International Journal of Science and Engineering Vol.5 No.2(2015):11-24

Success Catalyst or Hidden Impediment? How does the Time to Market Alter the Innovative Performance Effect of Technological Heterogeneity and Network Resource Asymmetry

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***Abstract* --Research and development (R&D) alliance is of great importance among various strategic alliances in high-tech industries, and it has become a vital strategy for many corporations to achieve competitive advantage in international business. This study aims to examine the links between network resource asymmetries and innovative performance from both economic and social dual perspectives and focusing on biopharmaceutical industries. We found that there are no significant linear or non-linear relationships between technological heterogeneity and innovative performance, while an inverse U-shaped relationship between network resource asymmetry and innovative performance was observed. Furthermore, time to market weakens the positive relationship between network resource asymmetry and innovative performance when the alliance was created by contract without financial investment and biotech-pharm (BP) partner type alliances. Overall, this study makes important theoretical and practical contributions to partner selection literature on R&D alliances in the biopharmaceutical industry.**

Keywords -- Technological Heterogeneity, Network Resource Asymmetry, Time to Market, Innovation, Biopharmaceutical Industry

I. INTRODUCTION

Research and development (R&D) alliances are of great importance in high-tech industries, like the biopharmaceutical industry. Firms engaged in innovation are aware of the necessity of establishing R&D cooperation to obtain access to expertise which cannot be generated in-house. Collaboration with other firms and institutions in R&D is a crucial way to of making external resources usable. It promises efficient resource exchange, knowledge transfer, organizational learning, and economies of scale (Jorde & Teece, 1990; Ahuja et al., 2008; Asakawa et al., 2010). One of the key management challenges in increasing R&D productivity is to raise the percentage of successful compounds in clinical trials, because the success rate is critical factor in valuing an individual drug, or a company's pipeline of drugs (Danzon et al., 2005). Therefore, biopharmaceutical firms invest a greater percentage of their sales in R&D alliance, and such alliances have become an important worldwide mechanism for biotechnology and pharmaceutical firms to excel in drug discovery, development, and commercialization under the pressure of mass resources needed in R&D and increasingly intense global competition.

An R&D alliance is not a guarantee of innovation for bio-pharmaceutical firms. Even though many bio-pharmaceutical firms benefited from R&D alliances, many of these alliances have failed. How come the high failure rate of R&D alliance happened? Prior researchers have proposed that the partner relationship plays a critical role for the performance of R&D alliance, For instance, the selection of the wrong partner, inefficient alliance governance, conflicts between partners, barriers to knowledge sharing, and cultural or economic distance result in inferior performance (Geringer, 1991; Duyster et al., 1999; Hitt et al., 2000; Baum et al., 2010; Islam et al., 2011). Hence, further empirical studies about the effects of partner relationships on alliance's performance were consequently suggested for future research (Lhuillery, 2009; Xia, 2011).

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2015.(5-2).02
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DOI：10.6159/IJSE.

partner is an important variable in the performance of alliance (Parkhe, 1991; Mohr & Spekman, 1994; Park & Ungson, 1997), because it influences the combination of skills and resources which will be available to thealliance and thus the ability of the alliance to achieve its strategic objectives (Geringer, 1991; Li & Glaister, 2006). Selecting the right partner is beneficial for firms' technology and financial performance; the wrong partner is harmful. In R&D alliances, various partners may be involved at different phases and their participation can lead to success or failure. Therefore, a company that launches an R&D alliance has to select its partners carefully.

There have been many studies of regarding partner selection, which is one of the most popular topics in the literature on international strategic alliances. There are several currents in this research field. Shah and Swaminathan (2008) proposed a contingency approach grounded in management control theory that suggests that the criteria that managers use in choosing alliance partners will depend on the alliance project. Roy and Oliver's (2009) research explored how the host-country's legal environment affects the criteria for the selection of international joint venture partners, and found that this environment negatively affects appropriation and coordination cost concerns, but positively influences partner-related criteria.

The second line of research is the effect of the partner's objective conditions, like type (source) of partner, on alliance performance. Belderbos et al. (2006) analyzed the performance effects of simultaneous engagement in R&D cooperation with competitors, clients, suppliers, universities and research institutes, and suggested that the joint adoption of cooperation strategies could be either beneficial or detrimental to firm performance, depending on firm size and strategy combinations.

The most recent stream explores the impact of partner's subjective dimensions, such as the relationship between partners, on alliance performance. Xia's (2011) research, for example, investigated the effects of mutual dependence, partner substitutability and repeated partnership on the survival of an alliance. Goerzen's (2007) research indicated that the negative effect of repeated partnerships on performance is strongest in environments of greater technological uncertainty.

The partner relationships have been regarded as a very important factor on alliance's performance (Belderbos et al., 2004). In response to recent calls for inquiry into the issue regarding the effects of mutual relationships between partners and to explore each research issue thoroughly, this study aims to examine the ways in which partner asymmetry(technological heterogeneity and network resource asymmetry) affect innovative performance from both organizational learning (economic) and social exchange (social) dual perspectives.

II. BACKGROUND AND HYPOTHESES DEVELOPMENT

We take advantages of two theories from both the economic and social perspectives (organizational learning perspective and social exchange perspective) to clarify the effect of technological heterogeneity and network resource asymmetry of alliance on innovative performance. Organizational learning theory expresses substantial technology consideration between partners, but social exchange theory explores mental sensation and interaction between partners.

2.1 Theoretical Background

The concept of organizational learning is a field of organizational theory that studies models and theories about the way an organization learns and adapts. In organizational development, learning is a characteristic of an adaptive organization, one that senses and responds to changes in signals from its internal and external environment (Argyris & Schön, 1978; Huber, 1991; Cyert & March, 1992). Organizational learning theory predicts that a firm's performance of an activity increases with the level of knowledge (Levitt & March, 1988; Argote, 1999; Delios & Beamish, 2001). Organizational search is one part of the organizational learning process through which firms attempt to solve problems in an ambiguous world (Huber, 1991). Organizations engage in a wide variety of searches, such as search for knowledge creation or innovation (Von Hippel & Tyre, 1995) and search for manufacturing methods (Jaikumar & Bohn, 1992; Katila & Ahuja, 2002). In R&D alliances, the technology capability most likely needs technological experience to collaborate with the technology source and to apply the knowledge for innovation (Hoang & Rothaermel, 2005; Sampson, 2005).

