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Corporate R&D Alliance and Innovation

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Abstract

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This paper studies on factors influencing the relationship between a focal firm's R&D alliance portfolio diversity and its knowledge acquisition from the portfolio (study I) and factors influencing joint innovation performance of multiparty alliances(study II).

Drawing upon organizational learning theory and transaction cost economics, I tested the effect of technological diversity of a firm's R&D alliance portfolio on its knowledge acquisition and examined the condition that a focal firm can raise benefit while reducing costs generated from the diversity of alliance portfolio in order to investigate the cost-effective composition of R&D alliance portfolio in study I. In study II, I examined the factors influencing joint patenting performance to which all of the participants in a multiparty R&D alliance contribute. I examine the effects of diversity in a multiparty alliance, attributes of ties composing the multiparty, and governance structure of the alliance with data of high-tech manufacturing firms during the period 1987-2013.

For empirical tests, I constructed a data set comprising the R&D alliance and patenting activities of firms in four high-tech manufacturing industries: semiconductor, electronics, computer manufacturing, and telecommunications industries. I construct the data set from the SDC (Securities Data Company) Database on Joint Ventures and Alliances and the USPTO (United States Patent and Trademark Office) database.

The results in study I shows that alliance are important to the global high-tech manufacturing industries to source diverse external knowledge and accelerate firm innovation as the data represents, but the learning benefits diminish with too much diversity in alliance portfolios due to increasing transaction costs. This study also highlight the trade-offs in managing diverse alliance portfolio between learning benefits and managerial complexity and costs. Greater technological diversity of alliance portfolios can be beneficial and contribute to knowledge acquisition of a focal firm when the firm includes technologically and culturally close partners in its R&D alliance portfolio. The results of study II shows that firms in multiple R&D alliance portfolios which has the moderate level of national diversity is most likely to succeed in jointly create innovative outcomes. Also, I found significant effects of multiple ties on joint patenting. Next, the results in this study suggest that a multiparty alliance which has a lot of co-opetition ties will exhibit lower possibility of joint patenting of members.

Keywords: R&D alliance, Alliance portfolio, Multiparty alliance, Knowledge acquisition, Joint patenting, Transaction cost economics, Organizational learning theory

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Chapter I.

Introduction

1. Research Objective

The dramatic growth of strategic alliances has been one of the most lasting features of the business world over the last two decades. Main reasons are that competition is increasingly knowledge-based and the life-cycles of technology become shorter, as firms strive to learn and to develop capabilities faster than their rivals (Prahalad and Hamel, 1990; D'Aveni, 1995; Teece and Pisano, 1994). These trends in today's business world has made it nearly impossible for any firm to build and sustain its technological competitive advantage without utilizing external knowledge and technologies. This is because the time between the identification of a problem and its arrival may not allow the firm to internally develop the knowledge and capabilities needed to respond effectively (Dierickx and Cool, 1989). This has led to a shift from traditional resource or risk-sharing alliances to alliances with learning from partners as a primary goal such as R&D alliances (Hamel, 1991; Huber, 1991). Such alliances for 'learning' enable firms to speed up capability development and minimize the inherent risks and uncertainties associated with technological innovation by acquiring and exploiting knowledge developed by other firms (Grant and Baden-Fuller, 1995).

For these reasons, firms in many high-tech industries, such as electronics, computer, semiconductors, telecommunications, are increasingly engaging in a wide array of R&D alliances to source external knowledge and accelerate innovation (Rigby and Zook, 2002; Wassmer, 2010). In addition, there is increasing demand for technology or products which need diverse knowledge to be integrated, forcing firms in technology-intensive industries to engage in multiple R&D alliances simultaneously with different partners in industry, technology, and even nationality. Also, among those R&D alliances, the number of multiparty alliances increase.

Researchers define the set of multiple alliance partners with which a focal firm sustain partnership at a certain period of time (usually in a year) as the focal firm's alliance portfolio (George et al., 2001; Bae and Gargiulo, 2004; Hoffmann, 2005, 2007; Lavie, 2007; Lavie and Miller, 2008). While partner firms in an alliance portfolio are independent with the other partners, a focal firm which has multiple different R&D alliance partners are facing the challenge to manage its alliance portfolio as a whole (Doz and Hamel, 1998; Gulati, 1998; Anand and Khanna, 2000; George et al., 2001; Bamford and Ernst, 2002; Hoffman, 2005, 2007; Lavie, 2007; Ozcan and Eisenhardt, 2009). For the focal firm, R&D alliance partners are not only the source of diverse knowledge, but also the relationship to manage and maintain which requires a great deal of efforts (Madhok and Tallman, 1998).

Multiparty R&D alliances also, provide several benefits for participating firms (De Rochemont et al., 2007). First, increasing the number of partners also raises the benefits the alliance may generate. In a multiparty alliance, the amount of resources pooled by the partners increases and each partner brings unique R&D resources to the cooperation (Browning et al., 1995). Thus, participants have diverse and broadened pool of knowledge and resources. Secondly, the higher the number of partners, the higher the positive feedback and network externalities that partners can gain from the alliance (Doz and Hamel, 1998). This is because the possibilities that the technology or the product configuration developed in the alliance is imposed as a standard or a dominant design in an industry increase (Afuah, 1999). Moreover, firms cooperating with multiple firms in an alliance enjoy additional scale effects. According to a previous study, Agri-Food firms in the Dutch tomato industry develop new cultivating techniques with partners in a multiparty alliance. This R&D would take too much time and resources to be carried out by individual firm. By joining resources and knowledge, each firm in a multiparty alliance is able to tap into new techniques which improve their competitive position while

reducing costs and risks associated to innovative activities.

However, as previous research has shown, a higher number of partners increase coordination and monitoring costs (Oxley, 1997) with increased transaction costs. Each partner requires additional efforts and resources to be committed so that the alliance works well (Garcia-Canal et al., 2003). Meanwhile, increased number of partners make decision-making processes more difficult with the increased risk of conflicts. Moreover, firms in a multiparty alliance face the increased danger of opportunistic behaviors of participants (Dyer et al., 2000; Das et al., 2003). Opportunistic partners in a multiparty alliance may willingly participate in knowledge-sharing activities to acquire the desired knowledge at first, and then refuse to contribute its knowledge and cooperate to make joint innovation. Thus, the creation of useful knowledge in a multiparty alliance has the potential for 'free riders' (Dyer et al., 2000). Such opportunistic behaviors of partners can also undermine the development of trust among participants (Das et al., 2003).

Therefore, firms face trade-offs as the diversity of R&D alliance portfolio increases. On the one hand, alliance partners are social capital for a focal firm and mutual learning partners (Hamel, 1991; Mowery et al., 1996, 1998; Koka and Prescott, 2002). A highly diversified portfolio provides broadened knowledge pool and access to enriched search options, creating a great deal of opportunities for value creation and capability development. Thus, diversity of knowledge in an alliance portfolio is the important factor influencing on a focal firm's learning and innovation performance (e.g. Goerzen and Beamish, 2005; Kim and Song, 2007). On the other hand, increased diversity of knowledge in R&D alliance portfolios can bring more complexity and potential for conflicts, thus increasing coordination and managerial costs for a focal firm (Oxley, 1997). Thus, the benefits from increased diversity in the R&D alliance portfolio come at the cost of managing such complexity and possibilities of conflicts. It is also the case for the firms engaging in multiparty alliances.

In spite of the importance of research on such trade-offs which occur for firms with alliance portfolios or in multiparty alliances, prior studies have a lot of limitations and research gaps. Prior studies mainly focused on the relationship between the diversity of alliance portfolios and firm financial or innovation performance, mostly showing curvilinear relationships (e.g. Lavie, 2007; Zhang et al., 2010). Another research stream paid attention to the alliance management capability, but most of them focused on individual (dyadic) alliances (e.g. Anand and Khanna, 2000; Hoang and Rothaermel, 2005; Sampson, 2007). Although most traditional research on alliance has focused on single alliances, various studies recently have paid attention to the alliance portfolio as a unit of analysis and portfolio management capability. For example, Hoffmann (2005) analyzed the multi-alliance management practices of European companies to answer the question of what management tasks arise in companies with multiple alliances and how global firms deal with such tasks. In this study, he argued that it is the only way that companies with multiple alliances exactly identify important tasks of the portfolio management and create a committed alliance function and develop company-wide standards in order to attain the company's strategic goals through alliance portfolios. Also, recent researches have increasingly focused on the way of composing cost-effective alliance portfolio (Jiang et al., 2010) to fully utilizing the resources of alliance partners. However, existing researches are not fully covering the variables related to the efficient composition of alliance portfolio influencing firm innovation performance.

Previous studies on multiparty alliance mainly focused on conceptualization of multiparty alliances and offered propositions, without providing empirical testing for their propositions (Zeng and Chen, 2003; Das et al, 2003). Most of existing research on this topic has been carried out using case study research, and lacks external validation with empirical evidences. In addition, most prior research took a single perspective in approaching the antecedents of multiparty alliance performance: a social governance

view (Das et al., 2003; Jones et al., 1997; Zeng and Chen, 2003), a formal governance perspective (Garcia-Canal et al., 2003; Lavie et al., 2007), or game theory (Hwang et al., 1997). Recently, scholars have recognized that understanding performance of multiparty cooperation demands a multi disciplinary approach (e.g. Vanhaverbeke et al., 2006). Vanhaverbeke et al. (2006) focused on value creation and appropriation from an open innovation perspective. Thus, while multiparty alliance management requires a multi disciplinary approach, previous research has not yet been able to investigate this phenomenon comprehensively.

The purpose of this study is to fill such gaps and answer the following two important questions with empirical data:

1. ***What factors influencing the relationship between a focal firm's R&D alliance portfolio diversity and its knowledge acquisition from the portfolio?***
2. ***What factors influencing joint innovation performance of multiparty alliances?***

2. Empirical Setting

For these empirical tests, I constructed a data set comprising the R&D alliance and patenting activities of firms in four high-tech manufacturing industries: semiconductor, electronics, computer manufacturing, and telecommunications industries. Those industries undergo the rapid pace of technology development, and thus firms frequently collaborate in R&D to gain access to external complementary capabilities and spread the

risk and expense of development. Further, patents are an important means for appropriating the returns from innovation for firms in such high-tech industries.

I construct the data set from two main sources: the SDC (Securities Data Company) Database on Joint Ventures and Alliances and the USPTO (United States Patent and Trademark Office) database. SDC database includes information on all forms of strategic alliances to identify alliance portfolios for firms in the global high-tech manufacturing industry during the period from January 1987 to October 2013. The SDC database contains information on all types of alliances and is compiled from publicly available sources. Thus, it is among the most comprehensive sources of information on alliances and widely used for large-scale empirical studies on alliances (e.g. Anand & Khanna, 2000; Sampson, 2007). Focusing only on the R&D alliances, I collected various information related to alliances such as participants (firms) in an alliance and the announcement date and Standard Industrial Classification (SIC) code for each alliance, and its activities. The collected data also include country origins or locations of the participants. From 1987 to 2013, total number of R&D alliances is 2,303, including 1,981 dyadic alliances and 332 multiparty alliances (more than three partners) of 1,616 firms. Total number of dyadic relationships is 7,751 and about 50% of the relationships are international (3,414 cross-border relationships).

I combine these data on firm alliances with data from USPTO (United States Patent and Trademark Office) database, which contains information on patents such as assignee (firm) name, filed data, accepted data, patent technological classification, the location of assignee, the number of forward and backward citation, and etc. USPTO issued more than 150 thousands global patents every year. Firm patent has come into the spotlight for a long time in the field of business and economics research as an index of the outcomes of R&D investments and technological capabilities (Hall et al., 2000; Lin and Chen, 2005). Patent data is systematically organized, includes detailed information on each patent and

can be structured into time-series data. Thus, patent data is proper for empirical research on knowledge transfer and acquisition. Moreover, information of patents issued in the U.S. includes detailed information on forward patent which an assignee cited in the process of research and development like references of academic papers. Using this information on forward citations, we can analyze the flows of knowledge or technology among firms (Jaffe and Trajtenberg, 2002; Almeida et al, 2002; Song et al., 2003). Information on patents and patent citation obtained from the USPTO database is appropriate for this study focusing on knowledge acquisition of a focal firm from alliance portfolio. Finally, longitudinal panel (1,999 alliance portfolios) of 964 firms for the period 1990-2006 was created to examine the effect of alliance portfolios on a lagged measure of firms' knowledge acquisition from alliance partners in the portfolios. Retaining portfolio over this time frame allowed us to measure five-year-lagged knowledge acquisition over 1991-2011. Also, final data set for the examination on multiparty alliance included 285 multiparty alliances of 764 firms for the period 1990-2008 was created. Retaining multiparty alliances over this time frame allowed us to measure five-year-lagged joint patents over 1991-2013.

3. Overview of Contents

In study I, I investigate the efficient composition of R&D alliance portfolio by examining the ways firms can optimize the learning and resource benefits while limiting the complexity and coordination costs of managing a diverse alliance portfolio.

First, I test the effect of knowledge (technological) diversity of a firm's R&D alliance portfolio on its knowledge acquisition (the number of backward citation of a focal firm

from alliance partners' patents). Knowledge acquisition from firms in a R&D alliance portfolio could be more direct and appropriate measurement than that in existing studies. Most of the prior studies used the increase in the post-alliance patenting activities as a measure of R&D alliance performance (e.g. Sampson). However, post-alliance innovation of a firm cannot be a direct measure of learning from partners in its portfolio, thus inappropriate for estimating the costs and benefits of retaining diverse partners in the portfolio.

Secondly, I examine the condition that a focal firm can raise benefit while reducing costs generated from the diversity of alliance portfolio in order to investigate the cost-effective composition of R&D alliance portfolio. Drawing on transaction cost economics, two sources of transaction costs are considered: distances between a focal firm and partners in its portfolio (technological and cultural distances) and opportunistic behaviors of partners in the portfolio. Conditions are clarified that a firm can control transaction costs which are caused by such factors and maximize benefits from knowledge (technological) diversity of its alliance portfolio. I expect that he level of knowledge sourcing from alliance portfolio partners with diverse knowledge bases will be maximized when a focal firm is more able to absorb knowledge and technologies of alliance partners. These arguments will be empirically tested using a panel data of high-tech manufacturing firms during the period 1987-2013.

In study II, I examine the factors influencing joint innovation performance (joint patenting in this study) to which all of the participants in a multiparty R&D alliance contribute. Drawing upon organizational learning theory and transaction cost economics, I examine the effects of diversity in a multiparty alliance (technological and national diversity), attributes of ties composing the multiparty alliance (multiple, repeated, and co-opetition ties), and governance structure of the alliance with data of high-tech manufacturing firms during the period 1987-2013.

Chapter II.

Alliance Portfolio and Knowledge Acquisition

: Focusing on cost and benefit sides of knowledge acquisition in R&D alliance portfolio

1. INTRODUCTION

The rapid proliferation of strategic alliances has been one of the most lasting features of the business world over the last two decades. Main reasons are that competition is increasingly knowledge-based and the life-cycles of technology become shorter, as firms strive to learn and to develop capabilities faster than their rivals (Prahalad and Hamel, 1990; D'Aveni, 1995; Teece and Pisano, 1994). These trends in today's business world has made it nearly impossible for any firm to build and sustain its technological competitive advantage without utilizing external knowledge and technologies. This is because the time between the identification of a problem and its arrival may not allow the firm to internally develop the knowledge and capabilities needed to respond effectively (Dierickx and Cool, 1989). This has led to a shift from traditional resource or risk-sharing alliances to alliances with learning from partners as a primary goal such as R&D alliances (Hamel, 1991; Huber, 1991). Such alliances for 'learning' enable firms to speed up capability development and minimize the inherent risks and uncertainties associated with technological innovation by acquiring and exploiting knowledge developed by other firms (Grant and Baden-Fuller, 1995).

For these reasons, firms in many high-tech industries, such as electronics, computer, semiconductors, telecommunications, are increasingly engaging in a wide array of R&D alliances to source external knowledge and accelerate innovation (Rigby and Zook, 2002; Wassmer, 2010). In addition, there is increasing demand for technology or products which need diverse knowledge to be integrated, forcing firms in technology-intensive industries to engage in multiple R&D alliances simultaneously with different partners in industry, technology, and even nationality.

Researchers define the set of multiple alliance partners with which a focal firm sustain partnership at a certain period of time (usually in a year) as the focal firm's alliance portfolio (George et al., 2001; Bae and Gargiulo, 2004; Hoffmann, 2005, 2007; Lavie, 2007; Lavie and Miller, 2008). While partner firms in an alliance portfolio are independent with the other partners as seen from the figure 1 (firm A and B), a focal firm which has multiple different R&D alliance partners are facing the challenge to manage its alliance portfolio as a whole (Doz and Hamel, 1998; Gulati, 1998; Anand and Khanna, 2000; George et al., 2001; Bamford and Ernst, 2002; Hoffman, 2005, 2007; Lavie, 2007; Ozcan and Eisenhardt, 2009). For the focal firm, R&D alliance partners are not only the source of diverse knowledge, but also the relationship to manage and maintain which requires a great deal of efforts (Madhok and Tallman, 1998).

