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Asymmetric Partnership:
The Effect of Experience on Innovative Performance in Strategic Alliances between Incumbents and Startups

비대칭적 제휴: 대기업과 스타트업 간의 전략적 제휴에서 경험이 공동 혁신성과에 미치는 영향

2023 년 2 월

서울대학교 대학원
경영학과 경영학전공

박신영

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Abstract

In strategic management research, the rapidly growing attention on interfirm alliances and asymmetric partnerships with startups has reflected how firms continuously strive for innovation through diversified collaborations under technological discontinuity. Regarding alliance performance, experience may act as a catalyst to precipitate joint innovation during an alliance period. In this study, I categorize experience into two types: (1) when a startup has prior alliance experience with other firms and forms an alliance with a new incumbent, and (2) when a startup has prior alliance experience with an incumbent and forms a repeated alliance with the same incumbent partner. Building upon the asymmetric alliance and experience capability literature, I investigate the impact of these two types of experience on joint innovation performances generated by an asymmetric alliance between a startup and an incumbent. This study combines analysis of asymmetric alliances between startups and incumbents formed between 2000 and 2008 in E-business industries and citation-based measures of co-patents granted within a set of observation periods. The results of this study support the hypothesis that when a startup forms a partnership with a new incumbent partner, the quality of their joint innovation performance is positively related to the number of the startup's prior alliance experiences with other firms. Although the other hypotheses are not fully supported, the results provide bifurcating insights into how a repeated alliance between a startup and an incumbent can be a double-edged sword for their joint innovation performance.

Keywords: strategic alliance, dynamic capability, prior experience, repeated alliance experience, joint innovation, relational embeddedness

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Table of Contents

1. Introduction

Witnessing the erosion of closed innovation, open innovation has reflected a paradigm shift in the 21st century as firms often confront challenges to adapt and survive under radical and rapid technological change (Rothaermel, 2002; Chesbrough, 2003). Such penetration of open innovation has manifested how firms engage in the usage of external technologies and manage knowledge flows across the organization boundary (Chesbrough, 2003). With the rising emphasis on cooperative relationships through open innovation, strategic alliances, defined as voluntary and cooperative agreements pursuing joint objectives, have enabled firms to adapt to today's rapidly changing technologies and blurring industry boundaries (Das & Teng, 2002, Gulati, 1993). Over the past few decades, extensive literature has discussed the roles of strategic alliances between firms have become more critical as they serve as a strategic vehicle to gain complementary assets, share risk, and build new knowledge and technical capabilities (Teece, 1986; Cohen & Levinthal, 1989; March, 1991; Hagedoorn, 1993; Eisenhardt, 1996). Not only alliance formations that are not bounded by organization types, industries, or nations, but asymmetric alliances between firms who share disparate features and characteristics also started to gain interest. In an asymmetric alliance, asymmetries between firms in resource and capabilities, organizational structures, and power imbalance have been increasingly discussed in various ways in an interfirm knowledge sourcing (Rothaermel, 2006; Lin et al., 2012; Minshall et al., 2010; Das & He, 2006; Pfeffer & Salancik, 2003). Particularly, recent studies reveal how asymmetric alliances between incumbents and startups are correlated with radical technological innovations (Gao & Zhang, 2008).

Despite the growing attention on the roles of alliances to adapt to radical and rapid technological changes in strategic management, however, research on how asymmetric alliances between incumbents and startups are contradictory to alliances between similar firms is sparse (Huang et al., 2018; De Groote & Backmann, 2020; El Hanchi & Kerzazi, 2020). Moreover, research on how types of experience affect innovation performance in such asymmetric partnerships is lacking. In this paper, I attempt to address the question of how experience affects innovation performance in a strategic alliance between an incumbent and a startup, in which the two firms share asymmetric features and characteristics. Specifically, I have individuated a prior experience into two conditions: (1) a situation in which a startup possesses prior alliance experiences with other incumbents, and (2) a situation in which a startup and an incumbent possess prior alliance experience and form a repeated alliance. Acknowledging an absence of consensus on whether a repeated alliance between two firms would bring a positive or negative outcome, I have investigated both implications on the impact of innovation performance of repeated alliance between two asymmetric firms by empirically testing two competing hypotheses in Hypothesis 2. First, this paper contributes to asymmetric alliance literature by discussing how disparate capabilities and resources of incumbents and startups become complementary assets. Second, this paper adds the expansion of dynamic capability perspectives by analyzing how startups use their prior experience in building alliance management capabilities and absorptive capacity. Thirdly, the paper provides dyadic perspectives on repeated alliances between incumbents and startups. On one hand, the paper proposes relational embeddedness theory and transaction cost economics to advocate the positive relationship between a repeated alliance and joint innovation performance. On the other hand, the paper presents an exploitation trap to bolster the negative relationship between a repeated alliance and joint innovation performance.