The concept of social exchange is defined as "voluntary actions of individuals that are motivated by the returns they bring from others" (Blau, 1964). Unlike macro and micro economic theories, which were designed to examine economic exchanges, social exchange theory was designed to examine interpersonal exchanges that were not considered to be purely economic. As such, the theory analyses people's social behavior in terms of exchanges of resources (Bignoux, 2006). Social exchange theory was developed since Homans' (1958) article "Social Behavior as Exchange." He argued that people are willing continue with certain behaviors is that they have received benefits from those behaviors. Within a dyad relationship, people interact only on the basis of good exchange relationships, and they need to adjust their behaviors dynamically to meet their opponents' requirements under various contingencies (Hallén et al., 1991). Blau (1964) proposed that reciprocity is the crucial element in mutual exchange. The exchange type could be divided into economic and social. The former regards formal contracts, precise principles and practical rewards, such as transaction contracts; the later has no definite obligations, principles and rewards, instead, it is based on trust, such as mental contracts. This concept could be extended to the organizational and inter-organizational levels, like R&D alliance. Within an alliance, economic exchange relationships assess the value of target transaction objects, and emphasize the balance of input and output. However, the key factor in the social exchange relationship is the quality of interaction between partners; in other words, the better the quality, the higher the exchange benefit.

2.2 Technological Heterogeneity and Innovative Performance

Generally speaking, the technology owned by biotech firms (ex. biotechnology) is different from that owned by pharmaceutical firms (ex. synthetic technology). Biopharmaceutical R&D alliance consists of multiple types of partners, including biotechnology firms, two pharmaceutical firms, even universities and government laboratories, and alliances made by divergent types of partners might generate technological heterogeneity. In contrast to alliances between two biotech firms, alliances between one biotech firm and one pharmaceutical firm might have greater technological heterogeneity.

According to the social exchange perspective, exchange is created and maintained by the scarcity of resources, prompting actors to engage with one another to obtain valuable inputs (Das &Teng, 2002). Reciprocal resource commitments and relational influence between partners will ensure collaboration and alliance success (Das & Teng, 1998; Steensma & Lyies, 2000; Muthusamy et al., 2007). Because reciprocity and mutual influence between partners are tangible norms and manifest as mutual control and power sharing or joint decision making, they can supplement trust in collaboration (Steensma & Lyies, 2000). Partners are willing to exchange their knowledge once they predict that they can benefit from it. R&D alliances made by firms with high technological heterogeneity might help them to have divergent knowledge pooling and to establish the essential conditions of knowledge exchange. Technological heterogeneity contributes to knowledge exchange because partners would like to access and integrate knowledge that their rivals possess and they themselves do not. The interaction of knowledge is the most important ingredient of knowledge creation and innovation, and the higher level of technological heterogeneity is an incentive, which would trigger the knowledge exchange (Lin & Huang, 2010; Bertsch et al., 2011). For instance, when a pharmaceutical firm with synthetic technology forms a R&D alliance with a biotech firm with biotechnology, the pharmaceutical company may contribute to the synthetic technology about screening the molecular structure of drug; conversely, the biotech firm may use its biotechnology about gene transfer and duplication to develop new products.

Organizational learning theory helps us to understand the difference between homogeneous and heterogeneous technology. Through various types of technology searches, an organization could choose the right technology to access and learn from R&D alliances, and then enhance its innovation speed. A technology search could be local search or distant (Stuart &Podolny, 1996; Rosenkof & Nerkar, 2001). A local search focuses on homogeneous technology, creates incremental innovations, and becomes more expert in its domain (Rosenkof & Nerkar, 2001). In distant research, firms focus on other kinds of heterogeneous technology. Previous studies have indicated that firms could easily accumulate expertise and acquire competitive advantages from local searches. Other empirical studies have found a linearly positive relationship between local search and the frequency of exploratory innovation (Methé, Swaninathan, & Mitchell, 1996). At the same time, a distant search leads to recombination inefficiency, because technological heterogeneity increases knowledge integration costs and time (Katila & Ahuja, 2002). The more divergent the knowledge to be integrated, the more complex the problems of creating and managing integration (Grant, 1996). In terms of the innovative performance of R&D alliance, cooperation with partners that have homogeneous technology can enable firms to adopt local searches and create incremental innovations through the development of routines, and to generate innovation more easily than distant search.

Actually, both too much and too little technological heterogeneity may be detrimental to innovation. As mentioned above, local search helps firms to access homogeneous technology, to increase technology capability and development of routines, and to speed up innovation. However, the competence made by local search might lead firms to develop core rigidities or fall into competency traps (Levitt & March, 1988; March, 1991; Leonard-Barton, 1995; Rosenkof & Nerkar, 2001), because those organizations exploit only the value of existing knowledge (Cohen & Levinthal, 1990), and organizations with homogeneous resources have limited opportunities for development. However, even though technological heterogeneity triggers the exchange of technology, and the acquisition of heterogeneous technology by distant search also contributes to the probability of successful R&D, leaning heterogeneous technology from a partner is not easier than learning homogeneous technology, because more time and money must be invested in learning it. In addition, heterogeneous technology is not readily integrated, because every technology has its limits, especially for biopharmaceutical high-technology. Recent developments in research on absorptive capacity contradicts this point of view, for which there is an enhanced role for absorptive capacity as a facilitator for more distant search, thus enabling more explorative learning (Lavie & Rosenkopf, 2006). Furthermore, the majority of conflicts of alliances happened when partners had different technology and objectives.