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Therefore, firms face trade-offs as the diversity of R&D alliance portfolio increases. On the one hand, alliance partners are social capital for a focal firm and mutual learning partners (Hamel, 1991; Mowery et al., 1996, 1998; Koka and Prescott, 2002). A highly diversified portfolio provides broadened knowledge pool and access to enriched search options, creating a great deal of opportunities for value creation and capability development. Thus, diversity of knowledge in an alliance portfolio is the important factor influencing on a focal firm's learning and innovation performance (e.g. Goerzen and Beamish, 2005; Kim and Song, 2007). On the other hand, increased diversity of

knowledge in R&D alliance portfolios can bring more complexity and potential for conflicts, thus increasing coordination and managerial costs for a focal firm (Oxley, 1997). Thus, the benefits from increased diversity in the R&D alliance portfolio come at the cost of managing such complexity and possibilities of conflicts.

Prior studies mainly focused on the relationship between the diversity of alliance portfolios and firm financial or innovation performance, mostly showing curvilinear relationships (e.g. Lavie, 2007; Zhang et al., 2010). Another research stream paid attention to the alliance management capability, but most of them focused on individual (dyadic) alliances (e.g. Anand and Khanna, 2000; Hoang and Rothaermel, 2005; Sampson, 2007). Although most traditional research on alliance has focused on single alliances, various studies recently have paid attention to the alliance portfolio as a unit of analysis and portfolio management capability. For example, Hoffmann (2005) analyzed the multi-alliance management practices of European companies to answer the question of what management tasks arise in companies with multiple alliances and how global firms deal with such tasks. In this study, he argued that it is the only way that companies with multiple alliances exactly identify important tasks of the portfolio management and create a committed alliance function and develop company-wide standards in order to attain the company's strategic goals through alliance portfolios. Also, recent researches have increasingly focused on the way of composing cost-effective alliance portfolio (Jiang et al., 2010) to fully utilizing the resources of alliance partners. However, existing researches are not fully covering the variables related to the efficient composition of alliance portfolio influencing firm innovation performance.

The purpose of this study is to fill such gaps and answer the following important question:

What factors influencing the relationship between a focal firm's R&D alliance portfolio diversity and its knowledge acquisition from the portfolio?

(What factors influencing the extent that a firm can gain from knowledge diversity of its R&D alliance portfolio?)

Specifically, I investigate the efficient composition of R&D alliance portfolio by examining the ways firms can optimize the learning and resource benefits while limiting the complexity and coordination costs of managing a diverse alliance portfolio.

First, I test the effect of knowledge (technological) diversity of a firm's R&D alliance portfolio on its knowledge acquisition (the number of backward citation of a focal firm from alliance partners' patents). Knowledge acquisition from firms in a R&D alliance portfolio could be more direct and appropriate measurement than that in existing studies. Most of the prior studies used the increase in the post-alliance patenting activities as a measure of R&D alliance performance (e.g. Sampson). However, post-alliance innovation of a firm cannot be a direct measure of learning from partners in its portfolio, thus inappropriate for estimating the costs and benefits of retaining diverse partners in the portfolio.

Secondly, I examine the condition that a focal firm can raise benefit while reducing costs generated from the diversity of alliance portfolio in order to investigate the cost-effective composition of R&D alliance portfolio. Drawing on transaction cost economics, two sources of transaction costs are considered: distances between a focal firm and partners in its portfolio (technological and cultural distances) and opportunistic behaviors of partners in the portfolio. Conditions are clarified that a firm can control transaction costs which are caused by such factors and maximize benefits from knowledge

(technological) diversity of its alliance portfolio. I expect that he level of knowledge sourcing from alliance portfolio partners with diverse knowledge bases will be maximized when a focal firm is more able to absorb knowledge and technologies of alliance partners. These arguments will be empirically tested using a panel data of high-tech manufacturing firms during the period 1987-2013.

The remainder of the paper is structured as follows. In Section 2, I develop a set of hypotheses for the empirical analysis. Section 3 presents the specific research methods and the databases we used for our empirical analysis. Finally, I show the results from empirical tests and conclude with some discussion points in section 4 and 5 respectively.

2. THEORY AND HYPOTHESES

In this study, the alliance portfolio of a focal firm is defined as a set of multiple alliance partners with which a focal firm sustain partnership at a certain period of time (usually in a year) according to the previous studies (George et al., 2001; Bae and Gargiulo, 2004; Hoffmann, 2005, 2007; Lavie, 2007; Lavie and Miller, 2008). Also, I chose to include only R&D alliances in my alliance portfolio definition.

The main reason firms engage in multiple R&D alliances simultaneously is most likely to source diverse knowledge from the partners. Firms face trade-offs, however, as it increase diversity of R&D alliance portfolio to broaden knowledge pool and grow opportunities to learn from partners. This is because increased diversity of knowledge in R&D alliance portfolios can bring more complexity and potential for conflicts, thus

increasing coordination and managerial costs for a focal firm.

Parkhe (1991) distinguished between two types of partner diversity in his study of inter-firm diversity. Type I diversity is associated to partner's complementary resources. In this context, increasing the number of partners also raises the benefits (value creation opportunity) firm may generate from its alliance portfolio, facilitating development and collaborative effectiveness of R&D alliances. Type II diversity refers to the differences in partner characteristics. The increase in Type II diversity might impede inter-firm communications and increase coordination costs (value appropriation opportunity).

The balance between value creation opportunity and value appropriation opportunity might break, as costs generated from Type II diversity outweigh benefits gained from Type I diversity (Lavie, 2007; Zhang et al., 2010). Parkhe also argued that costs from Type II diversities go down and benefits from Type I diversity increase over time. Thus, at the alliance portfolio level, firms can reap net gain benefits from partner diversity when the benefits from Type I diversity outsize the costs resulting from Type II diversity. I examine the condition that a focal firm can raise benefit while reducing costs generated from the diversity of alliance portfolio.

2.1. Technological diversity of Alliance portfolio and knowledge acquisition

I define R&D alliance portfolio diversity as the degree of variance in technology among partners in a focal firm's alliance portfolio (Bae and Gargiulo, 2004; Lavie, 2007). Most prior studies have focused on partner diversity at the dyad (e.g. Parkhe, 1991; Sampson, 2007). My notion of alliance portfolio partner diversity is similar to network diversity in Goerzen and Beamish's study (2005), referring to the degree of variance in

partners' knowledge and technological bases.

Also, in a lot of literatures on innovation and knowledge management, it has been noted that new knowledge creation often results from the recombination of existing elements of knowledge into new syntheses (Henderson and Clark, 1990; Katila and Ahuja, 2002; Kogut and Zander, 1992). According to the prior literatures, knowledge acquisition from the alliance portfolio means that a focal firm creates new knowledge (technology) by utilizing knowledge of partners in its alliance portfolio (Vasudeva and Anand, 2011).

According to the organizational learning theory, technological capability which has been cumulated over time inside a firm creates its knowledge base. A firm could have opportunities to access other firms' knowledge based via R&D alliances, and thus R&D alliance portfolios of the firm play a role as its external knowledge base. As technological diversity in a R&D alliance portfolio increases, a focal firm enjoys benefits in that the firm can have access to more non-redundant and diverse information (Burt, 1980; Granovetter, 1973; Duysters and Lokshin, 2011). Such alliance portfolio provides benefits that are additive rather than redundant (Burt, 1997), and encourages the incorporation of diverse perspectives. Alliance partners which have overlapped knowledge or technology with a focal firm would less contribute to the firm's knowledge base (Vassolo et al., 2004; Anand et al., 2007), and this sub-additive alliance portfolio could reduce learning sources and motivation for the firm. In contrast, partners with diverse technology in alliance portfolios diverse facilitate a focal firm's learning motivation and access to information, knowledge, technologies, and other important tangible and intangible resources, enabling a focal firm to have opportunities to acquire more knowledge from its alliance portfolio and to offset technological uncertainty with an opportunity set of viable alternatives (Sirmon et al., 2007; Vassolo et al., 2004)

Meanwhile, the positive effect would diminish at much higher levels of diversity.

Using the diverse knowledge and technology which reside in an alliance portfolio is not costless. As a firm's alliance portfolio becomes more technologically diverse, there would be more non-redundant and non-overlapping external knowledge. Utilizing such new knowledge may need more learning resources to stretch the firm's absorptive capacity (Vasudeva and Anand, 2011), which means "a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends (Cohen and Levinthal, 1990: 128)." This is because a focal firm would have fewer opportunities for redeployment of relational assets when partners' in an alliance portfolio are very diverse in their technological capabilities (Dyer and Singh, 1998; Mesquita et al., 2008). It is related to the argument that lower compatibility among diverse partners may reduce the substitutability or applicability of experiences across alliances (Dyer and Singh, 1998; Vassolo et al., 2004; Mesquita et al., 2008). The lower levels of shared experiences across alliances increase burden on a firm's learning capability to source new technology and consequently, reduce knowledge acquisition from the firm's alliance portfolio.

Combining the above perspectives, I suggest that too little technological diversity in the alliance portfolio imposes a cost by reducing exposure to alternatives and greater redundancy for a firm engaged in multiple R&D alliances simultaneously. At the same time, too much diversity excessively burdens the firm's absorptive capacity, make the firm underutilize diverse knowledge of alliance portfolio. At both cases, the costs exceed the expected knowledge acquisition benefits from alliance portfolios (Cording et al., 2008; Vasudeva and Anand, 2011). Therefore, firms whose R&D alliance portfolios has the moderate level of technological diversity is most likely to enjoy the highest level of knowledge acquisition from the portfolio. Thus, I hypothesize:

Hypotheses 1. There is an inverted U-shaped relationship between technological

diversity in a focal firm's alliance portfolio and its knowledge acquisition.

2.2. Two Sources of transaction costs in alliance portfolios

Strong learning motivation does not always lead to successful knowledge acquisition. Whereas, some firms source knowledge from its alliance portfolio much more than expected. To delve into the relationship between the technological diversity of a focal firm's alliance portfolio and its knowledge acquisition from the portfolio, we have to be focused on the boundary condition that the firm can minimize the transaction costs generated from contractual hazards in the relationship with various partners and, at the same time, maximize the benefits from the diversity in its alliance portfolio. The level of knowledge acquisition from the portfolio largely depends on the focal firm's capability of utilizing the portfolio in efficient and effective ways.

2.2.1. Distances between a focal firm and partners

With the development of multinational companies and the geographic dispersion of knowledge, technological and cultural diversity is also increasing in a firm's R&D alliance portfolio. Thus, in this study, I focus on the two distances as the source of transaction costs in the portfolio which enhance complexity in learning and coordination costs among partners: technological and cultural distances between a focal firm and its alliance partners.

Technological distance between a focal firm and partners

Technological distance is a different concept from technological diversity. Technological distance means gaps of technological experiences and knowledge bases between a focal firm and its partners (Jaffe, 1986; Mowery et al., 1998; Knoben and Oerlemans, 2006), while technological diversity means the degree of variance in technological base among partners in a focal firm's alliance portfolio.

Some overlaps between a focal firm's internal knowledge stock and the technologies of alliance partners have a positive impact on knowledge acquisition of a focal firm from diverse knowledge pool in alliance portfolios by creating capacity to understand the value of partner's technology and utilize the variety of technologies of alliance portfolio. According to the absorptive capacity literature, a certain level of knowledge overlap is necessary for a focal firm to exploit the knowledge stock of alliance partners because a firm's ability to use new knowledge elements depends largely upon the firm's existing knowledge stock (Cohen and Levinthal, 1990; Rosenkopf and Almeida, 2003; Tallman et al., 2004).

However, technologically distant partners may limit a focal firm's learning capability because a focal firm may not have the capacity to absorb the technologies of such distant partners (Zhang et al., 2010). When the partner's technology is too distant, a focal firm do not have internal related knowledge to recognize the value of various knowledge elements of alliance partners and learn them. it is even more difficult for a focal firm to combine various knowledge of alliance partners to its own knowledge stock to create new innovative outcomes. Nooteboom (2000) argued that there is a trade-off between newness and understandability of knowledge. That is, high level of novelty of partner's knowledge could widen the cognitive distance between a focal firm and its alliance partner, thus

making the novel knowledge difficult for the firm to understand. Also, too much technological distance may imply problems of communication and mutual understanding. Technological distance between a focal firm and its partners, thus, may enhance complexity in learning and coordination costs.

A greater diversity of technology combined with large technological gap may signal a situation in which sourcing from the diversity are likely to occur at a low level or seldom likely to occur. Therefore, I argue that:

Hypothesis 2. Technological distance will moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has higher level of technological distance with alliance partners will exhibit lower level of knowledge acquisition from its alliance partners

Cultural distance between a focal firm and partners

Vantage Partners in 2003 reported that conflicts generated from cultural difference consists of more than 50% of the reasons of alliance failure, based on its studies on over 130 cases of alliances. With the development of multinational companies and the geographic dispersion of knowledge, cross-border R&D alliances are rapidly increasing. As an increasing number of firms are including alliance partners from various nations, cultural diversity is also increasing in a firm's R&D alliance portfolio.

Cultural distance in this study means averaged cultural gaps between a focal firm and its alliance partners. Cultural distance emanates from differences in language, social

norms, and mindsets. A smaller cultural distance between a focal firm and its partners can improve the focal firm's absorptive capacity (Cohen and Dal Zotto, 2007) and it facilitates knowledge flow between them. In contrast, high level of cultural distance limit the absorptive capacity (Cohen and Dal Zotto, 2007). Different language and methods of communication could impede learning, lowering the level of knowledge acquisition from partners from various nations (Cohen and Dal Zotto, 2007). A study showed that cultural distance negatively moderates the impact of coordination capabilities on effective knowledge transfers (Chini and Ambos, 2005).

Because of differences in culture and social backgrounds, there is always a culture gap between a focal firm and its alliance partners. By shortening the cultural gap, a focal firm and its partners can align their competencies and motives. Interpersonal knowledge sharing between a focal firm's employees and its external partners also improve the effectiveness of learning from R&D portfolio. However, reducing the cultural gap is costly. In order to reduce this gap and facilitate learning between firms, a focal firm needs to develop mutual cultural understanding with alliance partners. The firm needs to increase the number of interactions and encourage the inter-personal exchanges. Thus, managerial and coordination cost of a portfolio is multiplied as a culturally distant partner is added to the alliance portfolio. Such costs impede effective and efficient knowledge transfer from the alliance portfolio to the focal firm (Hansen and Lovas, 2004; Chini and Ambos, 2005; Tihany et al., 2005).

Cultural distance between a focal firm and its partners, thus, may enhance complexity in learning and coordination costs. When a greater diversity of technology combined with large cultural gap, a focal firm's learning from the diversity are likely to occur at a low level or seldom likely to occur. Therefore, I contend:

Hypothesis 3. Cultural distance will moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has higher level of cultural distance with alliance partners will exhibit lower level of knowledge acquisition from its alliance partners.

2.2.2. Opportunistic behaviors of partners

Alliances usually entail significant uncertainty about future transaction costs and benefits due to the possibility of opportunistic behavior of partners. The lack of clear relationships based on a single authority is another reason for the uncertainty. Moreover, alliances involve a risk of technology leakage, as there are inherent risks of unilaterally losing proprietary technologies to the partner. Firms may confront different transaction costs generated from the partners' opportunistic behaviors according to their alliance experiences and the composition of the alliance portfolios in terms of the relationships between focal firms and partners. In this study, I focus on the factors influencing the possibility of opportunistic behaviors of partners such as general alliance experiences of focal firms, prior alliance experiences with current partners, and the portion of direct competitors in alliance portfolios, and thus, having impacts on the level of knowledge acquisition from technological diversity in the alliance portfolios.

General alliance experience and opportunistic behaviors of partners

In this study, general alliance experiences are defined as all prior alliance experiences

(dyadic relationships) of a focal firm except for the former relationships with partners currently in its alliance portfolio following the previous studies (e.g. Hoang and Rothaermel, 2005).

In the relationships among R&D alliance partners, opportunism of alliance partners could be the source of transaction costs which hinder knowledge acquisition from each other. These impediments emanate from uncooperative partners in sharing and transferring their knowledge, especially tacit knowledge which requires intimate interactions to acquire. When a focal firm cannot predict and control the partners' opportunistic behaviors, it may lost its proprietary knowledge to partners while failing to source the partners' knowledge. However, firms with cumulated experiences through multiple alliance activities could source partners' knowledge efficiently by developing alliance management capabilities.

From a organizational learning theory (Levitt and March, 1988), an alliance portfolio can be viewed as a repository of experience as well as a vehicle for learning. Also, it can be argued that firms learn how to manage alliances and gain values from them through repeated engagements in such organizational forms with diverse partners (Anand and Khanna, 2000). Moreover, when a new alliance is added to an alliance portfolio, past experience matters for the value that firms extract from them (Anand and Khanna, 2000; Reuer et al., 2002).