This study has focused on E-business industries that have gained the most recognition in the early 2000s. I test my hypotheses by using strategic alliance data between startups and incumbents headquartered in the United States, identifying startups with prior experience with other incumbents as well as classifying repeated alliance formations between incumbents and startups. Then, I have also utilized the U.S. co-patent data from these alliances to measure joint innovation performance via citation-based measure of each co-patent from the alliance throughout the total 14 years of observation periods.

2. Theoretical Backgrounds and Hypotheses

2.1 Asymmetric Alliances between Startups and Incumbents: Complementary Assets

While there exists an affluent prior literature in open innovation focused on alliances between incumbents, studies on asymmetric partnerships between startups and incumbents are relatively scarce (De Groote & Backmann, 2020; Das & He, 2006). An asymmetric alliance is known as a contractual agreement between firms joined by partners who are characterized by disparities in resources including financial resources and size or network position (Lin et al., 2012). Alternately, Minshall et al (2010) have distinguished the disparity between the two firms by juxtaposing capabilities and resources. Das and He (2006) have defined an asymmetric alliance as an alliance between an incumbent and a startup that tend to have asymmetric objectives (e.g., exploiting a startup's technology vs. exploiting an incumbent's financial resource) and asymmetric organizational structures (e.g., a huge, bureaucratic and somewhat conservative organization versus a small yet agile and unorthodox organization). This study defines startups as innovation-striving ventures that have been in business for less than 12 years up to the date of an alliance formation and are not subsidiaries of any established incumbent (Blank, 2013; El Hanchi & Kerzazi, 2020). With such discrepancies, a question arises on the growing trend of collaborations between different firms, especially incumbents and startups that are contrasting with each other. How could asymmetric partnerships between startups and incumbents spawn innovative synergy? To answer this question, distinct asymmetries between startups and incumbents serve as complementarity.

Complementary assets can be a determinant of an alliance because a combination of diversified, specialized assets of two partnering firms can become mutual benefits (Rothaermel, 2002; Teece, 1986). Startups or new ventures are known to have specialized technology assets and fast market responsiveness which most incumbent firms do not possess (El Hanchi & Kerzazi, 2020; De Groote & Backmann, 2020; Kalaignanam, 2007). Moreover, they tend to be more open to changes such as radical and disruptive innovations, they usually do not face structural inertia (Hyytinen et al., 2015). However, startups are relatively young and lacking in experience, financial resources, and social approval which may jeopardize them to market failure (Baum et al., 2000; Eisenhardt, 1996; De Groote & Backmann, 2020). On the other hand, most incumbents or established firms have abundant financial resources, stable organization routines, strong network positions, and proven operating procedures (Baum et al., 2000). However, their standardized and inflexible firm structures, slow market response, and risk-averse propensity may lead them into a dilemma in making fast technological innovations. Due to these firm structures, large incumbents are more likely to face difficulty in possessing and exploiting unique technological capabilities in niche areas (Gao & Zhang, 2008).

To source new knowledge quickly and spur radical innovations, asymmetric alliances between startups and incumbents can be more effective than alliances between firms with similar structures (Jackson & Richter, 2017; De Groote & Backmann, 2020; O'Connor, 2006). From a startup perspective, startups can tremendously benefit from alliances with incumbent firms that possess abundant financial and personnel resources, fulfilling their disadvantage in resource scarcity and narrow knowledge base (Baum et al., 2000). Subsequently, they can actively engage in technological R&D by internally developing their technical skills with access to external complementary assets that incumbents possess. Through partnering with large incumbents, startup firms can overcome liabilities of their newness (e.g. lack of legitimacy or experience) or smallness (e.g. lack of financial or personnel resources) through partnering with incumbents (Freeman & Engel, 2007; Baum et al., 2000; Hoang & Antoncic, 2003; Stuart, 2000). In incumbent perspectives, incumbent firms can exploit specific technologies of the partner startups, use the startups' agility and specialist expertise, reduce time spent in technological R&D, and enter new markets quickly that they are not currently participating (Ahuja, 2000; Spender et al, 2017; De Groote & Backmann, 2020). Combinations of specialized complementary assets that startups and incumbents share via alliances become strong competitive advantages (Teece et al, 1997).