We argue that technology heterogeneity between partners will be both beneficial and harmful to innovation speed. When a biotechnology company allies with a pharmaceutical company, they might have a better innovation speed, since they have heterogeneous technology; however, extremely different technology comes at a high cost and difficulty of integration and cooperation.

H1: Technological heterogeneity has a curvilinear (inverted U-shaped) relationship with innovative performance, with the slope positive at low levels of technological heterogeneity and negative at high levels of technological heterogeneity.

2.3 Network Resource Asymmetry and Innovative Performance

Alliance activity is a way for companies to obtain external resources from partnerships. A prospective partner's resources are a factor that a firm has to consider. Apart from internal resources like assets, number of employees, number of patents, and financial returns, external resources like number of alliance partners is also an important consideration. The number of friends an organization has is a good indicator of its external social resources. A company with more friends has higher status and a better reputation in the industrial structure. Once a company makes an alliance with a partner that has more friends, it has access to more resources. In a dyadic alliance, the distance of partner's number of alliance partners could be observed. When the distance is small, we have a "matched dyad," otherwise, a "non-matched dyad." "Matched dyads" include alliances of two firms with abundant network resources or two firms with limited network resources; "non-matched dyads" include alliances made by one firm with abundant network resources and one firm with limited network resource.

In general, the larger technology (R&D) alliance network has broader technology (knowledge), and the smaller technology (R&D) alliance network has deeper technology (knowledge). According to the organizational learning perspective, local search encourage firms to integrate similar knowledge and to generate synergy, which deepens technology, while distant search allows firms to integrate divergent knowledge and generate radical innovation, which widen the scope of technology (Katila & Ahuja, 2002). "Matched dyads" might have large technology scope ("large-large" network resource) or deep technology ("small-small" network resource); while "non-matched dyads" have both wide and deep technology ("large-small" network resource). Both "search depth" and "search scope" enable firms to achieve innovation, however, the possession of both deep and large network resources enable R&D alliances to become more innovative more easily, because those alliances have high quality (depth) and number (scope) of technology. Therefore, greater network resource asymmetry ("non-matched dyad") is helpful for biopharmaceutical R&D alliance, because they have a combination (interplay) of high technology depth and scope.

The "matched dyad" in a R&D alliance could be explained with reference to social exchange theory. Within a dyadic alliance, the effort one partner would like to put in the alliance is related with its cognition of its partner's input. Once the inputs from both sides are not equal, the conflicts between partners may be occurred, and their innovation speed and performance of alliance would be influenced accordingly. This phenomenon was easily happened in "non-matched dyad," because one who has more alliances need to be deal with has less attention on this target alliance, and it would not pay full effort to the alliance due to the perceived unfairness. On the contrary, "matched dyad" with relatively equal resource will trigger partners to put more effort to the R&D alliance and initiate more innovation. In this case, "matched dyad" might be a more stable alliance than a "non-matched dyad."

On the bases of these perspectives, we propose that moderate level of "matched dyad" is beneficial for innovation, because too many "matched dyads" have only technology depth without a combination of depth and scope (economic perspective) and too many "non-matched dyads" reduce social exchange (reciprocity) (social perspective).

H2: Network resource asymmetry has a curvilinear (inverted U-shaped) relationship with innovative performance, with the slope positive at low levels of network resource asymmetry and negative at high levels of network resource asymmetry.

2.4 Moderating Effects of Time to Market

R&D alliances generated along the product development states. Early-stage collaborations within the biopharmaceutical industry are vital in driving innovation evolution through therapeutic and technological diversification (Belsey & Pavlou, 2005). DiMasi (2002) examines the financial benefits that can accrue to drug developers from improvements in drug development. He proposed that whether faster development times, quicker termination decisions or higher success rates derive from public policy initiatives, better management, or new technologies, the impact on R&D costs can be substantial. Ultimately, increased efficiency could result in more innovation and new therapies reaching patients sooner.

The effects of technological heterogeneity on innovative performance are supposed to be different for divergent stages of collaborating products. In many cases, the technology behind earlier-stage product belongs to academic and fundamental technology, such as basic chemical structure analysis, biological identification technology, because early-stages along with the development process focus on finding active substances and exploring their toxicity, only single basic technology is needed for those products. On the contrary, it is necessary that companies integrate heterogeneous technology for developing later-stage products, because more complicated technology should be applied to examine the toxicity, safety and effectiveness during the later stages. For example, theaims for developing phase II or phase III products consist evaluating safety, appropriate dosages, potential side effects for numerous patients in the clinical trials, and complicated technology like pharmacokinetics, gene transferring, monoclonal antibodies hybridism technique and other testing technology for clinical trials. Therefore, technological heterogeneity in R&D alliance is more important for developing later-stage products than those of earlier-stage products in order to reach innovation easily and efficiently.

H3: Among alliances which focus on new products closer to commercial stage, the technological heterogeneity between partners leads to better innovative performance.

Likewise, partner network resource asymmetry is more crucial for developing later-stage products than those of earlier-stage products. As mentioned above, "non-matched dyads" have both wide and deep resources and capabilities, because the combination of both "search depth" and "search scope" enable firms to achieve innovation more easily. Take a R&D alliance made by a firm with a large network resource and a firm with a small network resource as example, the alliance has both wide and deep technology as well as divergent capabilities, experiences, and even financial supports, and these resources help partners gain innovation easily. Hence, we argue that the stage of product affects the relationship between network resource asymmetry and innovative performance, and the network resource asymmetry is more demand for reaching innovation when the collaborating product is in the later stages.

H4: Among alliances which focus on new products closer to commercial stage, the network resource asymmetry between partners leads to better innovative performance.

III METHODOLOGY

These studies have extended our understanding of partner selection in strategic alliances. Drawing on a range of perspectives, the present study explored the effects of technological heterogeneity (distance of technology) and network resource asymmetry (distance of network resource) on innovative performance. We also examined the indirect moderating effects of "time to market" on the previous relations. Furthermore, several factors, including alliance type, prior cooperation experience, time of contract and partner type were used as control variables in this study.