Organizational learning occurs iteratively when firms engage repeatedly in an activity (Levitt and March, 1988). For example, when a focal firm engage in multiple alliances over time, the firm draws inferences from their alliance experiences and store them for the future engagements in other alliances. Learning outcomes from the past alliance experiences might be encoded in organizational routines (Nelson and Winter, 1982). Routines that result from experience constitute the kinds of intangible resources more

likely to be the source of performance improvements in future alliances (Barney, 1991). In the alliance activities, a focal firm codifies knowledge of managing alliances gained through reflection on past alliance experiences into manuals, databases, diagnostic tools, and simulations. Such embodied knowledge may aid the firm in assessing current alliance activities and guide it in selecting appropriate alliance partners in the future.

For example, experiences may result in new intra- and inter-organizational routines that help a focal firm select future partners who seem not to behave opportunistically. Also, prior experiences with diverse partners aid in developing a firm's alliance capabilities to notice partners' opportunistic behaviors in advance and take proper actions, which facilitates internal coordination in an alliance portfolio. In the current business world, some firms are showing that it is needed to enhance alliance performance that develop experiences among dedicated alliance managers and institutionalize alliance experience.[1] In general, firms with rich experiences in alliance activities are more likely to establish a dedicated alliance function, which contributes to improved alliance performance.

In addition, firms that have had considerable alliance experience are more incapable of getting access to partners' knowledge bases. Experienced organizations are thus likely to be more effective than others less experienced. That is, repeated allying practice enhances alliance capabilities by helping organizations understand and develop processes to efficiently access information (Eisenhardt and Martin, 2000).

In short, general alliance experiences of a focal firm may contribute to reducing transaction costs related to the opportunistic behaviors of partners. Although there is a

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[1] In 1999, Eli Lilly established an Office of Alliance Management in and it considers this dedicated alliance function as an "integrator, intermediary and catalyst for best practice performance" (Gueth, Sims, and Harrison, 2001: 4).

greater diversity of technology in an alliance portfolio, a focal firm with rich alliance experience would learn from the diversity more than a firm with little alliance experience. Therefore, I argue:

Hypothesis 4. General alliance experience will moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has more general alliance experience will exhibit higher level of knowledge acquisition from its alliance partners

Partner-specific alliance experience and opportunistic behaviors of partners

I argued that general alliance experience is derived from a portfolio of alliances with diverse partners. However, knowledge and skills that accumulate from recurrent allying with specific partners over time may also be important experiences. Prior alliance experiences with current portfolio members is partner-specific alliance experience (Hoang and Rothaermel, 2005). Firms with cumulated experiences through repeated alliance activities with specific partners could source the partners' knowledge efficiently by reducing transaction costs.

First, repeated ties between partners over time may develop mutual trust (Gulati, 1995; Hagedoorn et al., 2003). High levels of trust between partners increase accessibility to each other's rich information (Uzzi ,1996; 1997). This is because trusting firms may have greater commitment to make the alliance work and the development of norms of sanctions for the violation of trust deters partner's opportunistic behavior (Coleman,

1988), and thus partners share rich information with confidence. The idea of trust emerging from repeated partnerships is also based on the premise that firms can learn about each other through ongoing interaction, including how to understand and predict each other's patterns of behavior (Dyer and Chu, 2000). As knowledge between partners increases, behavioral uncertainty decreases by reducing information asymmetries (Casciaro, 2003). Previous research found that greater partner-specific alliance experience is linked with firms' abilities to manage alliance conflicts (Simonin, 1997).

Moreover, learning accumulated through partner-specific alliance experience can facilitate the development of inter-firm knowledge-sharing routines of coordinating resources and tasks successfully with the partner (Zollo et al., 2002). Technology sharing requires wide-ranging, continuous, and intense interactions between firms (Kogut, 1988). Repeated ties with a partner enables a firm to better understand their partner's goals and motives. Also, firms can learn about each other's ways of doing business through recurrent alliances and interpret meaning from each other's actions. The refinement of partner-specific interfaces and the development of partner-specific decision making as well as conflict resolution routines should enhance mutual understanding. Such routines of inter-firm knowledge sharing create a basis for partner-specific absorptive capacity that enables alliance partners to recognize the value of each other's knowledge and effectively transfer it across inter-firm boundaries (Dyer and Singh, 1998).

In addition, experienced partners can skip the relationship-building processes that are necessary for partners working together for the first time (Inkpen, 2000), saving times and resources. Usually, the type of knowledge to be sourced may be tacit and can be gained more efficiently and accurately through direct and close interaction between people who possess the knowledge. Seen from the view of learning-by-doing argument, as firms gain experience in solving a particular problem, they do not have to pay conscious attention to it over time (Bereiter and Scardamalia, 1993). Experienced

organizations are thus likely to be more effective than others with little experience.

Therefore, the relational routines and mutual trust created through repeated alliances reduce the fear of opportunistic behavior, allow for greater openness, and facilitate the coordination of each partner's respective technologies (Kale et al., 2000). Although there is a greater diversity of technology in an alliance portfolio, a focal firm having more partners with prior alliance experiences in its portfolio would source knowledge from the diversity at a higher level than a firm having partners with little previous ties. Hence, I hypothesize:

Hypothesis 5. Partner-specific alliance experience will moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has more partner-specific alliance experience will exhibit higher level of knowledge acquisition from its alliance partners.

Alliance with competitors and Opportunistic behaviors of partners

Industry analysts and academic researchers report a increasing number of incidence and growing importance of alliances among competitors. Purposes of alliance with competitors vary including technology and product development, joint manufacturing, and market entry or expansion (Doz, 1996; Park and Russo, 1996; Sakakibara, 1997). We call the collaboration (alliance) with partners from the same industry as co-opetition. Due to hyper-competition in technology development and the short life-cycle of new technology, co-opetition for knowledge sharing is now very common across high-tech

industries. Figure 2 shows the latest situation of co-opetitions for technology development for hybrid or electric cars in the global automobile industry.[2]

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Insert Figure 2 about here

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Although there are a lot of drivers to force firms to ally with their direct competitors, collaboration with competitors entails great risks in many ways. First, there is technological risk. If a firm fail to monitor or control the opportunistic behaviors alliance partners in direct competition, there is high possibility that it lose its secret, proprietary knowledge or core technology to such partners (Gnyawali and Park, 2009). Either party can opportunistically use the alliance to learn the other's business or technological secrets (Bucklin and Sengupta 1993) while being reluctant to open its own to the other. For these reasons, firms do not always seek the most capable partners, but select the most trusting partners although resource-based view tells us that it is natural for firms to select the most

[2] Toyota was well known for "pure bloodism" as it made all of the car components such as sunroofs by itself. After several times of crisis including currency rate fluctuations and recalls, however, the firm began to actively search for alliance partners. Now it allies with direct competitors to co-develop core technology which would be competitive dynamics in the future. Toyota and BMW group announced that they would cooperate in order to develop the technology of future in January 2013 and now in partnership for the development of fuel cell system, next generation sports car and lightweight technology.

competent firms as alliance partners even if they are competitors.

In reality, it is very difficult for competing firms to collaborate for knowledge sharing. Two basic types of alliances between competitors have been distinguished as link alliances and scale alliances (Porter and Fuller, 1986; Hennart, 1988; Dussauge et al., 2000; Mitchell et al., 2002). Partners in scale alliances contribute similar resources to the alliances (e.g. alliances for sharing knowledge and co-development of technology), while partners in link alliances contribute substantially different resources to the alliances (e.g. alliances for cost reduction or market expansion). Mitchell et al.(2002) showed in their empirical study that competing firm alliances that involve R&D resources are more likely to be scale alliances than link alliances because scale efficiency incentives are even stronger. R&D resources may offer greater opportunities for link alliances, but such link alliances involving R&D resources would generate appropriation risks when combined with a competitor's production or marketing resources (Hamel, 1991; Hennart et al., 1999). Therefore, we expect firms to be reluctant to combine their R&D resources with competitors by creating link alliances. Instead, when forming link alliances, firms will contribute only existing designs and previously developed products, excluding R&D resources from the activities of the alliance.

In addition, valuable knowledge is often tacit, such that the direct interaction with knowledge holders is essential. Such interactions allow firms to source alliance partner's technological knowledge more efficiently (Iwasa and Odagiri, 2004). However, there are competing expectations from both cooperative and competitive relationships in co-opetition relations, generating role conflicts for managers engaging in co-opetition (Bengtsson and Kock, 2000; Raza-Ullah et al., 2013). Also, there can be conflicts of interest and learning races among partners in the same industry. Such things increase monitoring and safeguarding costs (Park & Ungson, 2001; Jiang et al., 2010). Although learning is a possible benefit of the alliance, conflicts associated with learning could

block the functioning of the alliance (Park & Russo, 1996). This is because partners may be reluctant to make investments in relational assets with competitors that may result in undesired knowledge transfers (Kale et al., 2000)

Thus, a greater diversity of technology combined with direct competition in an alliance portfolio may signal a situation in which sourcing from the diversity are likely to occur at a low level or seldom likely to occur. Therefore, I argue:

Hypothesis 6. Portion of the competitors in an alliance portfolio will moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has more competitors as its alliance partner will exhibit lower level of knowledge acquisition from its alliance partners.

Figure 3 shows the research model for this study.

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Insert Figure 3 about here

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3. EMPIRICAL SETTING AND METHODS

3.1. Data

For these empirical tests, I constructed a data set comprising the R&D alliance and patenting activities of firms in four high-tech manufacturing industries: semiconductor, electronics, computer manufacturing, and telecommunications industries. Those industries undergo the rapid pace of technology development, and thus firms frequently collaborate in R&D to gain access to external complementary capabilities and spread the risk and expense of development. Further, patents are an important means for appropriating the returns from innovation for firms in such high-tech industries.

I construct the data set from two main sources: the SDC (Securities Data Company) Database on Joint Ventures and Alliances and the USPTO (United States Patent and Trademark Office) database. SDC database includes information on all forms of strategic alliances to identify alliance portfolios for firms in the global high-tech manufacturing industry during the period from January 1987 to October 2013. The SDC database contains information on all types of alliances and is compiled from publicly available sources. Thus, it is among the most comprehensive sources of information on alliances and widely used for large-scale empirical studies on alliances (e.g. Anand & Khanna, 2000; Sampson, 2007). Focusing only on the R&D alliances, I collected various information related to alliances such as participants (firms) in an alliance and the announcement date and Standard Industrial Classification (SIC) code for each alliance, and its activities.[3] The collected data also include country origins or locations of the

[3] The activity of an alliance means the purpose of the alliance such as co-operations for marketing,

participants. From 1987 to 2013, total number of R&D alliances is 2,303, including 1,981 dyadic alliances and 332 multiparty alliances (more than three partners) of 1,616 firms. Total number of dyadic relationships is 7,751 and about 50% of the relationships are international (3,414 cross-border relationships).

I combine these data on firm alliances with data from USPTO (United States Patent and Trademark Office) database, which contains information on patents such as assignee (firm) name, filed data, accepted data, patent technological classification, the location of assignee, the number of forward and backward citation, and etc. USPTO issued more than 150 thousands global patents every year. Firm patent has come into the spotlight for a long time in the field of business and economics research as an index of the outcomes of R&D investments and technological capabilities (Hall et al., 2000; Lin and Chen, 2005). Patent data is systematically organized, includes detailed information on each patent and can be structured into time-series data. Thus, patent data is proper for empirical research on knowledge transfer and acquisition. Moreover, information of patents issued in the U.S. includes detailed information on forward patent which an assignee cited in the process of research and development like references of academic papers. Using this information on forward citations, we can analyze the flows of knowledge or technology among firms (Jaffe and Trajtenberg, 2002; Almeida et al, 2002; Song et al., 2003). Information on patents and patent citation obtained from the USPTO database is appropriate for this study focusing on knowledge acquisition of a focal firm from alliance portfolio.

After collection, I excluded firms with no patents granted by the USPTO and no index for cultural index (e.g. Afganistan) from the collected data. And then, I tracked each

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research and development or manufacturing. An alliance can have multiple purposes. The database classified alliance activities into licensing, research and development, marketing, and etc.

firm's yearly alliance portfolio configuration. Alliances typically last for more than one year, but termination dates are rarely reported. According to previous research (e.g. Schilling and Phelps, 2007; Stuart, 2000; Vasudeva and Anand, 2011), I assumed a productive life span from a knowledge-building perspective of five years. Also, portfolios with more than three partners are included in the final sample to calculate technological diversity. Finally, longitudinal panel (1,999 alliance portfolios) of 964 firms for the period 1990-2006 was created to examine the effect of alliance portfolios on a lagged measure of firms' knowledge acquisition from alliance partners in the portfolios. Retaining portfolio over this time frame allowed us to measure five-year-lagged knowledge acquisition over 1991-2011.

3.2. Measures

3.2.1. Dependent Variable

Knowledge acquisition from portfolio. Knowledge acquisition was measured as the number of citation from patents of partners in an alliance portfolio in the lagged five-year window following an observation year (Hausman et al., 1984; Jaffe et al., 1993; Vasudeva and Anand, 2011). For example, if an alliance commenced in 1993, post-alliance patent citation was constructed from patents applied for in 1994 – 98. the Higher the number of patent citation of a focal firm from its alliance portfolio is, the greater the level of knowledge acquisition of the firm is. This measure differs substantially from those used in the past studies on the contribution of alliances to firm innovation. Some research used post-alliance patenting activities (e.g. Sampson, 2007), and others captured

alliance success with survey-based questions on the extent of inter-firm learning (e.g. Lane & Lubatkin, 1998). Although these and other past studies considerably contribute to understanding of the effect of alliances on firm outcomes, a more direct test of whether particular composition of R&D alliance portfolios increase firm's knowledge acquisition will improve understanding of how firms should configure and manage alliance portfolios to maximize the level of knowledge acquisition with efficiency.

3.2.2. Independent Variable

Alliance partners' technological diversity. I define R&D alliance portfolio diversity as the degree of variance in technology among partners in a focal firm's alliance portfolio (Bae and Gargiulo, 2004; Lavie, 2007). Most prior studies have focused on partner diversity at the dyad (e.g. Parkhe, 1991; Sampson, 2007). However, the dyadic technological overlap is the concept which is closer to technological distance between partners rather than technological diversity. In this study, I only calculated technological diversity among firms in a focal firm's portfolio excluding the focal firm. To measure the diversity, a modified version of Herfindahl index was used following the existing study (Bae and Koo, 2009) for a given alliance portfolio as follows:

$$\textbf{Technological diversity of alliance portfolio} = 1 - \sum_{i=1}^{N}\left(\frac{P_i}{P_N}\right)^2$$

Where N is the total number of technology classes of firms in a focal firm's alliance portfolio, and P_N is the total number of patents of the portfolio members. P_i is the total

number of patents of portfolio members in technology class *i*. As portfolio members' patents are spread evenly across the total set of technology classes of the portfolio, the value will be high. In contrast, if portfolio members' patents are concentrated around a certain technology class, the value will become small. The index was calculated for each alliance portfolio.

3.2.3. Moderating Variables

Technological distance between a focal firm and alliance partners (average). Technological distance is a different concept from technological diversity. Technological distance means gaps of technological experiences and knowledge bases between a focal firm and its partners (Jaffe, 1986; Mowery et al., 1998; Knoben and Oerlemans, 2006), while technological diversity means the degree of variance in technological base among partners in a focal firm's alliance portfolio. To measure the technological distance, I calculate the Euclidean distance (Song et al., 2003). The formula is as follows:

$$\textbf{Technological distance} = \sqrt{\sum_{j=1}^{n}(p_j - p_j')^2}$$

Where p_j is the percentage of patents of the citing firm (a focal firm) in class j and p_j' is the percentage of patents of the cited firm (firms in the alliance portfolio) in patent class j, n is the total number of patent classes. The larger the value of Euclidean distance, the larger the technological distance between a focal firm and its alliances partners. The averaged number of technological distances between a focal firm and multiple partners

was used as a proxy variable.

Cultural distance between a focal firm and alliance partners (average). Cultural distance in this study means averaged cultural gaps between a focal firm and its alliance partners. Each distance was calculated using Kogut and Singh's (1988) index which is based on Hofstede's aggregate scores (1980). The scores have been widely used in various studies (e.g. Lee et al, 2008; Agarwal and Ramaswami, 1992, Barkema et al., 1997)**.**

General alliance experiences. Drawing data from our alliance database, as a proxy for general alliance experience I used total number of prior alliances excluding alliance with current partners according to previous studies (e.g. Hoang and Rothaermel, 2005). As noted above, this measure is a reflection of the experience and capability of the firm in managing alliances over time. I excluded prior alliances with current partners that would be counted as partner-specific alliance experiences from the general alliance experience measure, to ensure the independence of two experience measures.