2.2 The Impacts of Startup's Prior Alliance Experience with Other Partners

While an incumbent has to form a new strategic alliance with a new startup that has not been allied with the incumbent, an incumbent is likely to face a challenge in selecting the right partner because the success of an alliance cannot be estimated easily, which may lead to uncertainty (Rothaermel, 2006; Das & Teng, 2002). Because uncertainty always exists when a firm has to choose a new partner among unknown pools, firms tend to choose a partner that has more alliance experience because they regard partners with more experience would have more capabilities in handling alliances (Das & Teng, 2002; Rothaermel, 2006). According to dynamic capabilities that refer to "a firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997), these views imply how a firm acquires additional capabilities and learnings throughout the process of managing and exploiting its resources (Adner & Helfat, 2003; Cohen & Levinthal, 1990; Teece, 2007). With dynamic capability perspectives in alliance literature, effectively managing an alliance can become a firm's core dynamic capability if the firm can sense the right asymmetric partners with mutual objectives, seize complementary assets and transform them into resource alignment and innovations (Rothaermel & Deeds, 2006; Teece, 2007). The study reveals how experience amplifies such alliance-managing competencies by introducing alliance management capabilities and absorptive capacity.

(1) Alliance Management Capability from Experience

Building on dynamic capability literature, prior research has provided empirical evidence on how a partner's prior alliance experiences can become a vital source of learning and capability in managing further alliances, which can become experiential learning (Shan et al., 1994; Dyer & Singh, 1998; Rothaermel & Deeds, 2006). Such experiential learning becomes one essential way to estimate the partner's alliance management capability (Shan et al., 1994; Kale et al., 2000; Rothaermel & Deeds, 2006). By definition, alliance management capability is "a firm's ability to effectively manage alliances" despite the target firm's size, the type of alliances, or the target firm's nation (Rothaermel & Deeds, 2006). Several provocative studies have witnessed high-tech startups with greater alliance experience have higher alliance management capability and become more effective in problem-solving skills and process management, which are directly related to innovation performance (Das & Teng, 2002; Rothaermel & Deeds, 2006).

(2) Absorptive Capacity from Experience

Within the learning and capability context, a firm with greater alliance experience is likely to possess a higher absorptive capacity. Absorptive capacity is defined as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial end" (Cohen and Levinthal, 1990). Extensive prior studies on organizational learning have manifested how absorptive capacity also reveals a firm's capability to turn experiences into exploitable knowledge (Lane & Lubatkin, 1998; Eriksson & Chetty, 2003). Moreover, such absorptive capacity from experiential learning becomes technological capabilities, indicating that firms with more accumulated experience and absorptive capacity are better at effectively using their technological capabilities and eventually turning them into innovative performance (Song et al., 2003). Building on this literature, a startup's prior alliance experience would have a high level of absorptive capacity so that it can reconfigure and assimilate new resources and knowledge assets effectively (Cohen and Levinthal, 1989; De Groote & Backmann, 2020). For instance, a firm with higher absorptive capacity would better sense tacit knowledge, absorb new technologies, and manage alliances with its know-how embedded from past alliance experiences. Particularly for startups who are relatively new in the market and lacking in experience, it is a priority for these startups to build relationship capabilities from experiential learning to overcome the liability of their smallness and newness (Baum et al., 2000; El Hanchi & Kerazi, 2020).

Prior studies demonstrate how startups with more experience become more mature in coordination, decision-making, formalism, and internal process (Hanchi &

Kerzazi, 2020; Berends et al., 2014). With these theoretical perspectives, startups would also gain these advantages from many prior experiences. Thus, I expect that with a new, asymmetric partner, a startup that has prior alliance experience with other incumbents can better absorb, manage and exploit complementary resources as well as effectively combine their specialized technological capabilities with the incumbent's resources. Subsequently, I expect incumbent firms would be more attracted to form an alliance contract with a startup that has built alliance management capabilities from prior experience with other firms. Along with this context, I hypothesize when an incumbent forms a new strategic alliance with a startup, the number of a startup's prior alliance experiences with other incumbents would have a positive impact on their innovation performance.

Hypothesis 1: When a startup forms an alliance with a new incumbent partner, the number of a startup's prior alliance experiences with other firms is positively related to the quality of joint innovation performance.