The considerations motivated the choice of the biopharmaceutical industry as the setting of the study. First, biotechnology and pharmaceutical firms invest a greater percentage of sales in R&D than any other industry (Danzon et al., 2005). Technological innovation behavior in the biopharmaceutical industry appears more often than it does in other industries. Second, R&D alliances have become an important mechanism for drug discovery, clinical trials, development and commercialization (Audretsch & Feldman, 2003; Xu, 2006).

3.1 Data Collection

We use data from the REDCap (Research Electronic Data Capture) database to obtain essential information about R&D alliances, including partner's name, core technology of firms, co-patent from each alliance, time of alliance, the number of alliance, size of alliance, type of parties, and clinical stage. REDCap (Research Electronic Data Capture) is an EDC software package available to academic institutional partners of Vanderbilt University. It is not open source, and the license specifically prohibits using REDCap as the basis for providing a contract service to any commercial (for profit) entity. REDCap originated out of the Vanderbilt Institute for Clinical and Translational Research. It is a web-based system for data collection. Data entry operators enter data in a web browser, either locally or from remote locations. The data is stored centrally in a secure MySQL database.

There are several criteria for exclusion and inclusion. Our data set analyzes the R&D alliance activity of bio-pharmaceutical firms and research institutes from 1981 to 2010. It includes all medical treatment products for human beings (drug and diagnosis reagent), and excludes all medical prevention products (medical electric devices). In addition, is limited to alliances that have only two members and excludes those alliances with three members or more. We select only alliances with at least one co-patent. Data with many missing values were excluded. Since the majority of parties belong to three categories: biotech-biotech (BB), academic-biotech (AB) and biotech-pharmaceutical (BP), only these types of alliance were included in our research.

3.2 Measures

3.2.1 Dependent Variable

<u>Number of Co-patents</u>

A patent represents a company's capability of innovation, technology and production (Griliches, 1990). For this reason, number of patent is a reliable indicator of innovative performance. Since this research is about alliances, not firms, the research used the number of co-patents as a measurement of the quantity innovative performance of alliance.

3.2.2 Independent Variables

(1) Technological heterogeneity

This research used the data of main technology category for each organization in REDCap database to recognize the discrepancy in technology between partners within the alliance. Five levels of technological heterogeneity were classified: low, lower medium, medium, higher medium and high technological. Since REDCap database uses the name of technology rather than technical code system to identify different technologies of firms, and there is no linkage between the name of technology and technical code in other database, we used the following criteria and process which was agreed upon by experts in the biotech and pharmaceutical technology fields to identify and categorize partners' technology. First, each technology was divided into biotech and synthetic two groups. The scores from one to three were given to those partners' technology that belonged to the same group, otherwise, scores from three to five were given. Second, biotechnology was subdivided into two subgroups: basic technology (ex. DNA, RNA, proteins, peptides, monoclonal antibody…) and applied technology (ex. stem cells, gene therapy, vaccines…); synthetic technology was subdivided into two subgroups: basic technology (ex. molecular structure, receptors/inhibitors…) and applied technology (ex. drug delivery, support anti-cancer agent, diagnosis…). According to whether or not partners' technology are always the same (1), belong to the same subgroup (2), belong to the same group but different subgroups (3), belong to different groups but both of them are either basic or applied technology (4), totally different groups and subgroups (5), the final score of technological heterogeneity was given to each alliance.

(2) Network resource asymmetry

The number of prior alliance (friends) an organization has is a good indicator of its external social resources. A company with more alliance (friends) has larger network scale. In this research, the distance of partners' number of alliance was used to measure the asymmetry of network scale for each alliance. We first counted each partner's number of alliance prior to the target alliance, and then used following formula to measure the value of network resource asymmetry.

$$\textit{Network resource asymmetry} = \sqrt{\left|\,\textit{Partner A's number of alliance prior to the target alliance} - \textit{Partner B's number of alliance prior to the target alliance}\,\right|}$$

3.2.3 Moderating Variable

Time to market

This research uses the stage of clinical trial of production to analyze the time to market. There are nine types of stage of clinical trial of production in REDCap database, and it is based on the process of drug development: "Formulation," "Discovery," "Lead Molecule," "Preclinical," "Phase I," "Phase II," "Phase III," "BLA/NDA Filed," and "Approved." We assigned number 9 (long time) to 1 (short time) for to represent time to market.

3.2.4 Control Variables

(1) Alliance Type (Contract or Joint Venture)

We obtained the information about whether the alliance contains capital transaction from the REDCap database. We assigned 0 to those alliances that belonged to contract (without capital transaction), and 1 to those belonged to a joint venture (with capital transaction).

(2) Prior Cooperation Experience

This variable represents whether the target dyadic partners has had cooperation experience before the alliance. If the target alliance is the first cooperation within our collected data, we assume that they have 0 prior cooperation experience. Likewise, if the target alliance is not the first cooperation, we assume that they have at least 1 prior cooperation experience.

(3) Time of Contract

We gained the data about the year of contract for each alliance from REDCap database. Each time of contract was categorized into three groups: 1981-1990, 1991-2000 and 2001-2010. Since the variable belongs to category variable, this research took advantage of the dummy variable method before running the regression.

(4) Partner Type

In this research, there are three categories of alliance: biotech-biotech (BB), academic-biotech (AB), biotech-pharm (BP). Since the variable belongs to category variable, this research used the dummy variable before conducting the regression.

3.3 Analysis Approach

Negative binomial regression method was used in this study, since number of patent is times of event and belongs to count data, which are not continuous data with the same distance among each scale. The negative binomial regression method was often used for those sample with larger variance compared with the mean or there might be cluster for collected samples. In addition, this research carried out interaction analysis by moderators (time to market) to see the indirect effects among variables, since it might significant affect the innovation performance. Moreover, we also used alliance type (contract or joint venture), prior cooperation experience, time of alliance and partner type as control variables in this study. In the mean time, this research also used these control variables to be the subgroups, and to see the correlation between independent and dependent variables under various subgroups and conditions. For category data, this research used the dummy variable method before running regression. In order to achieve the research purposes and test the hypotheses, this study used SAS and STATA software for data analysis.