Partner-specific alliance experiences. To measure partner-specific alliance experience, I first checked whether a focal firm had prior R&D alliances with partners currently in its alliance portfolio. Then, I calculated the ratio of partners in a focal firm's portfolio which have the past alliance experience with the focal firm as a proxy variable of partner-specific alliance experience.

Competition Ratio. To measure the competition ratio in an alliance portfolio, direct competitors were first defined. Firms in the relationship of direct competition were classified based on the four-digit SIC code. For example, direct competitors in electronics industry are firms whose main SIC at the four-digit level is among 4812, 4813, 3663 or 3669. I first checked whether a focal firm is involved in the same business with each partners in its alliance portfolio, and then, I calculated the ratio of partners in a focal firm's portfolio which are direct competitors of the firm as a proxy variable of competition ratio.

3.2.4. Control Variable

To control for firm and alliance portfolio level confounding factors that might explain a focal firm's knowledge acquisition from the alliance portfolio, I included a number of variables based on past research. I controlled for the year in which an alliance was initiated (announced year). I also tested if alliance portfolios' technological capabilities affect knowledge acquisition of a focal firm. To measure technological capabilities of alliance portfolios, I calculated total number of patents of all firms in an alliance portfolio, and also the mean and variance. In this context, increasing number of patents of portfolios may affect the amount of resources which can be pooled by a focal firm, and also raise possibility of knowledge acquisition.

I also controlled for the focal firms' technological competency that can has an impact on the level knowledge acquisition from alliance portfolio. Total number of patents of each focal firm was obtained. Technological variables were standardized because their different scales could influence the coefficients.

I also noted whether an alliance was an equity-based alliance or not, since an equity-based alliance (joint venture) is viewed as potentially more stable and controlled and thus entails low level of risks related to partner's opportunistic behaviors (Oxley, 1997). I included the ratio of partners in an equity-based alliances as a control variable. In addition, I coded industries into four categories where semiconductor industry is '0,' electronics industry '1,' computer manufacturing industry '2,' and telecommunications industry '3.'

3.3. Analytical Approach

Our sample consisted of an unbalanced panel of global high-tech manufacturing firms over 29 years (1985-2013). For the panel data method, I needed to decide to use fixed effect or random effects. The key issue distinguishing between fixed effects and random effects is whether there are unobserved individual effects which are correlated with the unobserved explanatory variables in the model. If there is no correlation between the unobserved effects and the regressor variables, random effects should be used. Otherwise, the fixed effects model is more appropriate. I used the Hausman test for this choice, and the results of the test showed that explanatory variables in this study are correlated with the unobserved effects. Thus, I chose to use a fixed-effects model for my analysis.

As I measure knowledge acquisition via the number of citation from partners in alliance portfolios in post-alliance patenting, the empirical model has to accommodate the nature of these counts as positive, integer values. Also, there are two other issues to be considered: the preponderance of zero values and the small integer values of many firm citation counts. To account for these issues, I use a negative binomial specification (Hausman et al., 1984). Zero and small values of the dependent variables are naturally

incorporated into the model. Also, negative binomial regression is more appropriate than Poisson regression since dependent variables of this study are overly dispersed from zero to tens of thousands.

4. RESULTS

Descriptive statistics for the model and correlations of all variables in this study are provided in Table 1 and 2 respectively. To ensure that the results of this study are not affected by multicollinearity, I calculated the variance inflation factors (VIFs) associated the model covariates. All VIFs showed below ten, the recommended level, suggesting that there is no bias in the estimated model results from multicollinearity problem.

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Insert Table 1 about here

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Insert Table 2 about here

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Table 3, 4, and 5 presents the results from negative binomial regression on knowledge acquisition of a focal firm from its alliance portfolio. Model 1 includes control variables only. Results of model 1 suggest that technological capabilities of a focal firm is positively related to the knowledge acquisition of the firm ($p < .001$). This result is along with the argument of absorptive capacity. Further, technological capabilities of an alliance portfolio is positively related to the knowledge acquisition of the focal firm ($p < .001$). The results mean that the abundance of knowledge bases of the alliance partners can contribute to the focal firm's knowledge acquisition by broadening the focal firm's resource pool. Whereas, the portion of equity-based alliance in an alliance portfolio has a negative and significant effect on the knowledge acquisition ($p < .01$), showing the opposite direction from the expected.

Model 2 adds the main effect of technological diversity of an alliance portfolio. From model 3, I tested the models adding moderating variables and interaction terms. Model 15, a full model, includes all of the variables in this study. All of the estimated models have high power of explanations (p-value<0.001), and the value of log likelihood qui square increases as explanatory variables are added.

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Insert Table 3 about here

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Insert Table 4 about here

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Insert Table 5 about here

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Hypothesis 1 states that lagged knowledge acquisition has an inverted U-shaped relationship with technological diversity. Results from model 2 show that hypothesis 1 is supported (p<.01). That is, firms whose R&D alliance portfolios has the moderate level of technological diversity is most likely to enjoy the highest level of knowledge acquisition from the portfolio.

From hypothesis 2 to 6, they states that there are effects of moderating factors on the level of knowledge acquisition from technological diversity of alliance portfolio. Hypothesis 2 proposes that the highest level of knowledge acquisition occurs at a lower level of technological diversity when technological distance is higher and vice versa. Results from model 4 show a significant and negative coefficient for the interaction between the technological diversity and technological distance. Model 4 also yields a positive but not significant coefficient for the interaction between the squared technological diversity and technological distance. Therefore, hypothesis 2 is partially supported (p<.05). Considering the main and interaction effect together, model 4 suggest

that a firm which has higher level of technological distance with alliance partners will exhibit lower level of knowledge acquisition from its alliance partners.

Hypothesis 3 proposes that the highest level of knowledge acquisition occurs at a lower level of technological diversity when cultural distance is higher and vice versa. Results from model 6 show a significant and negative coefficient for the interaction between the technological diversity and cultural distance. Model 6 also yields a positive and significant coefficient for the interaction between the squared technological diversity and cultural distance. Therefore, hypothesis 3 is strongly supported ($p<.001$). Considering the main and interaction effect together, model 6 suggest that a firm which has higher level of cultural distance with alliance partners will exhibit lower level of knowledge acquisition from its alliance partners.

Hypothesis 4 proposes that the highest level of knowledge acquisition occurs when a focal firm has a higher level of general alliance experiences. Model 9 includes the interaction terms of technological diversity and general alliance experiences. Results from model 9 show a positive effect of the moderating variable, but it is not significant. Therefore, hypothesis 4 is not supported.

Hypothesis 5 proposes that partner-specific alliance experience will positively moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has more partner-specific alliance experience will exhibit higher level of knowledge acquisition from its alliance partners. Results from model 11 show a significant, but negative coefficient for the interaction between the technological diversity and partner-specific alliance experience. Model 11 also yields a positive coefficient for the interaction between the squared technological diversity and partner-specific alliance experience. Therefore, hypothesis 5 is not supported. Considering the main and interaction effect together, model 11 suggest that a firm which

has many partners with prior ties in the current alliance portfolio will exhibit lower level of knowledge acquisition from its alliance partners.

Hypothesis 6 proposes that portion of the competitors in an alliance portfolio will moderate the inverted U-shaped relation between technological diversity and knowledge acquisition such that a firm which has more competitors as its alliance partner will exhibit lower level of knowledge acquisition from its alliance partners. Results from model 14 show a significant but positive (p<.10) coefficient for the interaction between the technological diversity and competition ratio. Model 14 also yields a positive but not significant coefficient for the interaction between the squared technological diversity and competition ratio. Hypothesis 6 is not supported. Model 14 suggest that a firm which has higher level of competition ratio will exhibit higher level of knowledge acquisition from its alliance partners.

I will cover the discussion on the results about partner-specific alliance experiences and competition ratio (hypotheses 5 and 6) in the next section.

To gain further insights into the moderating effects of distances and alliance experiences on knowledge acquisition from technological diversity from an alliance portfolio, I plotted the results obtained in model 4, 6, and 9 which are depicted in figure 4.

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Insert Figure 4 about here

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5. CONCLUSION AND DISCUSSION

In this study, I investigated the efficient composition of R&D alliance portfolio by examining the ways firms can optimize the learning and resource benefits while limiting the complexity and coordination costs of managing a diverse alliance portfolio, using a panel data of high-tech manufacturing firms during the period 1987-2013.

First, I tested the effect of technological diversity of a firm's R&D alliance portfolio on its knowledge acquisition. Secondly, I examined the boundary condition that a focal firm can raise benefit while reducing costs generated from the diversity of alliance portfolio in order to investigate the cost-effective composition of R&D alliance portfolio. Drawing on transaction cost economics, two sources of transaction costs were considered: distances between a focal firm and partners in its portfolio (technological and cultural distances) and opportunistic behaviors of partners in the portfolio.

The results in this study shows that alliance are important to the global high-tech manufacturing industries to source diverse external knowledge and accelerate firm innovation as the data represents, but the learning benefits diminish with too much diversity in alliance portfolios due to increasing transaction costs. This study also highlight the trade-offs in managing diverse alliance portfolio between learning benefits and managerial complexity and costs. Greater technological diversity of alliance portfolios can be beneficial and contribute to knowledge acquisition of a focal firm when the firm includes technologically and culturally close partners in its R&D alliance portfolio. Technologically distant partners may limit a focal firm's learning capability because a focal firm may not have the capacity to absorb the technologies of such distant partners. Also, too much technological distance may imply problems of communication and mutual understanding. Technological distance between a focal firm and its partners,

thus, may enhance complexity in learning and coordination costs. As the results show, a greater diversity of technology combined with large technological gap may signal a situation in which sourcing from the diversity are likely to occur at a low level or seldom likely to occur.

Cultural distance emanates from differences in language, social norms, and mindsets. High level of cultural distance limit the absorptive capacity. Also, reducing the cultural gap is costly. Thus, managerial and coordination cost of a portfolio is multiplied as a culturally distant partner is added to the alliance portfolio. Such costs impede effective and efficient knowledge transfer from the alliance portfolio to the focal firm. Thus, cultural distance between a focal firm and its partners enhances complexity in learning and coordination costs. When a greater diversity of technology combined with large cultural gap, a focal firm's learning from the diversity are likely to occur at a low level or seldom likely to occur as shown in this study.

Meanwhile, I found significant effects of partner-specific alliance experiences and competition ratio, but not in the expected direction. First, the results in this study suggest that a firm which has many partners with prior ties in the current alliance portfolio will exhibit lower level of knowledge acquisition from its alliance partners. In other words, repeated alliances with old partners do not contribute to knowledge acquisition of a firm. In the hypothesizing stage, I conjectured that prior alliance experience with specific partners will have positive effect on knowledge acquisition from diverse alliance partners. The conjecture was based on arguments of previous studies that repeated ties between partners over time may develop mutual trust, and high levels of trust between partners increase accessibility to each other's rich information. Moreover, prior studies showed that learning accumulated through partner-specific alliance experience can facilitate the development of inter-firm knowledge-sharing routines of coordinating resources and tasks successfully with the partner and experienced partners can skip the relationship-

building processes that are necessary for partners working together for the first time, saving times and resources. However, the results from this study drew different conclusion.

I surmise that attributes of partners' knowledge bases are more important than partners' cooperation as a variable which contribute to knowledge acquisition from alliance portfolios. Even though the mutual trust developed and absorptive capacity to source partner's knowledge increased, learning motivation of a focal firm decreases if there is no novelty in the old partner's knowledge base. Some prior research pointed out that additional alliances with the same partner may provide only redundant information (Gulati, 1995) and can also lead to inertia between partners. Also, other empirical work showed that inter-firm tacit knowledge accumulated over time exhibits diminishing returns due to knowledge ossification (Berman et al., 2002).

Next, the results in this study suggest that a firm which has higher level of competition ratio will exhibit higher level of knowledge acquisition from its alliance partners. I also can find some explanations for this results. According to the previous studies, competitors may be the greatest learning target through imitation and absorptive capacity due to an overlap in experiences, technology, and knowledge bases (Cohen and Levinthal, 1990). When partners have interests in the same industry, it is easier for them to define resource combinations that can create synergies among them. In addition, they can easily take advantage of the acquired knowledge since it is easier for them to use what they have learned immediately(Park and Russo, 1996). This is because competitors in the same industry often confront similar issues and problem-solving sets (Gnyawali and Park, 2009). This close cognitive distance raise efficiency of innovation efforts, reducing time span of R&D and risks.

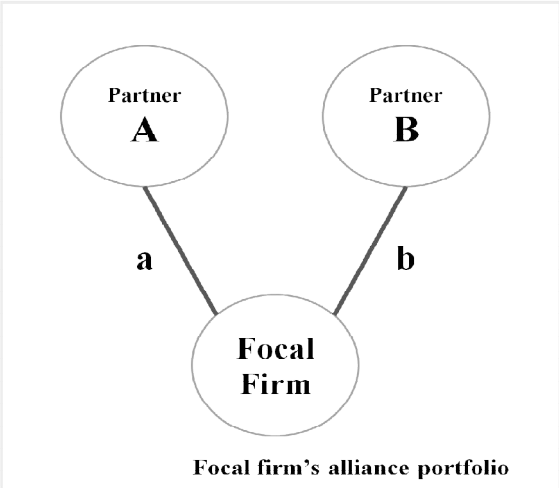
In addition, as for the case of learning and exploiting partner's knowledge, motivation

to outcompete a rival in their industry can much more prevail than motivation to cooperate: “The alliance becomes a race to learn, with the company that learns fastest dominating the relationship and becoming, through cooperation, a more formidable competitor” (Parkhe, 1991). That is, co-opetition may perform as competitive strategy to surpass rivals by offering the opportunities to access to the competitor's knowledge. Although beyond the scope of this current study, these results could be examined in the future studies with different perspective from transaction cost economics.

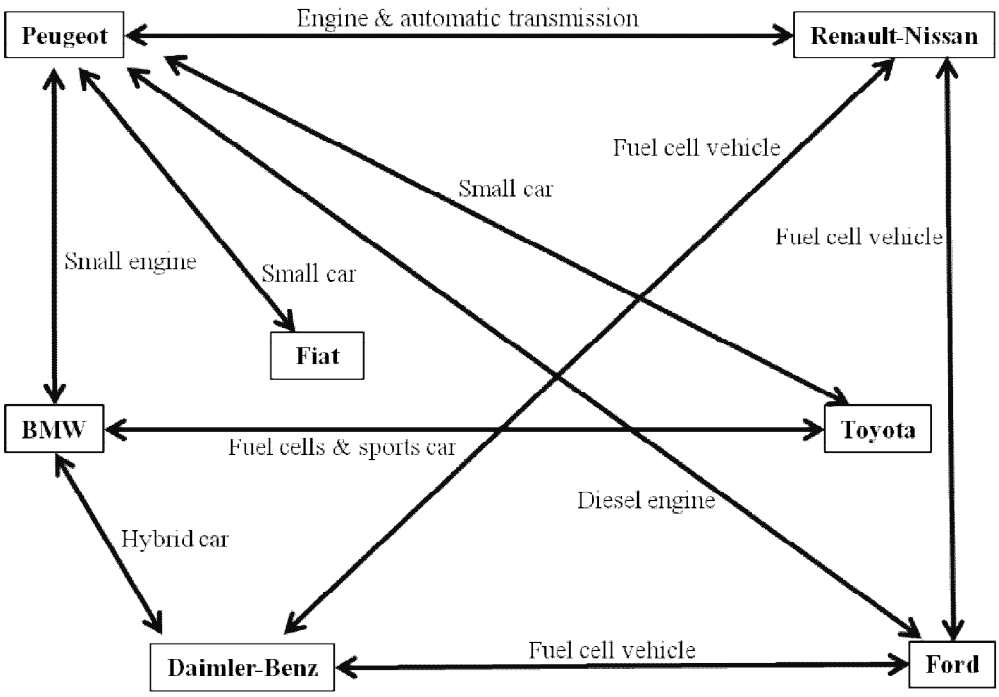
One of the key contribution of this study is to examine the ways firm can optimize the learning and resource benefits while limiting the complexity and coordination costs of managing a diverse alliance portfolio. Also, this study is extending prior works focused mostly on partner's attributes and dyadic relationship which are factors influencing alliance performance. By measuring alliance performance via knowledge acquisition from alliance portfolio, I focused more direct effect of alliance portfolio composition on firm's innovation. Knowledge acquisition from firms in a R&D alliance portfolio could be more direct and appropriate measurement than that in existing studies. Most of the prior studies used the increase in the post-alliance patenting activities as a measure of R&D alliance performance (e.g. Sampson). However, post-alliance innovation of a firm cannot be a direct measure of learning from partners in its portfolio, thus inappropriate for estimating the costs and benefits of retaining diverse partners in the portfolio.

Managers should understand that there is cost effective way to compose R&D alliance portfolios to access diverse pools of resources and knowledge and enhance value appropriation from the pool. I advice managers not to overly try to ally with technologically and culturally distant partners when they add partners with different knowledge pools from existing partners in the alliance portfolio.

