; Ziedonis, 2004). Building upon the resource-based view of the firm and organizational learning theory, I studied this relationship from a unique lens, arguing that the net impact depends on the knowledge resource similarity (in both amount and structure) between the firm and its competitors. Using a longitudinal dataset collected in the U.S. pharmaceutical industry, I tested and found support for the following two hypotheses. First, competition can have a negative impact on the firm's innovation when rivals have a relative larger amount of knowledge. Second, such negative impact is reduced as the knowledge structure similarity between the firm and its competitors increases. The marginal rate of reduction declines as the similarity increases.

The third essay focuses on the development of relational capital within the workplace, which is a critical condition for the creation of innovation in organizations (Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998). Specifically, I studied, from the perspective of the conservation of resources theory, the impact of network diversity on the development of social trust in the workplace, an important form of relational capital (Leana & Van Buren, 1999; Putnam, 1993). Using data collected from two field studies, I found that while employees' network diversity in the community was positively related to their social trust in the workplace in both individualistic and collectivistic societies, employees' network diversity in the workplace was associated with their social trust in the workplace in the collectivistic society only, and not the individualistic one.

Several important implications regarding the creation of innovation can be derived from this dissertation. First, while it is well-known that a firm can improve its innovation performance by establishing strategic alliances with other firms (Ahuja & Katila, 2001; Gulati & Singh, 1998; Kale, Dyer, & Singh, 2002; Lavie & Miller, 2008; Mowery, Oxley, & Silverman, 1998), findings in this dissertation suggest that alliances can have a negative impact on innovation when prior allies become competitors. An important take-away message for decision-makers is that they can increase their innovation performance by choosing strategically which innovation races to join, taking into considerations the number of different types of former allies in the competitions. Second, the findings also suggest when making such strategic choices, it is also important to consider the knowledge resource similarity between the firm and its potential rivals. It is typically not beneficial to compete with knowledge-abundant rivals, yet the liability of knowledge-amount smallness can be reduced or even turned into advantage by exploiting the knowledge structure similarity between the firm and its knowledge-abundant competitors. Third, prior research has suggested that innovation performance is not only determined by external factors such as competition, but also by internal factors such as relational capital within the workplace (Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998). The findings of this dissertation suggest important mechanisms through which relational capital, i.e., trust, is developed within the workplace. An important practical implication for the managers is to encourage diversified networking of employees in the community (in both collectivistic and individualistic cultures) and in the workplace (only in collectivistic cultures).

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APPENDICES

APPENDIX I: Most Common Research Areas in the U.S. Pharmaceutical Industry

1	ADHD treatment	11	Analgesic	21	Anesthetic
2	Antiallergic	12	Antibacterial	22	Anticoagulant
3	Anticonvulsant	13	Antidepressant	23	Antidiabetes
4	Antidiuretic	14	Antifungal	24	Antihistamine
5	Antihyperlipidemic agents	15	Antihypertension	25	Anti-inflammation
6	Antinausea	16	Antineoplastics	26	Anti-peptic
7	Antipsychotic	17	Antiviral	27	Asthma Treatment
8	Bone Dermatology	18	Cardiology	28	Gastrointestinal
9	Hormone Therapy	19	MRI Contraceptive	29	Nephrology
10	Neurology	20	Oncology	30	Smoking cessation

APPENDIX II: Measurement of the Dependent and Independent Variables

Diversity of Social Networks in the Community is measured based on the following information:

Please indicate the number of one-to-one personal contacts you have in the following organizations in which you have been actively involved in the past twelve months:

Professional associations, alumni associations, political associations, religious organizations, ethnically-based organizations, charity associations, activist groups, social/interest clubs, sports teams/associations, and other voluntary associations.

Diversity of Social Networks in the Workplace (Items developed based on Stolle, 1998):

Within your present organization, please indicate the percentage of time you spend, on average, interacting with the following groups of people:

1. People with different races or ethnicities
2. People in different age groups
3. People of the opposite gender
4. People with different professional/functional backgrounds

Social Trust in the Workplace (Items adapted from Yamagishi and Yamagishi, 1994).

Please rate the following items concerning your current workplace on a 7-point scale: (1 = “strongly disagree”, 4 = “neither disagree nor agree”, and 7 = “strongly agree”)

1. I trust a typical employee in this organization
2. It is best not to share concerns or complaints with coworkers because they will probably use this information to harm you (reverse coded)
3. Most employees don’t like to work and will avoid it if they can (reverse coded)
4. Despite what they may say, managers really don’t care if employees lose their jobs (reverse coded)
5. If someone in this organization makes a promise, others within the organization will almost always trust that the person will do his or her best to keep the promise
6. There is a high level of trust throughout this organization