IV. RESULTS

4.1 Descriptive Statistics

The sample size of this study is 506 dyad R&D alliances: 102 in 1981-1990, 339 PubMed in 1991-2000 and 65 in 2001-2010. Among 506 dyad alliances, 148 are AB type, 98 are BB type, and 260 are BP type. The mean of technological heterogeneity is 3.25; the mean of network resource asymmetry is 5.03; the mean of number of co-patents following the R&D alliances is 8.01. The descriptive statistics with means, standard deviations and correlations of variables regarding research in technology discrepancy are depicted in Table 1.

[Insert Table 1 here]

4.2 Regression Results

Table 2 presents the results of negative binomial regression. The second model reports the effects of alliance types (contract or joint venture), prior cooperation experience, time dummy, partner types included and time to market as controls. This model served as a baseline from which the analysis proceeded. From model 3 to 6, we introduced technological heterogeneity to assess the possibility of its linear and nonlinear effects on innovation quantity. However, we did not find any significant relationships about them.

In model 7, we introduced network resource asymmetry to assess the possibility of its linear effects on innovation quantity, and we found a significant positive relationship between them. Then, we introduced network resource asymmetry and its squared term to assess the possibility of its nonlinear effects on innovation, and a significant downward curve correlation (inversed U-shape) between network resource asymmetry and number of co-patent following the alliance was observed ($\beta1= 0.12$, $p<0.01$; $\beta2= -0.01$, $p<0.05$) (Model 9 and Figure 1). The regression equation is as follows:

Number of co-patents *= 1.46 + 0.45 (Alliance Type) – 0.16 (Prior Cooperation Experience) + 0.06 (Time of Contract [1991-2000 vs. 1981-1990]) – 0.26 (Time of Contract [2001-2010 vs. 1981-1990]) + 0.11 (Partner Type [BB vs. AB]) – 0.04 (Partner Type [BP vs. AB]) – 0.02 (Time to Market) + 0.12 (Network resource asymmetry) – 0.01 (Network resource asymmetry)*^{2} *+ e.*

Even though the moderating effect of “Time to market” on the above linear relation between network resource asymmetry and innovation quantity was not observed (model 8), the results of subgroup analysis indicate that “Time to market” weakens the previous positive linear relationship when the alliances belong to contract rather than joint venture ($\beta1= 0.17$, $p<0.05$; $\beta2= -0.02$, $p<0.1$) (Model 11 and Figure 2) and when the alliances were made by a biotechnology firm and a pharmaceutical firm (BP type) ($\beta1= 0.09$, $p<0.1$; $\beta2= -0.01$, $p<0.1$) (Model 12 and Figure 3).

[Insert Table 2, Figure 1-3 here]

V. Discussion

Our hypotheses were developed on the basis of organizational learning theory, social exchange theory and practical ratiocination. It appears that some but not all of the hypotheses could be partially explained by established theories and practical points of view. In this section, we analyze our empirical results and discuss their implications.

According to our statistical results, we did not find a significant linear or inversed U-shaped non-linear relation between technological heterogeneity and innovation quantity, so Hypothesis 1 was not supported. In other words, technological heterogeneity of alliance has no important influence on innovation quantity.

According to the argument for Hypothesis 1 from social exchange perspective, technological heterogeneity contributes the interaction of knowledge and technology between partners due to the generation of reciprocity, which increases the innovation quantity. From organizational learning perspective, even though making alliances with high technological heterogeneity will create opportunities for a distant search, recombination inefficiency would be generated quite often due to the difficulties of integrating various types of technology, and it reduces the innovation quantity. However, above argument could only used to interpret the linkage between technological heterogeneity and innovation speed, rather than innovation quantity, which means technological heterogeneity makes innovation more efficiency, but it is not much helpful on the long-term innovation quantity. On the other hand, making alliances with higher technological heterogeneity will not have more opportunity to get a lot of innovation output. Undeniably, both social exchange perspectives and organizational learning are still useful explanations for overall conditions, since we did not find significant positive or negative linear relations between technological heterogeneity and innovation quantity for all cases.

According to the statistical results, we found a significant inverse U-shaped non-linear relation between network resource asymmetry and quantity of co-patent following the alliance, which supports Hypothesis 2. R&D alliances with moderate network resource asymmetry benefit more from innovation than do alliances with very low or very high levels of network resource asymmetry. In other words, both too low or too high network resource asymmetries result in poor innovation.

The larger network resource asymmetry (“non-matched dyad”) is helpful for biopharmaceutical R&D alliance from organizational learning perspective, because alliances with large network resource asymmetry have combination of high technology depth and scope immediately. However, too much “non-matched dyad” is worse than “matched dyad” for innovation due to the perceived unfairness, based on the social exchange theory. Our statistic results partially confirmed this finding, because either asymmetry or non-asymmetry can increase the innovation. Therefore, both organizational learning and social exchange perspectives are useful explanations.

This result is inconsistent with several previous studies of the asymmetry within alliances. For example, Veugelers and Kesteloot (1996) explored the asymmetry of size, R&D capability and production issues. They argued that the asymmetry between partners will influence the incentives to form a joint venture through their impact on the payoffs of own development. In addition, the larger the size of asymmetry, the larger (smaller) the big (small) firm's development profits. With lower asymmetries, profits in all scenarios are affected negatively (positively) for the big (small) firm.