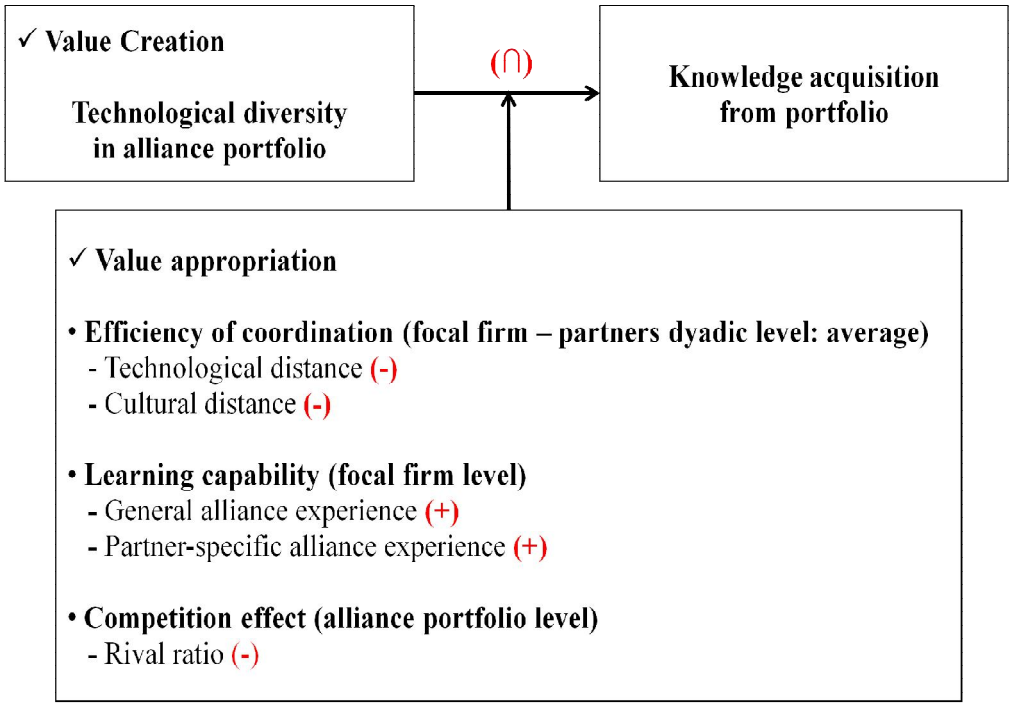
[Figure 1] An example of the alliance portfolio of a focal firm



[Figure 2] Alliances for co-development of technology and manufacturing in global automobile industry (August 2013)



[Figure 3] Research model



[Table 1] Descriptive statistics of variables (N=1,999)

Variables	Minimum	Maximum	Mean	Std. deviation
Knowledge acquisition, t+5	0.00	32,942.00	710.38	2,894.37
Technological diversity of portfolio	0.00	1.00	0.19	0.22
Technological distance (focal firm-portfolio)	0.29	1.00	0.62	0.17
Cultural distance (focal firm-portfolio)	0.00	88.53	5.12	15.14
General alliance experiences of focal firm	0.00	170.00	9.91	16.90
Prior ties with partners in portfolio (ratio)	0.00	1.00	0.84	0.30
Competitors in portfolio (ratio)	0.00	1.00	0.19	0.23
Technological capability of focal firm (LN)	0	10.72	4.81	2.69
Technological capability of portfolio (mean, LN)	1.10	10.46	6.90	1.44
Technological capability of portfolio (variance, LN)	0.00	20.88	14.15	2.90
Equity-based ties in portfolio (ratio)	0.00	1.00	0.21	0.33
Number of partners	3.00	24.00	6.15	4.37

[Table 2] Correlations of variables (N=1,999)

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Knowledge acquisition, t+5											
2. Technological diversity of portfolio	.01										
3. Technological distance	-.09***	-.01									
4. Cultural distance	-.07**	.01	.14***								
5. General alliance experiences of focal firm	.40***	.05	-.16***	-.05*							
6. Prior ties with partners in portfolio	.02	.02	-.05*	.04	.22***						
7. Competitors in portfolio	.10***	.02	-.03	-.05*	.06**	.03					
8. Technological capability of focal firm	.31***	-.01	-.22***	-.05*	.35***	.05*	-.03				
9. Technological capability of portfolio (mean)	.20***	-.00	-.07**	.01	.27***	.11***	-.01	.23***			
10. Technological capability of portfolio (variance)	.20***	.02	-.10***	-.02	.29***	.11***	-.02	.24***	.95***		
11. Equity-based ties in portfolio	.02	-.05*	-.05*	.01	.03	-.01	.03	.07**	-.06**	-.07**	
12. Number of partners	.38***	.04	-.40***	-.17***	.52***	.04	.05*	.32***	.25***	.31***	.03

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

Note: All model chi-squares are significant at $p < 0.01$

[Table 3] Negative binomial regression models estimating knowledge acquisition (distance)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	-0.75***(0.16)	-0.89***(0.18)	-0.14(0.27)	-0.87***(0.18)	-0.60***(0.16)	-0.82***(0.1)8	-0.80***(0.18)
Industry (reference: Semiconductor)							
- Electronics	-1.01*** (0.18)	-0.98*** (0.18)	-0.88*** (0.18)	-0.87*** (0.18)	-1.12*** (0.18)	-1.08*** (0.18)	-1.00*** (0.18)
- Computer	0.01 (0.17)	0.07 (0.17)	-0.07 (0.17)	-0.02 (0.17)	-0.13 (0.19)	-1.02 (0.17)	-0.13 (0.18)
- Telecommunications	-0.59*** (0.14)	-0.57*** (0.14)	-0.55*** (0.14)	-0.56*** (0.14)	-0.64*** (0.14)	-0.65*** (0.14)	-0.65*** (0.14)
Equity-based ties in portfolio	-0.59** (0.19)	-0.60** (0.19)	-0.53** (0.19)	-0.58** (0.19)	-0.70*** (0.19)	-0.71*** (0.19)	-0.68*** (0.19)
Technological capability of focal firm	0.98*** (0.02)	0.98*** (0.02)	0.95*** (0.02)	0.96*** (0.02)	0.96*** (0.02)	0.97*** (0.02)	0.95*** (0.02)
Technological capability of portfolio(mean)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Technological diversity of portfolio		1.50* (0.73)	5.42** (1.76)	5.44** (1.75)	4.91** (1.77)	1.83* (0.75)	4.91** (1.77)
Technological diversity squared		-2.16** (0.80)	-4.51* (2.32)	-4.55* (2.31)	-3.85 (2.36)	-2.38** (0.83)	-3.85 (2.36)
Technological distance			-1.41*** (0.34)	-1.34*** (0.24)			-1.03*** (0.11)
Technological diversity × Technological distance				-6.57* (2.71)			-5.20^{+}(2.77)
Technological diversity squared × Technological distance				4.00 (3.77)			2.46 (3.87)
Cultural distance					-0.02*** (0.00)	-0.03*** (0.00)	-0.02*** (0.00)
Technological diversity × Cultural distance						-0.12*** (0.03)	-0.10*** (0.03)
Technological diversity squared × Cultural distance						0.09*** (0.19)	0.08* (0.04)
n	1999	1999	1999	1999	1999	1999	1999
Log-likelihood χ^2	1253.46	1261.24	1269.73	1273.92	1275.80	1279.95	1289.42

*** $p < .001$ ** $p < .01$ * $p < .05$ $^{+}$ $p < .10$

Note: All model chi-squares are significant at $p < 0.01$

[Table 4] Negative binomial regression models estimating knowledge acquisition (Alliance experiences)

Variables	Model 8	Model 9	Model 10	Model 11	Model 12
Intercept	-0.74***(0.17)	-0.86***(0.19)	-0.21(0.23)	-0.97***(0.18)	-0.87***(0.19)
Industry Dummy	Yes	Yes	Yes	Yes	Yes
Equity-based ties in portfolio	-0.55** (0.19)	-0.59** (0.19)	-0.67*** (0.19)	-0.63*** (0.19)	-0.56** (0.19)
Technological capability of focal firm	0.99*** (0.02)	0.98*** (0.02)	0.97*** (0.02)	0.98*** (0.02)	0.96*** (0.02)
Technological capability of portfolio(mean)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Technological diversity of portfolio	1.43 (0.91)	1.31(0.81)	4.90** (1.62)	4.87** (1.52)	4.73** (1.63)
Technological diversity squared	-2.01* (0.71)	-2.05* (0.91)	-3.97(2.46)	-3.86(2.23)	-3.59(2.53)
General alliance experiences	0.03 (0.00)	0.01 (0.00)			0.01 (0.00)
Technological diversity × General experiences		0.02(0.03)			0.07^{+} (0.04)
Technological diversity squared × General experiences		-0.01(0.04)			-0.06(0.04)
Prior ties with partners in portfolio			-0.73*** (0.21)	-0.69*** (0.22)	-0.63*** (0.19)
Technological diversity × Prior ties				-4.36* (1.71)	-5.04** (1.81)
Technological diversity squared × Prior ties				2.60(2.76)	2.90(2.96)
n	1999	1999	1999	1999	1999
Log-likelihood χ^2	1254.95	1261.97	1277.54	1281.10	1286.19

*** $p < .001$ ** $p < .01$ * $p < .05$ $^{+}$ $p < .10$

Note: All model chi-squares are significant at $p < 0.01$

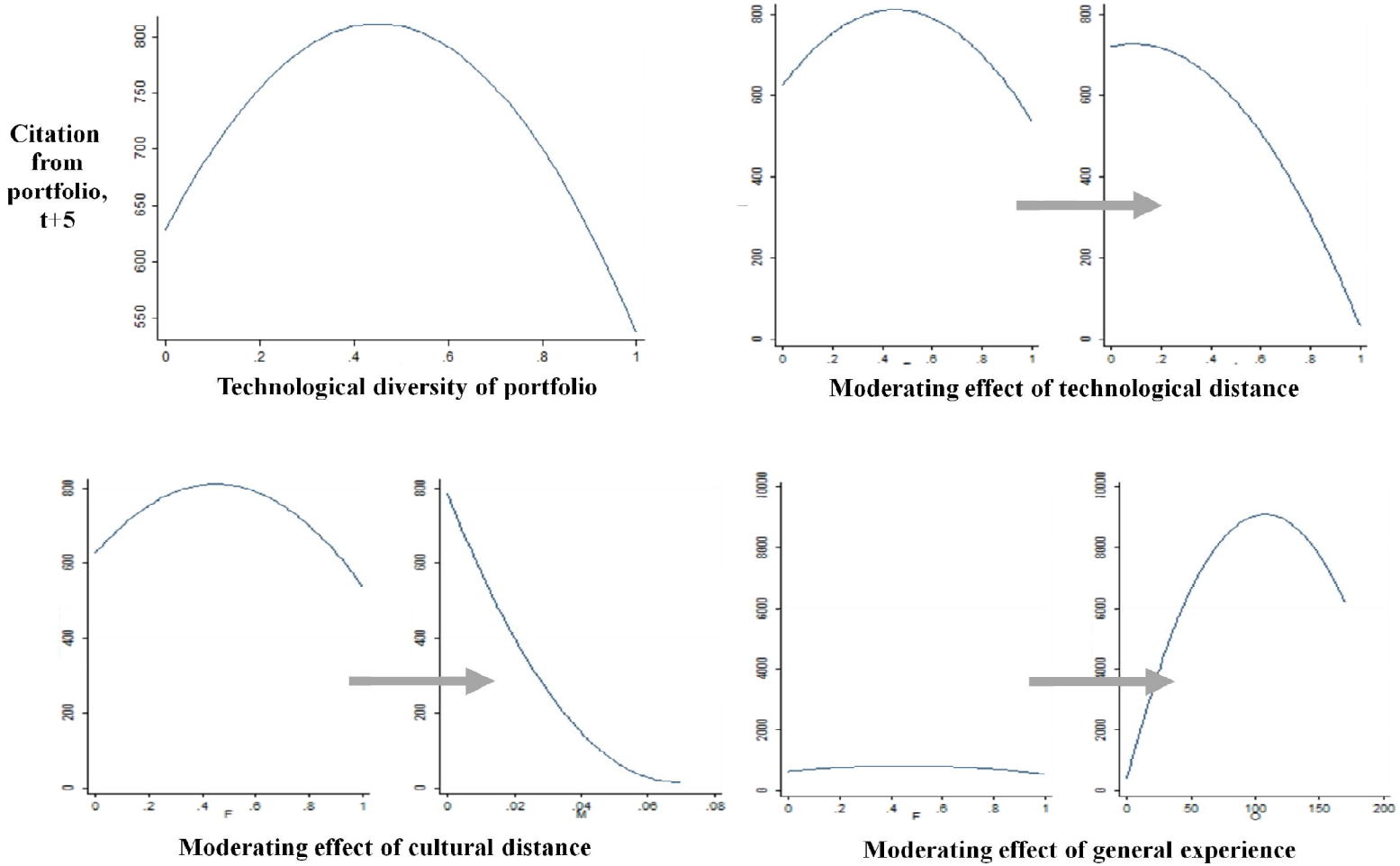
[Table 5] Negative binomial regression models estimating knowledge acquisition (Competitors and all)

Variables	Model 13	Model 14	Model 15
Intercept	-0.74***(0.17)		-0.86***(0.19)
Control variables	Yes	Yes	Yes
Technological diversity of portfolio	0.62(0.87)	0.61(0.85)	7.81**(2.42)
Technological diversity squared	-0.97(1.09)	-0.94(1.00)	-5.66^{+}(3.23)
Technological diversity × Technological distance			-5.11^{+}(2.89)
Technological diversity squared × Technological distance			3.33(3.96)
Technological diversity × Cultural distance			-0.09**(0.03)
Technological diversity squared × Cultural distance			0.06(0.04)
Technological diversity × General experiences			0.05(0.04)
Technological diversity squared × General experiences			-0.04(0.04)
Technological diversity × Prior ties			-5.46***(1.71)
Technological diversity squared × Prior ties			3.98(2.56)
Competitors in portfolio	0.76** (0.30)	0.73** (0.23)	0.70** (0.22)
Technological diversity × Competitors in portfolio		4.62^{+} (2.56)	4.86^{+}(2.57)
Technological diversity squared × Competitors in portfolio		-6.36(4.09)	-7.16^{+}(4.03)
n	1999	1999	1999
Log-likelihood χ^2	1260.41	1264.6	1311.2

*** $p < .001$ $^{**}p < .01$ $^{*}p < .05$ $^{+}p < .10$

Note: All model chi-squares are significant at $p < 0.01$

[Figure 4] Moderating effects of variables



Chapter III.

Multiparty Alliances and Innovation

: When does a multiparty R&D alliance work?

1. INTRODUCTION

The rapid proliferation of strategic alliances has been one of the most lasting features of the business world over the last two decades. Main reasons are that competition is increasingly knowledge-based and the life-cycles of technology become shorter, as firms strive to learn and to develop capabilities faster than their rivals (Prahalad and Hamel, 1990; D'Aveni, 1995; Teece and Pisano, 1994). These trends in today's business world has made it nearly impossible for any firm to build and sustain its technological competitive advantage without utilizing external knowledge and technologies. This is because the time between the identification of a problem and its arrival may not allow the firm to internally develop the knowledge and capabilities needed to respond effectively (Dierickx and Cool, 1989). This has led to a shift from traditional resource or risk-sharing alliances to alliances with learning from partners as a primary goal such as R&D alliances (Hamel, 1991; Huber, 1991). Such alliances for 'learning' enable firms to speed up capability development and minimize the inherent risks and uncertainties associated with technological innovation by acquiring and exploiting knowledge developed by other firms (Grant and Baden-Fuller, 1995).

For these reasons, firms in many high-tech industries, such as electronics, computer, semiconductors, telecommunications, are increasingly engaging in a wide array of R&D alliances to source external knowledge and accelerate innovation (Rigby and Zook, 2002; Wassmer, 2010). In addition, there is increasing demand for technology or products which need diverse knowledge to be integrated, forcing firms in technology-intensive industries to engage in R&D alliances with multiple members participating in an alliance.

Researchers increasingly recognize the importance of alliances which contain more than three partners (Das et al., 2003; Lavie et al., 2007). These alliances are called

'multiparty alliances.' Multiparty R&D alliances are now observed in various high-tech industries (Browning et al., 1995; Das et al., 2003; Lavie et al., 2007). Figure 5 gives a more detailed overview of the number of partners in all new R&D alliance announcements during 1987-2013 in high-tech manufacturing industries (semi-conductor, electronics, computer manufacturing, and telecommunications). About 14% (322 alliances) of all new alliances consisted of more than three partners. This means that almost one out of seven new alliances were multiparty alliances.