In Hypothesis 3, we proposed that time to market moderates the linear relationship between technological heterogeneity and quantity of innovative performance, however, this relationship was not observed. So Hypothesis 3 was not supported. In Hypothesis 4, we proposed that time to market moderates the linear relationships between network resource asymmetry and quantity of innovative performance, so that the correlations are affected by the clinical development stage of products. Although there is no significant moderating effect of time to market overall, the results of subgroup analysis indicate that time to market weakens the positive relationship between network resource asymmetry and innovation quantity when the alliance was created by contract without financial investment. Figure 2, show that network resource asymmetry is beneficial for the innovation quantity of later-stage products (negative slope) but is a little bit detrimental for that of earlier-stage products (positive slope) under specific conditions (contract type alliances). Similarly, for BP type R&D alliances, the beneficial effects of network resource asymmetry on innovation quantity become more obvious (larger slope) when the target product is closer to market. In other worlds, for those R&D alliances focusing on later-stage products, selecting partners with higher network resource asymmetry benefits their future innovation quantity (figure 3). Therefore, H8 was partial supported.

Several researchers have explored the role of the stage of new product development on the outcomes in biopharmaceutical industry. Frahm et al. (2007) argued that the success of a new product depends on the stage of product discovery pipeline. They proposed that firms have to adapt divergent strategies and behaviors on products in different stages. Some previous studies suggested that later stage biopharmaceutical products have higher potential for innovation and success than earlier stage products (Vanderbyl & Kobelak, 2007). However, our results further indicate that R&D alliances focusing on early products gain more innovation than late products; while the network resource asymmetry helps partners receive more co-patents for later products. In other words, the stage of new product development moderates the relationship between network resource asymmetry and quantity of innovative performance, especially for those products closer to market.

The study contributes to the literature in many ways. First, based on organizational learning theory (economic perspective) and social exchange theory (social perspective) these two lenses, as well as practical logics, we designed an integrated framework to explain a complex phenomenon, presented our arguments, developed our hypotheses, and clarify the effects of technological heterogeneity and network resource asymmetry on innovation speed. Second, the unit of analysis should emphasize the selection of an alliance partner. Dyadic approach is a better than a firm-specific one, since selecting optimal partner merely relies on the perspective from only one of partners is inadequate; while the dyadic approach for partner asymmetry study is more objective. Following this trend, we look at the technological heterogeneity and network resource asymmetry in dyadic approach instead of using one partner's resource as a research object. Third, in terms of the measurement of alliance performance, most previous studies rely on financial indicators, market value, and patents of distinct partners rather than on the performance of the alliance itself (e.g. Lunnan & Haugland, 2008; Gulati et al., 2009; Lin et al., 2009; Chiesa et al., 2009; Jiang et al, 2010; O'Regan & Kling, 2011). However, the measurement of individual performance might not reflect real outcomes of the alliance. This study uses "innovation of target alliance" as the construct of performance of alliance in order to measure the outcomes more precisely. Forth, we often see alliances composed of both biotechnology firms and pharmaceutical firms or of both universities and biotechnology firms. In fact, beyond inter-firm alliance, the R&D cooperation has been made by universities or academic institutions and bio-pharmaceutical firms. Since this study covers academic institutions, biotechnology firms, and pharmaceutical firms, the finding will broaden the choices for diversified organizations in this industry. The results of this study contribute to the industry's future decision making of partner selection. Finally, this study discusses the effects from multiple perspectives, at the industrial (partner type), organizational (prior cooperation experience and timing of alliance), and product levels (the stage of products). Over the past couple of years, the emergence of biotechnology has provided another new technology for drug development. In the real world, these factors influence innovative performance of alliance. These results might also provide several helpful suggestions for partner selection of biopharmaceutical R&D alliances.

Despite its findings, the study does have some limitations. First, this study has proposed that partner asymmetry on technology and network resource should be considered before forming a R&D alliance. However, this study is concerned with technological heterogeneity and network resource asymmetry, and focused on the effect of these factors on innovation. These points are not only ways to select a partner. Other factors to be considered are partner's complementary experience, government model, stockholders' characteristics, shared values, reciprocity. Much more also needs to be known about other determinants of innovative performance. Further, this study provides a descriptive basis for additional research. Fine-grained future research will provide additional insight into the issue of partner selection for a strategic alliance. Moreover, even though we explored the innovative performance, the patents acquired by firms do not capture the full value of underlying innovations (Griliches, 1990; Sampson, 2007). Other indicators like quality of innovative permanence might be useful for understanding the impacts of various factors on innovation of R&D alliance. As empirical evidences increasingly show a strong correlation between the citations of a patent and the estimated value of the underlying invention (Trajtenberg, 1990), the more comprehensive measurements combined quantity, quality and speed are suggested for future studies.

VI. Conclusion

With the development of bio-pharmaceutical technology, R&D alliances provide companies with another way to integrate resources, knowledge and technologies, create more research and business ideas, and facilitate innovation. Despite many studies on partner selection of R&D alliance, less research has been done on topics of technological heterogeneity and network resource asymmetry. This study explored the relationships among these factors and presents the empirical results. We have developed a research framework and developed hypotheses which were tested by quantitative analysis approach using secondary data. The results confirm that there is an inverse U-shaped (non-linear) relationship between network resource asymmetry and innovative performance, while the effect of technological heterogeneity on innovative performance was not significant. Appropriate asymmetries of technology and network resource are suggested to be strategies for partner selection in order to get better innovative performance. Moreover, considering various factors and conditions prior to making decision is helpful for innovation of R&D alliance.

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BIOGRAPHIES

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Table 1. Results of Correlation Analysis

		Mean	Std. Dev.	C1	C2	C3a	C3b	C4a	C4b	M	X1	X2	Y
C1	Alliance Type (Contract or Joint Venture)	0.88	0.33	1									
C2	Prior Cooperation Experience	0.08	0.27	0.06	1								
C3a	Time of Contract (1991-2000 vs 1981-1990)	0.67	0.47	0.15	0.003	1							
C3b	Time of Contract (2001-2010 vs 1981-1990)	0.13	0.33	(-) 0.16	0.04	(-) 0.55	1						
C4a	Partner Type (BB vs AB)	0.19	0.4	(-) 0.12	0.04	(-) 0.05	0.34	1					
C4b	Partner Type (BP vs AB)	0.51	0.5	0.06	0.04	0.02	(-) 0.11	(-) 0.5	1				
M	Time to Market	6.43	2.06	(-) 0.05	(-) 0.04	(-) 0.01	(-) 0.15	(-) 0.1	0.03	1			
X1	Technological Heteogeneity	3.25	1.19	0.04	0.06	(-)0.01	0.04	(-) 0.29	0.82	0.07	1		
X2	Network Resource Asymmetry	5.03	3.67	0.02	0.07	0.01	0.03	(-) 0.17	0.45	(-) 0.06	0.36	1	
Y	Number of Co-patent	8.01	10.28	0.1	(-) 0.03	0.08	(-) 0.07	0.01	0.006	(-) 0.03	(-)0.01	0.06	1