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Insert Figure 5 about here

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Multiparty R&D alliances provide several benefits for participating firms (De Rochemont et al., 2007). First, increasing the number of partners also raises the benefits the alliance may generate. In a multiparty alliance, the amount of resources pooled by the partners increases and each partner brings unique R&D resources to the cooperation (Browning et al., 1995). Thus, participants have diverse and broadened pool of knowledge and resources. Secondly, the higher the number of partners, the higher the positive feedback and network externalities that partners can gain from the alliance (Doz and Hamel, 1998). This is because the possibilities that the technology or the product configuration developed in the alliance is imposed as a standard or a dominant design in an industry increase (Afuah, 1999). Moreover, firms cooperating with multiple firms in an alliance enjoy additional scale effects. According to a previous study, Agri-Food firms in the Dutch tomato industry develop new cultivating techniques with partners in a

multiparty alliance. This R&D would take too much time and resources to be carried out by individual firm. By joining resources and knowledge, each firm in a multiparty alliance is able to tap into new techniques which improve their competitive position while reducing costs and risks associated to innovative activities.

Nevertheless, a large number of alliances fail (Gates, 1993) to enjoy those benefits. Some predicts that the failure rate of alliances is as high as 70% (Business Week, 1986; Parkhe, 1993). Failure rate may be higher as for the case of multiparty alliances because multiparty alliances may be more difficult to manage than bilateral ones, since monitoring becomes more difficult with the addition of more partners (Oxley, 1997).

As previous research has shown, a higher number of partners increase coordination and monitoring costs (Oxley, 1997) with increased transaction costs. Each partner requires additional efforts and resources to be committed so that the alliance works well (Garcia-Canal et al., 2003). Meanwhile, increased number of partners make decision-making processes more difficult with the increased risk of conflicts. Moreover, firms in a multiparty alliance face the increased danger of opportunistic behaviors of participants (Dyer et al., 2000; Das et al., 2003). Opportunistic partners in a multiparty alliance may willingly participate in knowledge-sharing activities to acquire the desired knowledge at first, and then refuse to contribute its knowledge and cooperate to make joint innovation. Thus, the creation of useful knowledge in a multiparty alliance has the potential for 'free riders' (Dyer et al., 2000). Such opportunistic behaviors of partners can also undermine the development of trust among participants (Das et al., 2003).

Therefore, firms face trade-offs in a multiparty alliance. On the one hand, alliance partners are social capital and mutual learning partners (Hamel, 1991; Mowery et al., 1996, 1998; Koka and Prescott, 2002). Multiple participants with diverse knowledge provides broadened knowledge pool and access to enriched search options, creating a

great deal of opportunities for value creation and capability development. Thus, diversity in a multiparty alliance is the important factor influencing on successful joint outcomes from the alliance. On the other hand, increased diversity in a multiparty alliance can bring more complexity and potential for conflicts, thus increasing coordination and managerial costs for participating firms (Oxley, 1997). Thus, the benefits from diversity in the multiparty alliance come at the cost of managing such complexity and possibilities of conflicts. However, prior studies do not successfully reveal the antecedents of multiparty alliance performance.

Prior studies mainly focused on conceptualization of multiparty alliances and offered propositions, without providing empirical testing for their propositions (Zeng and Chen, 2003; Das et al, 2003). Most of existing research on this topic has been carried out using case study research, and lacks external validation with empirical evidences. In addition, most prior research took a single perspective in approaching the antecedents of multiparty alliance performance: a social governance view (Das et al., 2003; Jones et al., 1997; Zeng and Chen, 2003), a formal governance perspective (Garcia-Canal et al., 2003; Lavie et al., 2007), or game theory (Hwang et al., 1997). Recently, scholars have recognized that understanding performance of multiparty cooperation demands a multi disciplinary approach (e.g. Vanhaverbeke et al., 2006). Vanhaverbeke et al. (2006) focused on value creation and appropriation from an open innovation perspective. Thus, while multiparty alliance management requires a multi disciplinary approach, previous research has not yet been able to investigate this phenomenon comprehensively.

Adopting a longitudinal perspective in explaining multiparty alliance performance could lead to valuable insights which enable managers to improve the success rate of their multiparty alliances. The purpose of this study is to fill such gaps and answer the following important question with empirical data:

Specifically, I investigate the factors influencing joint innovation performance (joint patenting in this study) to which all of the participants in a multiparty R&D alliance contribute. Drawing upon organizational learning theory and transaction cost economics, I examine the effects of diversity in a multiparty alliance (technological and national diversity), attributes of ties composing the multiparty alliance (multiple, repeated, and co-opetition ties), and governance structure of the alliance with data of high-tech manufacturing firms during the period 1987-2013.

The remainder of the paper is structured as follows. In Section 2, I develop a set of hypotheses for the empirical analysis. Section 3 presents the specific research methods and the databases we used for our empirical analysis. Finally, I show the results from empirical tests and conclude with some discussion points in section 4 and 5 respectively.

2. THEORY AND HYPOTHESES

In this study, the multiparty alliance is defined as an alliance with more than three members according to the previous studies (Lavie et. al., 2007; Vanhaverbeke and Cloodt, 2006). I chose to include only multiparty R&D alliances in study. The main reason firms engage in multiparty R&D alliances is most likely to join diverse knowledge from the partners to speed up the development of desired technology or products. From the organizational learning perspective, diverse knowledge is related to innovation performance.

2.1. Diversity in a multiparty alliance and joint patenting performance

Technological diversity in a multiparty alliance and joint patenting performance

I define technological diversity in a multiparty R&D alliance as the degree of variance in technology among partners in the alliance (Bae and Gargiulo, 2004; Lavie, 2007). Also, I define joint innovation performance as joint patenting activities in which all of the participants in a multiparty alliance engage, in a highly conservative way. This is because I could not find the measurements for joint innovation performance in a multiparty alliance in previous studies, and it is not proper measurement to use dyadic patenting (between only two partners) as a proxy variable of innovation performance in a multiparty alliance.

According to the organizational learning theory, technological capability which has been cumulated over time inside a firm creates its knowledge base. A firm could have opportunities to access other firms' knowledge based via R&D alliances, and thus R&D alliance portfolios of the firm play a role as its external knowledge base. As technological diversity in a multiparty R&D alliance increases, participating firms enjoy benefits in that the firm can have access to more non-redundant and diverse information (Burt, 1980; Granovetter, 1973; Duysters and Lokshin, 2011). Such multiparty alliance provides benefits that are additive rather than redundant (Burt, 1997), and encourages the incorporation of diverse perspectives. Alliance partners which have overlapped knowledge or technology with a focal firm would less contribute to the firm's knowledge base (Vassolo et al., 2004; Anand et al., 2007), and this sub-additive alliance portfolio could reduce learning sources and motivation for the firm. In contrast, partners with diverse technology in alliance portfolios diverse facilitate a focal firm's learning

motivation and access to information, knowledge, technologies, and other important tangible and intangible resources, enabling a focal firm to have opportunities to acquire more knowledge from its alliance portfolio and to offset technological uncertainty with an opportunity set of viable alternatives (Sirmon et al., 2007; Vassolo et al., 2004)

Meanwhile, the positive effect would diminish at much higher levels of diversity. Using the diverse knowledge and technology which reside in a multiparty alliance is not costless. As a multiparty alliance becomes more technologically diverse, there would be more non-redundant and non-overlapping external knowledge. Utilizing such new knowledge may need more learning resources to stretch the participating firm's absorptive capacity (Vasudeva and Anand, 2011), which means "a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends (Cohen and Levinthal, 1990: 128)." This is because a member firm would have fewer opportunities for redeployment of relational assets when partners in a multiparty alliance are very diverse in their technological capabilities (Dyer and Singh, 1998; Mesquita et al., 2008). It is related to the argument that lower compatibility among diverse partners may reduce the substitutability or applicability of experiences in the alliance (Dyer and Singh, 1998; Vassolo et al., 2004; Mesquita et al., 2008). The lower levels of shared experiences in the alliance increase burden on a member organization's learning capability to source new technology and consequently, reduce joint innovation performance in the multiparty alliance.

Combining the above perspectives, I suggest that too little technological diversity in a multiparty alliance imposes a cost by reducing exposure to alternatives and greater redundancy for a firm engaged in the alliance. At the same time, too much diversity excessively burdens the firm's absorptive capacity, make the firm underutilize diverse knowledge of multiparty alliance. At both cases, the costs exceed the expected knowledge acquisition benefits from alliance portfolios (Cording et al., 2008; Vasudeva and Anand,

2011). Therefore, firms in multiple R&D alliance portfolios which has the moderate level of technological diversity is most likely to succeed in jointly create innovative outcomes. Thus, I hypothesize:

Hypothesis 1. There is an inverted U-shaped relationship between technological diversity of member organizations in a multiparty alliance and its joint patenting.

National diversity in a multiparty alliance and joint patenting performance

I define national diversity in a multiparty R&D alliance as the degree of variance in country origins among firms in the alliance. Alliances increasingly involve firms from different nation states. Cross-border alliances can enhance diverse knowledge bases and learning (Lubatkin et al., 2001), but can pose a high potential for conflicts.

If there are members with diverse country origins in a multiparty alliance, member firms could get exposed to a greater diversity of technologies, knowledge, and management practices (Zhang et al., 2010). They can offer various technology, knowledge, and management practices because countries differ in terms of diverse important dimensions such as geography, culture, domestic market, business system, administrative and institutional context, development stage, and competitive supremacy (Ghemawat, 2003; Zhang et al., 2010). Because of these differences, firms may supplement their existing technical capabilities by having partners with diverse country origins in alliances. Such partnership would allow them to access new technology, skills, or knowledge; which might be product, process, and/or managerial in nature (Cantwell,

1989; Wesson, 1993; Kuemmerle, 1999). Ahuja and Katila (2004) argued that firms can face idiosyncratic opportunities and changes in their countries and they can generate firm heterogeneity in their resources because those firms respond to the environments by creating unique paths. Those unique paths make national differences in technology, knowledge, and management practices (Ghemawat, 2003). Indeed, it is widely recognized that firms' strategic behaviors or technological paths vary with their country origins (Wan and Hoskisson, 2003).

Thus, members with diverse nationalities in a multiparty alliance get exposed to diverse technology, knowledge, and problem-solving sets, which promotes mutual learning[4] and facilitates innovation in the alliance. Empirical study also supports this argument, showing that the exposure to broad knowledge have a positive impacts on a firm's propensity to explore new and related knowledge (Van Wijk et al., 2001). Diverse knowledge and management practices can offer firms more opportunities to recombine those knowledge and practices to create new innovative outcome. In a lot of literatures on innovation and knowledge management, it has been noted that new knowledge creation often results from the recombination of existing elements of knowledge into new syntheses (Henderson and Clark, 1990; Katila and Ahuja, 2002; Kogut and Zander, 1992). Such recombination potential would be greater when national diversity of firms in a multiparty alliance is greater because the number of new combinations that can be created from the same set of technology or knowledge elements is limited (Katila and Ahuja, 2002).

However, differences in corporate culture, strategic direction, and management

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[4] Knowledge diversity in the environment 'provides a more robust basis for learning because it increases the prospect that incoming information will relate to what is already known' (Cohen and Levinthal, 1990: 131).

practices can cause conflicts and increase alliance costs. High national diversity in a multiparty alliance can create excessive coordination and integration costs due to the complexity in managing those differences. In a previous research, we can find different communication patterns between Americans and Japanese managers and get a typology that punctuates the difficulties in the interaction process involving partners from different countries (Tung, 1993). Thus, firms must deal with the downside of increased national diversity before they can reap net benefits.

Combining the above perspectives, I suggest that too little national diversity in a multiparty alliance imposes a cost by reducing exposure to alternatives and greater redundancy for a firm engaged in the alliance. At the same time, too much diversity makes the firm have difficulties in utilizing diverse knowledge in a multiparty alliance. Therefore, firms in multiple R&D alliance portfolios which has the moderate level of national diversity is most likely to succeed in jointly create innovative outcomes. Thus, I contend:

Hypothesis 2. There is an inverted U-shaped relationship between national diversity of member organizations in a multiparty alliance and its joint patenting.

2.2. Attributes of ties in a multiparty alliance and joint patenting performance

Firms face trade-offs, however, as they participate in multiparty R&D alliances to broaden knowledge pool and grow opportunities to succeed in innovation. This is because

increased number of partners in R&D alliances can bring more complexity and potential for conflicts, thus increasing coordination and managerial costs for participating firms.

Alliances usually entail significant uncertainty about future transaction costs and benefits due to the possibility of opportunistic behavior of partners. The lack of clear relationships based on a single authority is another reason for the uncertainty. Moreover, alliances involve a risk of technology leakage, as there are inherent risks of unilaterally losing proprietary technologies to the partner. Firms may confront different transaction costs generated from the partners' opportunistic behaviors according to the attributes of ties in a multiparty alliance. In this study, I focus on the factors influencing the possibility of opportunistic behaviors of partners such as repeated, multiple, and co-opetition ties between participants in a multiparty alliance and thus, having impacts on joint patenting performance of the alliance.

Repeated and multiple ties and joint patenting performance

Repeated ties mean the pair of firms which have prior alliance experience with each other in a multiparty alliance, while multiple ties mean the pair of firms which are currently engaging in another alliances.

Knowledge and skills that accumulate from recurrent allying with specific partners over time may be important experiences (Hoang and Rothaermel, 2005). Firms with cumulated experiences through repeated or multiple alliance activities with specific partners could source the partners' knowledge efficiently by reducing transaction costs.

First, repeated or multiple ties between partners over time may develop mutual trust (Gulati, 1995; Hagedoorn et al., 2003). High levels of trust between partners increase accessibility to each other's rich information (Uzzi ,1996; 1997). This is because trusting

firms may have greater commitment to make the alliance work and the development of norms of sanctions for the violation of trust deters partner's opportunistic behavior (Coleman, 1988), and thus partners share rich information with confidence. The idea of trust emerging from repeated partnerships is also based on the premise that firms can learn about each other through ongoing interaction, including how to understand and predict each other's patterns of behavior (Dyer and Chu, 2000). As knowledge between partners increases, behavioral uncertainty decreases by reducing information asymmetries (Casciaro, 2003). Previous research found that greater partner-specific alliance experience is linked with firms' abilities to manage alliance conflicts (Simonin, 1997).

Moreover, learning accumulated through partner-specific alliance experience can facilitate the development of inter-firm knowledge-sharing routines of coordinating resources and tasks successfully with the partner (Zollo et al., 2002). Technology sharing requires wide-ranging, continuous, and intense interactions between firms (Kogut, 1988). Repeated ties with a partner enables a firm to better understand their partner's goals and motives. Also, firms can learn about each other's ways of doing business through recurrent alliances and interpret meaning from each other's actions. The refinement of partner-specific interfaces and the development of partner-specific decision making as well as conflict resolution routines should enhance mutual understanding. Such routines of inter-firm knowledge sharing create a basis for partner-specific absorptive capacity that enables alliance partners to recognize the value of each other's knowledge and effectively transfer it across inter-firm boundaries (Dyer and Singh, 1998).

In addition, experienced partners can skip the relationship-building processes that are necessary for partners working together for the first time (Inkpen, 2000), saving times and resources. Usually, the type of knowledge to be sourced may be tacit and can be gained more efficiently and accurately through direct and close interaction between people who possess the knowledge. Seen from the view of learning-by-doing argument,

as firms gain experience in solving a particular problem, they do not have to pay conscious attention to it over time (Bereiter and Scardamalia, 1993). Experienced organizations are thus likely to be more effective than others with little experience.

Therefore, the relational routines and mutual trust created through repeated or multiple alliances reduce the fear of opportunistic behavior, allow for greater openness, and facilitate the coordination of each partner's respective technologies (Kale et al., 2000). Although there is a number of partners in a multiparty alliance, a lot of repeated or multiple ties would help to jointly develop technologies. Hence, I hypothesize:

Hypothesis 3. There is a positive relationship between repeated ties among member organizations in a multiparty alliance and its joint patenting.

Hypothesis 4. There is a positive relationship between multiple ties among member organizations in a multiparty alliance and its joint patenting.

Co-opetition ties and joint patenting performance

Industry analysts and academic researchers report a increasing number of incidence and growing importance of alliances among competitors. Purposes of alliance with competitors vary including technology and product development, joint manufacturing, and market entry or expansion (Doz, 1996; Park and Russo, 1996; Sakakibara, 1997). We call the collaboration (alliance) with partners from the same industry as co-opetition. Due to hyper-competition in technology development and the short life-cycle of new technology, co-opetition for knowledge sharing is now very common across high-tech

industries. Toyota was well known for "pure bloodism" as it made all of the car components such as sunroofs by itself. After several times of crisis including currency rate fluctuations and recalls, however, the firm began to actively search for alliance partners. Now it allies with direct competitors to co-develop core technology which would be competitive dynamics in the future. Toyota and BMW group announced that they would cooperate in order to develop the technology of future in January 2013 and now in partnership for the development of fuel cell system, next generation sports car and lightweight technology.

Although there are a lot of drivers to force firms to ally with their direct competitors, collaboration with competitors entails great risks in many ways. First, there is technological risk. If a firm fail to monitor or control the opportunistic behaviors alliance partners in direct competition, there is high possibility that it lose its secret, proprietary knowledge or core technology to such partners (Gnyawali and Park, 2009). Either party can opportunistically use the alliance to learn the other's business or technological secrets (Bucklin and Sengupta 1993) while being reluctant to open its own to the other. For these reasons, firms do not always seek the most capable partners, but select the most trusting partners although resource-based view tells us that it is natural for firms to select the most competent firms as alliance partners even if they are competitors.

In reality, it is very difficult for competing firms to collaborate for knowledge sharing. Two basic types of alliances between competitors have been distinguished as link alliances and scale alliances (Porter and Fuller, 1986; Hennart, 1988; Dussauge et al., 2000; Mitchell et al., 2002). Partners in scale alliances contribute similar resources to the alliances (e.g. alliances for sharing knowledge and co-development of technology), while partners in link alliances contribute substantially different resources to the alliances (e.g. alliances for cost reduction or market expansion). Mitchell et al.(2002) showed in their empirical study that competing firm alliances that involve R&D resources are more likely

to be scale alliances than link alliances because scale efficiency incentives are even stronger. R&D resources may offer greater opportunities for link alliances, but such link alliances involving R&D resources would generate appropriation risks when combined with a competitor's production or marketing resources (Hamel, 1991; Hennart et al., 1999). Therefore, we expect firms to be reluctant to combine their R&D resources with competitors by creating link alliances. Instead, when forming link alliances, firms will contribute only existing designs and previously developed products, excluding R&D resources from the activities of the alliance.

In addition, valuable knowledge is often tacit, such that the direct interaction with knowledge holders is essential. Such interactions allow firms to source alliance partner's technological knowledge more efficiently (Iwasa and Odagiri, 2004). However, there are competing expectations from both cooperative and competitive relationships in co-opetition relations, generating role conflicts for managers engaging in co-opetition (Bengtsson and Kock, 2000; Raza-Ullah et al., 2013). Also, there can be conflicts of interest and learning races among partners in the same industry. Such things increase monitoring and safeguarding costs (Park & Ungson, 2001; Jiang et al., 2010). Although learning is a possible benefit of the alliance, conflicts associated with learning could block the functioning of the alliance (Park & Russo, 1996). This is because partners may be reluctant to make investments in relational assets with competitors that may result in undesired knowledge transfers (Kale et al., 2000)

Higher number of co-opetition ties in a multiparty alliance would impede co-development of technologies. Hence, I hypothesize:

Hypothesis 5. There is a negative relationship between co-opetition ties among member organizations in a multiparty alliance and its joint patenting.

2.3. Governance structure of a multiparty alliance and joint patenting performance

Multiparty alliances can be structured as non equity-based alliance, symmetric equity-based alliance, and asymmetric equity-based alliance. A non equity-based alliance is a contractual arrangement in which partners pool their capabilities for the purposes of collaborative R&D but do not form a separate legal entity for the alliance. Firms under an equity-based alliance (joint venture) create a new organization which is jointly owned and operated by two or more collaborating firms (Oxley, 1997; Pisano et al., 1988).

It has been proven in a various research that the governance structure of alliances has great impact on alliance performance (e.g., Kogut, 1988; Oxley, 1997; Lavie, 2007; Santoro and McGill, 2005). The argument prevails that joint innovation is more easily obtained in equity-based alliance (especially symmetric equity-based alliance) than in non equity-based alliance for many reasons.

First, knowledge transfer in the alliances via more interactive ways in equity joint ventures. The most important and prevalent way of knowledge transfer between partners is the mobility of technical employees their close contacts. In equity joint ventures in particular, the key mechanism for knowledge transfer between partners is employee rotation and contacts among employees. Parent firms typically also supply needed technical support when transferring knowledge or resources to a joint venture.

Plus, other advantages of hierarchical organization was suggested in the past research (e.g. Arrow, 1974). Arrow (1974) argued that hierarchical organization has the ability to economize in communication via a common code and to coordinate activities via authority. Where such a common code is developed within organizational boundaries, authority over employees' activities allows better coordination among interdependent roles. Kogut and Zander (1992) also contended that hierarchical organization is a superior means of transferring knowledge or other tacit information because of the characteristics of firms. In the organization, members share knowledge, particularly complex or tacit knowledge, with ease through common stock of knowledge and organizing principles.

In the meantime, there is a threat of opportunism in multiparty R&D alliances because knowledge-based assets are imperfectly protected (e.g., Cohen et al., 2002) and outcomes from R&D activities are highly uncertain (Holmstrom, 1989). This makes it difficult for a firm to conjecture what its partners contribute to the alliance. According to the transaction cost logic, equity-based joint venture can minimize threats of opportunism that would otherwise hinder cooperation. Equity joint ventures have some fairly consistent governance attributes compared to non equity-based alliance that likely affect firm incentives to share knowledge.

The information-sharing and incentive-aligning mechanisms of equity joint ventures likely ease knowledge sharing and reduce the fear of opportunistic behavior, facilitating joint innovation. Hence, I contend:

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Hypothesis 6. Joint patenting is more likely to occur in a multiparty alliance when the governance structure of the alliance is equity-based joint venture than non equity-based alliance.

Figure 6 shows the research model for this study.

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Insert Figure 6 about here

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3. EMPIRICAL SETTING AND METHODS

3.1. Data

For these empirical tests, I constructed a data set comprising the multiparty R&D alliance and patenting activities of firms in four high-tech manufacturing industries: semiconductor, electronics, computer manufacturing, and telecommunications industries. Those industries undergo the rapid pace of technology development, and thus firms frequently collaborate in R&D to jointly develop technologies and spread the risk and expense of development. Further, patents are an important means for appropriating the returns from innovation for firms in such high-tech industries.

I construct the data set from two main sources: the SDC (Securities Data Company) Database on Joint Ventures and Alliances and the USPTO (United States Patent and Trademark Office) database. SDC database includes information on all forms of strategic

alliances to identify alliance portfolios for firms in the global high-tech manufacturing industry during the period from January 1987 to October 2013. The SDC database contains information on all types of alliances and is compiled from publicly available sources. Thus, it is among the most comprehensive sources of information on alliances and widely used for large-scale empirical studies on alliances (e.g. Anand & Khanna, 2000; Sampson, 2007). Focusing only on the R&D alliances, I collected various information related to alliances such as participants (firms) in an alliance and the announcement date and Standard Industrial Classification (SIC) code for each alliance, and its activities.[5] The collected data also include country origins or locations of the participants. From 1987 to 2013, total number of R&D alliances is 2,303, including 1,981 dyadic alliances and 332 multiparty alliances (more than three partners) of 1,616 firms. Total number of dyadic relationships is 7,751 and about 50% of the relationships are international (3,414 cross-border relationships).

I combine these data on firm alliances with data from USPTO (United States Patent and Trademark Office) database, which contains information on patents such as assignee (firm) name, filed data, accepted data, patent technological classification, the location of assignee, the number of forward and backward citation, and etc. USPTO issued more than 150 thousands global patents every year. Firm patent has come into the spotlight for a long time in the field of business and economics research as an index of the outcomes of R&D investments and technological capabilities (Hall et al., 2000; Lin and Chen, 2005). Patent data is systematically organized, includes detailed information on each patent and can be structured into time-series data. Thus, patent data is proper for empirical research

[5] The activity of an alliance means the purpose of the alliance such as co-operations for marketing, research and development or manufacturing. An alliance can have multiple purposes. The database classified alliance activities into licensing, research and development, marketing, and etc.

on knowledge transfer and acquisition. Moreover, information of patents issued in the U.S. includes detailed information on forward patent which an assignee cited in the process of research and development like references of academic papers. Using this information on forward citations, we can analyze the flows of knowledge or technology among firms (Jaffe and Trajtenberg, 2002; Almeida et al, 2002; Song et al., 2003). Information on patents and patent citation obtained from the USPTO database is appropriate for this study focusing on joint innovation of participating firms in a multiparty alliance.

After collection, I excluded firms with no patents granted by the USPTO and no index for cultural index (e.g. Afganistan) from the collected data. Finally, the data set including 285 multiparty alliances of 764 firms for the period 1990-2008 was created. Retaining multiparty alliances over this time frame allowed us to measure five-year-lagged joint patents over 1991-2013.

3.2. Measures

3.2.1. Dependent Variable

Joint patents from a multiparty alliance. The unit of analysis of this study is an alliance. I searched for alliances with joint patents in the alliance sample and checked whether there is a joint patent of all member organizations in a single alliance in the lagged five-year window following an observation year (Hausman et al., 1984; Jaffe et al., 1993; Vasudeva and Anand, 2011). Then I created dummy variables as follows: 1 = Yes

and 0 = otherwise.

3.2.2. Independent Variable

Technological diversity in a multiparty alliance. I define technological diversity in multiparty R&D alliance as the degree of variance in technology among partners in the alliance (e.g. Bae and Gargiulo, 2004; Lavie, 2007). To measure the diversity, a modified version of Herfindahl index was used following the existing study (Bae and Koo, 2009) for a given alliance portfolio as follows:

$$\textbf{Technological diversity of alliance portfolio} = 1 - \sum_{i=1}^{N}\left(\frac{P_i}{P_N}\right)^2$$

Where N is the total number of technology classes of firms in a multiparty alliance, and P_N is the total number of patents of the members. P_i is the total number of patents of participating members in technology class *i*. As alliance partners' patents are spread evenly across the total set of technology classes, the value will be high. In contrast, if alliance partners' patents are concentrated around a certain technology class, the value will become small. The index was calculated for each alliance.

National diversity in a multiparty alliance. To measure the national diversity of firms in a multiparty alliance, Herfindahl index was used according to the previous studies' measurement to create the entropy of the diversity of firms in a multiparty

alliance as follows:

$$H = \sum_{i=0}^{n} S_i^2$$

Where S_i is the number of firms with country origin i. Because a lower value of the Herfindahl index (H) indicates a higher level of diversity, I used the inverse measure (1/H -1) according to the Bowen and Wiersema's measurement (2005) so that a higher value indicates a greater national diversity of firms.

Repeated ties in a multiparty alliance. To measure the ratio of repeated ties in a multiparty alliance, I first checked whether each firm had prior R&D alliances with partners currently participating in the same multiparty alliance. Then, I calculated the ratio of repeated ties in all of the ties in a multiparty alliance. For example, four companies in a multiparty alliance create six dyadic ties. If two from those four firms have prior ties with each other, they make one repeated tie in the current alliance. In this case, the ratio of repeated tie is 1/6.

Multiple ties in a multiparty alliance. To measure the ratio of multiple ties in a multiparty alliance, I first checked whether each firm had relationships with current partners in other alliances. Then, I calculated the ratio of multiple ties in all of the ties in a multiparty alliance.

Co-opetition ties in a multiparty alliance. To measure the ratio of co-opetition ties in a multiparty alliance, direct competitors were first defined. Firms in the relationship of direct competition were classified based on the four-digit SIC code. For example, direct

competitors in electronics industry are firms whose main SIC at the four-digit level is among 4812, 4813, 3663 or 3669. I first checked whether a focal firm is involved in the same business with each partners in its alliance, and then, I calculated the ratio of co-opetition ties in the alliance.

Governance structure of a multiparty alliance. For governance structures of alliances, I coded each alliance into three categories: '1' = non equity-based alliance, '2' = symmetric equity share alliance, and '3' = asymmetric equity share alliance.

3.2.4. Control Variable

To control for firm and multiparty alliance level confounding factors that might explain joint patenting activities of the alliance partners, I included a number of variables based on past research. I controlled for the year in which an alliance was initiated (announced year). I also tested if a multiparty alliance's technological capabilities affect joint patenting of member firms. To measure technological capabilities of each alliance, I calculated total number of patents of all firms in the alliance, and also the mean and variance. In this context, increasing number of patents of multiparty alliances may affect the amount of resources which can be pooled by participants, and also raise possibility of joint innovation. I also controlled for the alliance size with the number of participating firms. In addition, I coded industries into four categories where semiconductor industry is '0,' electronics industry '1,' computer manufacturing industry '2,' and telecommunications industry '3.'

3.3. Analytical Approach

To test the hypotheses in this study, binary logistic regressions were employed. The logistic regression extends the ideas of multiple linear regressions to the situation where the dependent variable, y, is binary. In this paper, the dependent variable is dichotomous with 1 = joint patenting, and 0 = otherwise. The independent or predictor variables in the logistic regressions can take any form. That is, the logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related or of equal variance within each group.

4. RESULTS

Descriptive statistics for the model and correlations of all variables in this study are provided in Table 6 and 7 respectively. To ensure that the results of this study are not affected by multicollinearity, I calculated the variance inflation factors (VIFs) associated the model covariates. All VIFs showed below ten, the recommended level, suggesting that there is no bias in the estimated model results from multicollinearity problem.

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Insert Table 6 about here

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Insert Table 7 about here

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Table 8 presents the results from logistic regression on joint patenting of firms in a multiparty alliance. Model 1 includes control variables only. Model 2 adds the main effect of all explanatory variables. All of the estimated models have high power of explanations (p-value<0.001), and the value of log likelihood qui square increases as explanatory variables are added.

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Insert Table 8 about here

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Hypothesis 1 states that lagged joint patenting has an inverted U-shaped relationship with technological diversity. Results from model 2 show that hypothesis 1 is not supported. The result in the final model exhibits that the national diversity in a multiparty alliance has inverted U-shaped relationship with joint patenting of members, supporting hypothesis 2 (p<.01). Hypothesis 2 proposes that multiple R&D alliance portfolios which has the moderate level of national diversity is most likely to succeed in jointly create innovative outcomes.

Hypothesis 3 proposes that there is a positive relationship between repeated ties among

member organizations in a multiparty alliance and its joint patenting and Hypothesis 4 presents that there is a positive relationship between multiple ties among member organizations in a multiparty alliance and its joint patenting. Results from model 2 show a significant but negative coefficient for the relation between repeated ties and joint patenting. Therefore, hypothesis 3 is not supported. Model 2 yields a positive and significant coefficient for the relation between multiple ties and joint patenting, suggesting that hypothesis 4 is strongly supported ($p<.01$). Odds ratio for the multiple ties is 6.79. It implies that the odds of joint patenting become 6.79 times larger when the portion of multiple ties in a multiparty alliance increases by one when all other variables are constant.

Hypothesis 5 proposes that there is a negative relationship between co-opetition ties among member organizations in a multiparty alliance and its joint patenting. Results from model 2 show a significant and negative coefficient for the relation between co-opetition ties and joint patenting. Therefore, hypothesis 5 is supported($p<.05$). Hypothesis 6 proposes that joint patenting is more likely to occur in a multiparty alliance when the governance structure of the alliance is equity-based joint venture than non equity-based alliance. However, the results from the model do not show any significant relationship between the alliance structure and joint patenting.

5. CONCLUSION AND DISCUSSION

In this study, I investigated the factors influencing joint innovation performance (joint patenting in this study) to which all of the participants in a multiparty R&D alliance

contribute, drawing upon organizational learning theory and transaction cost economics. I examine the effects of technological and national diversity in a multiparty alliance, attributes of ties composing the multiparty alliance, and governance structure of the alliance with data of high-tech manufacturing firms during the period 1987-2013.

The results in this study shows that firms face trade-offs as they participate in multiparty R&D alliances to broaden knowledge pool and grow opportunities to succeed in innovation. This is because increased number of partners in R&D alliances can bring more complexity and potential for conflicts, thus increasing coordination and managerial costs for participating firms. This study also highlight that firms in multiple R&D alliance portfolios which has the moderate level of national diversity is most likely to succeed in jointly create innovative outcomes. If there are members with diverse country origins in a multiparty alliance, member firms could get exposed to a greater diversity of technologies, knowledge, and management practices. However, differences in corporate culture, strategic direction, and management practices can cause conflicts and increase alliance costs.

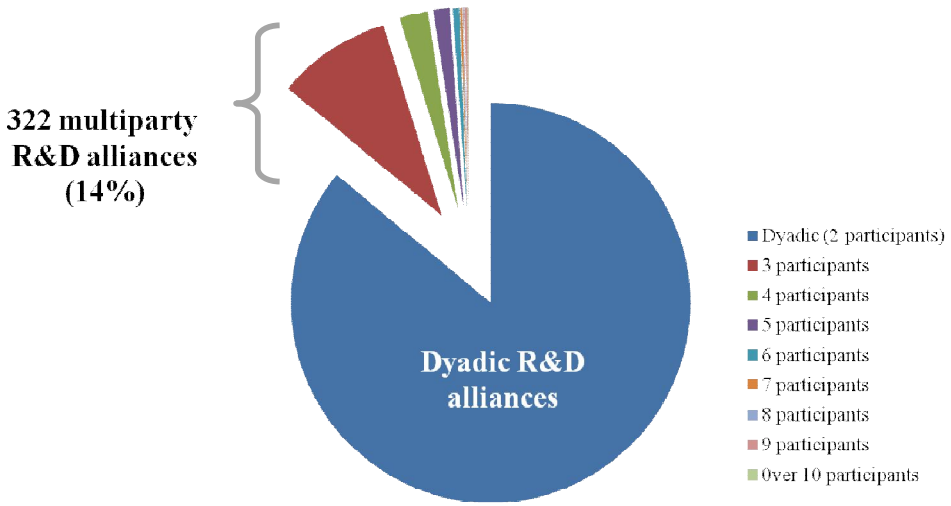
Meanwhile, I found significant effects of multiple ties on joint patenting. The results suggest that knowledge and skills that accumulate from recurrent allying with specific partners over time may be important experiences (Hoang and Rothaermel, 2005). Firms with cumulated experiences through multiple alliance activities with specific partners could source the partners' knowledge efficiently by reducing transaction costs.