+ p< .10; * p < .05; ** p < .01; *** p < .001

Table 2. Results of Negative Binomial Regression (n=506)

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
												Contract	BP		
constant		1.61***	1.77***	1.83***	2.42***	2.03***	2.20**	1.66***	1.56***	1.46***	1.72***	1.32+	0.89+	1.50***	1.84*
C1	Alliance Type (Contract or Joint Venture)	0.43**	0.43**	0.43**	0.40**	0.44**	0.41**	0.43**	0.44**	0.45**	0.46**		0.43*	0.44**	0.45**
C2	Prior Cooperation Experience	(-) 0.13	(-) 0.14	(-) 0.13	(-) 0.14	(-) 0.13	(-) 0.15	(-) 0.14	(-) 0.14	(-) 0.16	(-) 0.17	(-) 0.23	(-) 0.41+	(-) 0.14	(-) 0.15
C3a	Time Dummy (1991-2000 vs 1981-1990)	0.09	0.07	0.08	0.09	0.1	0.11	0.06	0.06	0.06	0.06	(-) 0.60*	0.2	0.07	0.09
C3b	Time Dummy (2001-2010 vs 1981-1990)	(-) 0.19	(-) 0.23	(-) 0.20	(-) 0.19	(-) 0.17	(-) 0.18	(-) 0.26	(-) 0.25	(-) 0.26	(-) 0.26	(-) 0.54	(-) 0.16	(-) 0.22	(-) 0.22
C4a	Partner Type (BB vs AB)	0.15	0.15	0.17	0.17	0.2	0.19	0.13	0.14	0.11	0.11	(-) 0.19		0.13	0.15
C4b	Partner Type (BP vs AB)	0.04	0.05	0.16	0.15	0.14	0.14	(-) 0.04	(-) 0.04	(-) 0.04	(-) 0.06	(-) 0.18		0.04	0.01
M	Time to Market		(-) 0.02	(-) 0.02	(-) 0.11+	(-) 0.02	(-) 0.05	(-) 0.02	(-) 0.004	(-) 0.02	(-) 0.06	0.1	0.10+	(-) 0.01	(-) 0.05
X1	Technology Heterogeneity			(-) 0.02	(-) 0.23	(-) 0.24	(-) 0.08							0.02	(-) 0.12
X1^2	(Technology Heterogeneity)^2					0.03	(-) 0.02								(-) 0.02
M1*X1	(Time to Market)*(Technology Heterogeneity)				0.03		(-) 0.01								(-) 0.01
M1*X1^2	(Time to Market)*(Technology Heterogeneity)^2						0.01								0.01
X2	Network Resource Asymmetry							**0.03***	0.04	**0.12****	(-) 0.03	**0.17***	**0.09+**	0.08	0.12*
X2^2	(Network Resource Asymmetry)^2									**(-) 0.01***	0.01				(-) 0.001
M*X2	(Time to Market)*(Network Resource Asymmetry)								(-) 0.003		0.02	**(-) 0.02+**	**(-) 0.01+**		(-) 0.004
M*X2^2	(Time to Market)*(Network Resource Asymmetry)^2										(-) 0.002				(-) 0.001+
X1*X2	(Technology Heterogeneity)*(Network Resource Asymmetry)													(-)0.01	
	N	506	506	506	506	506	506	506	506	506	506	62	260	506	506
	Log Likelihood	(-) 1577.13	(-) 1576.58	(-) 1576.33	(-) 1574.97	(-) 1575.75	(-) 1574.62	(-) 1574.59	(-) 1574.48	(-) 1572.36	(-) 1571.54	(-) 157.83	(-) 807.20	(-)1573.80	(-) 1569.18

+ p< .10; * p < .05; ** p < .01; *** p < .001

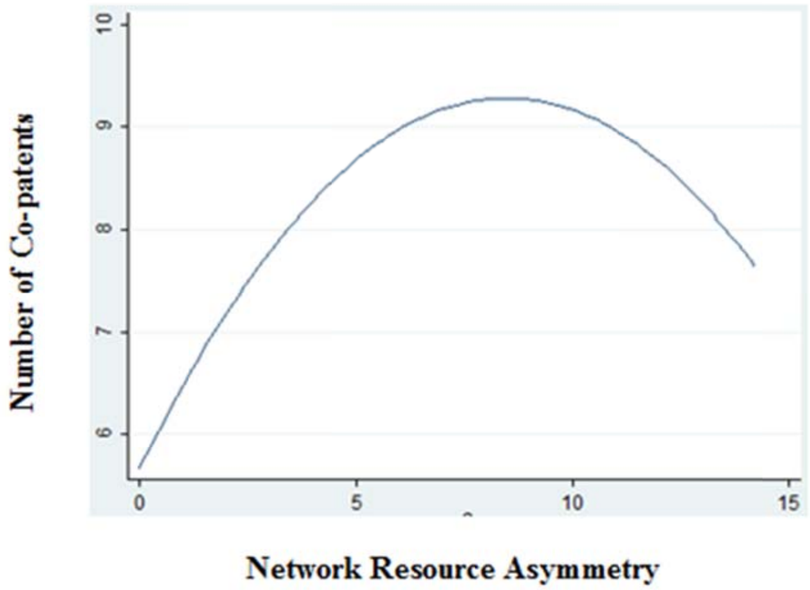

Figure 1. The relationship between network resource asymmetry and innovative performance (full sample)