Next, the results in this study suggest that a multiparty alliance which has a lot of co-opetition ties will exhibit lower possibility of joint patenting of members. As predicted, collaboration with competitors entails great risks in many ways.

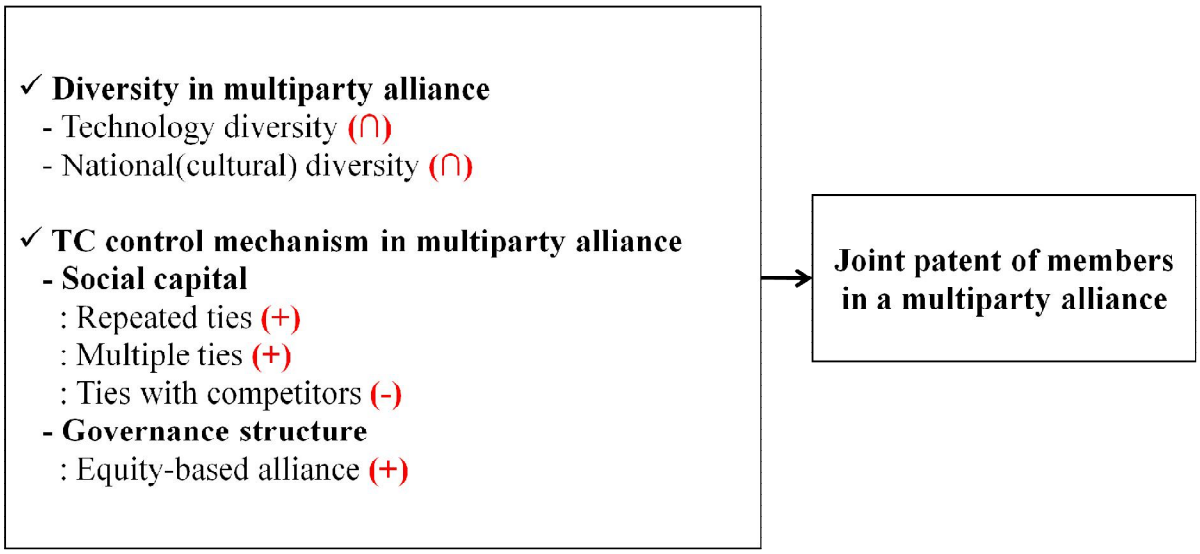
One of the key contribution of this study is that this is the first study to directly examine the joint innovation performance among firms in a multiparty alliance. Also, this

study is extending prior works drawing on a single perspective into more comprehensive research. In the future study, more specific definition and measurement could be used by analyzing the deal text of each alliance reported in the SDC database. The deal text specifies the technology or product which participating firms aim to jointly develop. I advice managers to pay attention to national diversity and co-opetition ties in a multiparty alliance when they want to jointly develop technology with multiple partners. As for the joint innovation, actual co-operating activities are more important than partners' technological capabilities or technological diversity.

[Figure 5] Multiparty R&D alliances during 1987-2013 in four high-tech manufacturing industries (semi-conductor, electronics, computer manufacturing, and telecommunications)



[Figure 6] Research Model



[Table 6] Descriptive statistics of variables (N=285)

Variables	Minimum	Maximum	Mean	Std. deviation
Joint patenting, t+5	0.00	1.00	0.04	0.18
Technological diversity in a multiparty alliance	0.01	1.00	0.21	0.27
National diversity in a multiparty alliance	0.00	1.00	0.33	0.33
Prior ties in a multiparty alliance (ratio)	0.00	0.96	0.25	4.66
Multiple ties in other alliances (ratio)	0.00	1.00	0.09	0.94
Ties with competitors in a multiparty alliance (ratio)	0.00	1.00	0.84	0.30
Technological capability of a multiparty alliance (mean, LN)	0.00	9.86	5.55	2.41
Technological capability of a multiparty alliance (variance, LN)	0.00	19.66	11.64	4.75
Alliance experiences of participants	0.00	417.00	40.78	69.24
Number of participants	3.00	11.00	3.76	1.39

[Table 7] Correlations of variables (N=285)

Variables	1	2	3	4	5	6	7	8	9
1. Joint patenting, t+5									
2. Technological diversity in a multiparty alliance	.01								
3. National diversity in a multiparty alliance	.08	.02							
4. Prior ties in a multiparty alliance	-.04	-.17**	-.10+						
5. Multiple ties in other alliances	.03	-.23***	-.18**	.27					
6. Ties with competitors in a multiparty alliance	-.09	-.03	.04	-.05	-.04				
7. Technological capability of a multiparty alliance (mean, LN)	-.01	-.07	-.05	.27***	.32***	.02			
8. Technological capability of a multiparty alliance (variance, LN)	-.02	-.72***	-.03	.25***	.27***	.02	.98***		
9. Alliance experiences of participants	-.01	-.32***	0.12	.79***	.38***	-.05	.51***	.48***	
10. Number of participants	-.08	-.12	-.16**	.32***	.14	-.06	.09	.11	.22***

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

[Table 8] Logistic regression models estimating joint patenting

Variables	Model 1(odds)	Model 1	Model 2(odds)	Model 2
Intercept	0.04	-3.11(2.46)	5.10	-12.19**(5.92)
Number of participants	0.81	-0.21(0.63)	1.54	0.43(0.68)
Technological capability in alliance(mean)	1.45	0.37 (0.60)	4.93	1.60(1.28)
Technological capability of portfolio(variance)	0.83	-0.19(0.30)	0.41	-0.90(0.61)
Governance (reference: Non-equity alliance)				
- Joint venture (symmetric)	0.79	-0,23(0.81)	0.64	-0.45 (0.93)
- Joint venture (asymmetric)	2.27	-0.17(.)	8.94	-20.84(.)
Industry (reference: Semiconductor)				
- Electronics	3.40	1.22(1.27)	5.37	1.68(1.47)
- Computer	1.28	-15.87(.)	8.19	-16.32(.)
- Telecommunications	6.77	1.91(1.15)	4.14	1.42(1.38)
Alliance experiences of participants	1.00	0.00(0.01)	1.04	0.04**(0.02)
Technological diversity			98.28	4.59(6.76)
Technological diversity squared			0.01	-4.51 (5.75)
National diversity			3.54	28.89**(12.48)
National diversity squared			8.71	-20.86** (8.81)
Prior ties			0.14	-2.00* (1.12)
Multiple ties			6.79	1.91** (0.96)
Ties with competitors			0.01	-4.60* (2.69)
n	285		285	
Log-likelihood χ^2	17.46		38.02	

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

Note: All model chi-squares are significant at $p < 0.01$

Chapter IV.

Conclusion

In this study, I examined the trade-offs firms face which engage in managing alliance portfolio or cooperating in multiparty alliances drawing on transaction cost economics and organizational learning theory. Through the empirical analysis using a data of high-tech manufacturing firms during the period 1987-2013, I found some significant explanatory variables on alliance performances from alliance portfolios and multiparty alliances.

In study I, I investigated the efficient composition of R&D alliance portfolio by examining the ways firms can optimize the learning and resource benefits while limiting the complexity and coordination costs of managing a diverse alliance portfolio, First, I tested the effect of technological diversity of a firm's R&D alliance portfolio on its knowledge acquisition. Secondly, I examined the boundary condition that a focal firm can raise benefit while reducing costs generated from the diversity of alliance portfolio in order to investigate the cost-effective composition of R&D alliance portfolio. Drawing on transaction cost economics, two sources of transaction costs were considered: distances between a focal firm and partners in its portfolio (technological and cultural distances) and opportunistic behaviors of partners in the portfolio. The results in this study shows that alliance are important to the global high-tech manufacturing industries to source diverse external knowledge and accelerate firm innovation as the data represents, but the learning benefits diminish with too much diversity in alliance portfolios due to increasing transaction costs. This study also highlight the trade-offs in managing diverse alliance portfolio between learning benefits and managerial complexity and costs. Greater technological diversity of alliance portfolios can be beneficial and contribute to knowledge acquisition of a focal firm when the firm includes technologically and culturally close partners in its R&D alliance portfolio. Technologically distant partners may limit a focal firm's learning capability because a focal firm may not have the capacity to absorb the technologies of such distant partners. Also, too much technological

distance may imply problems of communication and mutual understanding. Technological distance between a focal firm and its partners, thus, may enhance complexity in learning and coordination costs. As the results show, a greater diversity of technology combined with large technological gap may signal a situation in which sourcing from the diversity are likely to occur at a low level or seldom likely to occur.

Cultural distance emanates from differences in language, social norms, and mindsets. High level of cultural distance limit the absorptive capacity. Also, reducing the cultural gap is costly. Thus, managerial and coordination cost of a portfolio is multiplied as a culturally distant partner is added to the alliance portfolio. Such costs impede effective and efficient knowledge transfer from the alliance portfolio to the focal firm. Thus, cultural distance between a focal firm and its partners enhances complexity in learning and coordination costs. When a greater diversity of technology combined with large cultural gap, a focal firm's learning from the diversity are likely to occur at a low level or seldom likely to occur as shown in this study.

One of the key contribution of study I is to examine the ways firm can optimize the learning and resource benefits while limiting the complexity and coordination costs of managing a diverse alliance portfolio. Also, this study is extending prior works focused mostly on partner's attributes and dyadic relationship which are factors influencing alliance performance. By measuring alliance performance via knowledge acquisition from alliance portfolio, I focused more direct effect of alliance portfolio composition on firm's innovation. Knowledge acquisition from firms in a R&D alliance portfolio could be more direct and appropriate measurement than that in existing studies. Most of the prior studies used the increase in the post-alliance patenting activities as a measure of R&D alliance performance (e.g. Sampson). However, post-alliance innovation of a firm cannot be a direct measure of learning from partners in its portfolio, thus inappropriate for estimating the costs and benefits of retaining diverse partners in the portfolio.

In study II, I investigated the factors influencing joint innovation performance (joint patenting in this study) to which all of the participants in a multiparty R&D alliance contribute, drawing upon organizational learning theory and transaction cost economics. I examine the effects of technological and national diversity in a multiparty alliance, attributes of ties composing the multiparty alliance, and governance structure of the alliance. The results in this study shows that firms face trade-offs as they participate in multiparty R&D alliances to broaden knowledge pool and grow opportunities to succeed in innovation. This is because increased number of partners in R&D alliances can bring more complexity and potential for conflicts, thus increasing coordination and managerial costs for participating firms. This study also highlight that firms in multiple R&D alliance portfolios which has the moderate level of national diversity is most likely to succeed in jointly create innovative outcomes. If there are members with diverse country origins in a multiparty alliance, member firms could get exposed to a greater diversity of technologies, knowledge, and management practices. However, differences in corporate culture, strategic direction, and management practices can cause conflicts and increase alliance costs. Meanwhile, I found significant effects of multiple ties on joint patenting. The results suggest that knowledge and skills that accumulate from recurrent allying with specific partners over time may be important experiences (Hoang and Rothaermel, 2005). Firms with cumulated experiences through multiple alliance activities with specific partners could source the partners' knowledge efficiently by reducing transaction costs. Next, the results in this study suggest that a multiparty alliance which has a lot of co-opetition ties will exhibit lower possibility of joint patenting of members. As predicted, collaboration with competitors entails great risks in many ways. The major contribution of study II is that this is the first study to directly examine the joint innovation performance among firms in a multiparty alliance. Also, this study is extending prior works drawing on a single perspective into more comprehensive research.

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국문초록

기업 간 기술 제휴와 혁신

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경영학과 경영학 전공

본 연구는 기업 간 기술 제휴와 기업 혁신에 초점을 맞춘 연구로, 총 두 개의 실증 연구로 이루어져 있다. 첫 번째 연구에서는 다수의 기술 제휴를 동시에 맺고 있는 기업을 대상으로 하여 해당 기업이 자신의 기술 제휴 포트폴리오 (alliance portfolio) 로부터 지식을 습득하는 수준에 영향을 미치는 요인을 분석하였으며, 두 번째 연구에서는 다자간 기술 제휴 (multiparty alliance)를 분석 단위로 하여 다자간 기술 제휴에 속한 기업들이 공동으로 혁신 성과 (공동 특허)를 도출하는 데 영향을 미치는 요인을 밝혔다.

조직 학습 이론 (organizational learning theory) 및 거래 비용 경제학 (transaction cost economics)에 근거하여 다수의 제휴 파트너를 포함한 포트폴리오를 운영하는 기업과 다자간 기술 제휴에 참여한 기업이 마주하게 되는 이익과 비용의 상충관계 (trade-offs)에 관한 가설을 수립하였다. 가설을 테스트 하기 위해, SDC 데이터 베이스로부터 1987 년 1 월 1 일에서 2013 년 10 월 사이에 하이테크 제조업 (반도체, 전자, 컴퓨터 제조, 통신 산업)에서

일어난 기술 제휴에 관한 데이터를 수집하였다. 또한 기술 제휴와 기업의 혁신 성과 간의 관계를 보기 위해 기술 제휴를 맺은 기업들의 특허 정보를 USPTO 데이터 베이스를 통해 수집하였다.

실증 분석 결과, 기업들은 다양한 지식을 습득하고 결합하여 새로운 지식을 창출하기 위해 다수의 기술 제휴 파트너와 관계를 유지하지만, 지식의 다양성으로부터 오는 이익을 높은 수준으로 전유하기 위해서는 다양한 파트너와의 관계를 관리하고 조정하는 비용에 대한 고려가 반드시 필요하다는 것이 드러났다. 첫 번째 연구 결과는 기업이 보유한 기술 제휴 포트폴리오의 기술적 다양성은 적정 수준에서 기업의 지식 습득에 가장 많이 기여한다는 것을 보여준다. 그 다음으로, 포트폴리오의 지식이 다양할 경우, 해당 기업과 파트너 간의 기술적 거리와 문화적 거리가 가까울 수록 기업이 다양성을 많이 수급하는 것으로 드러났다. 한 편, 특정 파트너와의 이전 기술 제휴 경험과 포트폴리오 내 경쟁자 비중은 예상했던 것과 반대의 결과가 나왔다. 즉, 이전에 기술 제휴 경험이 있는 파트너와 다시 기술 제휴를 맺었을 경우, 기업은 오히려 낮은 수준의 지식 습득을 보였고 경쟁자와 기술 제휴가 많을 수록 지식 습득의 수준은 증가하였다.

두 번째 연구 결과, 다자간 기술 제휴에서 공동의 성과를 내기 위해서는 국적이 다른 기업들의 다양한 지식 기반이 필요하지만 참여 기업들의 국적이 지나치게 다양해 질 경우, 협력에 어려움을 겪을 수 있다는 것이 밝혀졌다. 또한 현재 기술 제휴를 맺고 있는 기업과 별도의 기술 제휴를 유지하고 있는 경우에는 협력 성과가 높았고, 반면 다자간 기술 제휴에 직접적인 경쟁관계에 놓인 기업들이 많이 포함되어 있을 수록 협력 성과는 낮았다.

두 실증 연구의 결과를 통해 기업이 파트너로부터 지식을 습득해 이후 혁신 활동에서 활용하는 것과 여러 파트너가 공동으로 참여하여 협력의 결과물을 도출하는 것은 서로 다른 기제가 작동한다는 함의를 도출할 수

있었다. 다시 말해, 포트폴리오로부터 지식을 습득하는 것에는 파트너의 협조보다는 포트폴리오 지식 기반의 특성 (구성)이 더 중요한 영향을 줄 수 있다는 것이다. 즉, 중복되는 지식이 적고 학습은 용이하여 적절한 학습 동기를 부여할 수 있는 지식 기반일 경우 기업이 높은 수준으로 지식을 습득할 수 있다고 추측할 수 있다. 반면, 공동의 결과물을 내야 하는 경우에는 파트너의 수가 많아질 수록 개별 파트너가 가진 지식의 크기나 종류보다는 서로 협력하려는 의지와 협력할 수 있는 환경의 조성이 더 중요할 수 있다는 시사점을 도출할 수 있다.

주제어: 기술 제휴, 제휴 포트폴리오, 다자간 제휴, 지식 습득, 공동 특허, 거래 비용 경제학, 조직 학습 이론

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