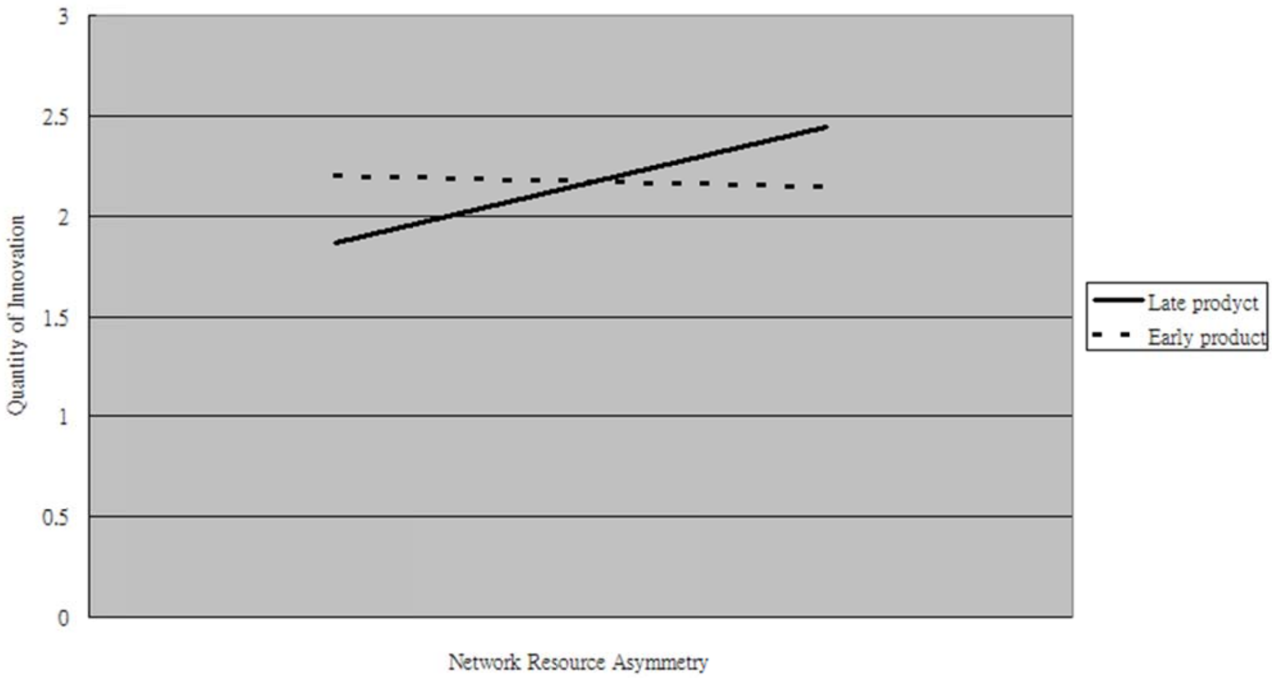

Figure 2. The moderating effect of time to market on the relationship between network resource asymmetry and innovation quantity (Contract)

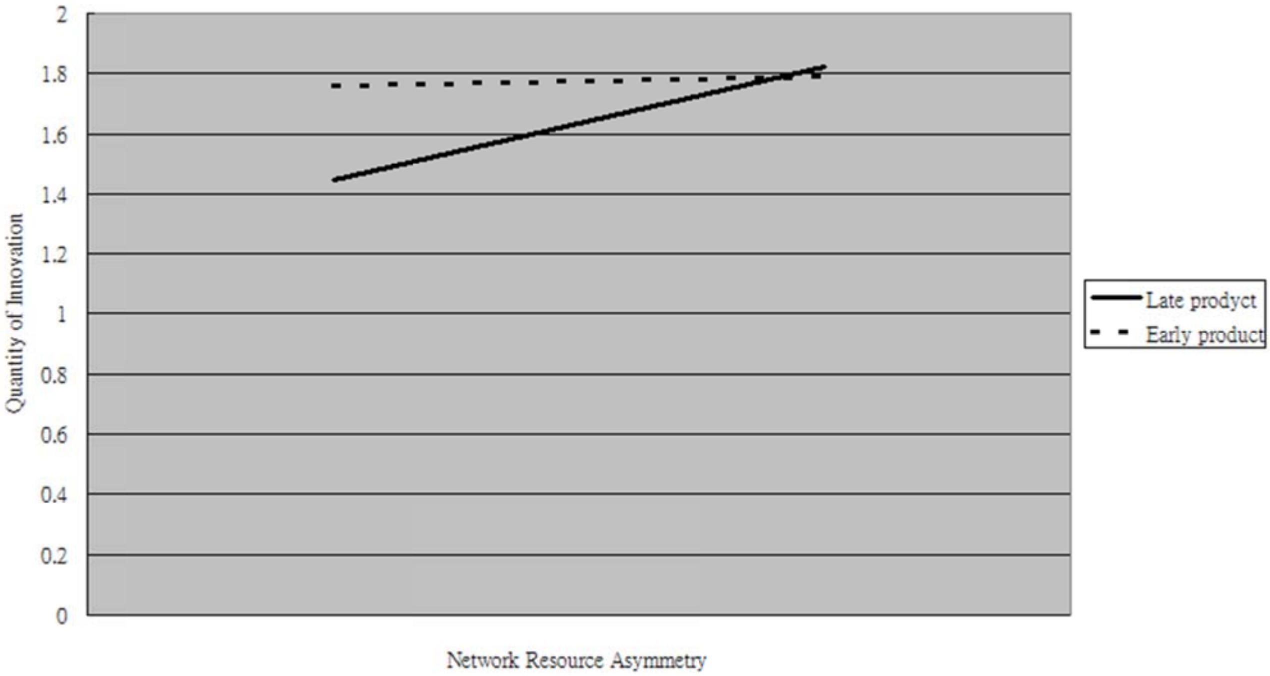

Figure 3. The moderating effect of time to market on the relationship between network resource asymmetry and innovation quantity (BP)