2.3 Advantages of Repeated Alliance: Prior Experience with the Same Partner

Particularly in turbulent industries where change is rapid and technical uncertainty is high, firms must cope with the diversely intricate and interrelated fields of technology and reduce uncertainty when facing a period of technological turmoil (Hagedoorn 1993; Goerzen, 2007). Within these ambivalent business environments, firms need to effectively use their organizational capabilities and complementary assets with partners whom they can harmonize well and create optimal synergy. In a new alliance formation, a firm tends to rely on its past alliance relationship, especially in technologically turbulent industries (Kogut et al, 1992; Gulati. 1993). While extensive literature asserts the positive relationship between repeated collaborations and positive innovation outcomes, some prominent scholars have documented how collaborating with the same partner may suppress the creativity of the participants and may lead the participants to lose exploratory behaviors when searching for new knowledge (March, 1991; Podolny, 2005; Skilton & Dooley, 2010). In this section, I have examined two bifurcating views on repeated alliances between two asymmetric firms, incumbents and startups, and how these multiple, repeated interactions would provoke their innovation outcomes.

(1) Relational Embeddedness Views of Repeated Alliances

In organizational learning literature, the underlying mechanisms present the size of interpersonal ties among alliance partners expands through repeated interactions and connections among organizations (Gulati 1995; Goerzen, 2007). Throughout these repeated collaborations, firms, regardless of their size, structures and industries gain a significant learning experience from each other, which is relational embeddedness (Moran,2005; Nahapiet & Ghoshal, 1998). Defined as 'personal relationships people have developed with each other through a history of interactions' (Nahapiet & Ghoshal, 1998), relational embeddedness includes interorganizational routines, partner-specific knowledge, tacit knowledge, resource integration, and interfirm trust (Simonin, 1997; Zaheer et al., 1998; Zollo et al., 2002; Goerzen, 2007; Kale and Singh, 2007). First, firms can establish interorganizational routines, repetitive patterns of interdependent actions embedded through multiple, repeated interactions, from repeated alliances with the same partners (Feldman & Pentland, 2003; Zheng & Yang, 2015). For instance, these routines enhance interfirm coordination in managing complex and innovative activities such as a knowledge codification process from routines developed in the past (Kale and Singh, 2007; Zollo et al., 2002; Simonin 1997; Gulati 1995). Such interorganizational routines also help firms to build collaborative know-how so that they can develop specialized knowledge and exploit it in the future (Simonin, 1997; Singh, 1999). Through repeated interactions in a repeated alliance, firms may also alleviate the challenges of integrating complementary assets from repeated collaborations (Goerzen, 2007). Moreover, relational embeddedness built from repeated alliances enables knowledge gain convenient and fast as it allows firms to acquire partner-specific knowledge and tacit knowledge, implicating who knows what directory of each other's knowledge stock

(Wang & Zajac, 2007; Zheng & Yang, 2015). While relational embeddedness provides firm−specific capabilities in cooperative coordination and knowledge transfer, it also nourishes trust and familiarity (Gulati, 1995; Zheng & Yang, 2015). As many prior studies have confirmed the positive relationship between a repeated alliance and an innovation performance based on relational embeddedness context and transaction cost paradigm, opportunistic behaviors would also decrease as two firms build trust through repeated alliances (Pisano, 1989; Teece, 1988; Goerzen, 2007). Specific to the asymmetric alliance context, 'asymmetry' between a startup and an incumbent such as information asymmetry, learning and capability asymmetry, resource asymmetry, commitment asymmetry, governance asymmetry, and organizational asymmetry can be alleviated through repeated partnerships (Gao & Zhang, 2008; Das & Rahman, 2010; De Groote & Backmann, 2020). Thus, trust embedded in past relationships is significant to information sharing among partners as trust tends to reduce firms' opportunistic behaviors or doubts about the partners so that they can share new ideas or technologies more easily and explicitly (Uzzi, 1997; Dyer & Chu, 2003). This trust engendered by repeated ties among allying firms enables firms to increase transaction efficiency by lowering transaction costs (Gulati, 1995; Goerzen, 2007).

(2) Transaction Cost Economics (TCE) Views of Repeated Alliances

When a firm chooses the same alliance partner in its subsequent alliance, it implies that the two firms have constructed some positive mutual understanding, trust, or familiarity from prior interactions (Gulati, 1995; Goerzen, 2007). Trust can be drawn as "one party's confidence that the other party in the exchange relationship will not exploit its vulnerabilities," and trust is critical in alliance literature (Barney & Hansen, 1994; Zaheer et al, 1998). Building trust with an alliance partner is especially more critical to non−equity alliances as they lack formal safeguards (Gulati & Singh, 1998). Thus, trust is substituted as an informal safeguard that may reduce transaction costs in the subsequent, repeated alliance (Gulati & Singh, 1998; Lavie et al., 2012). Referring to all costs involved with conducting exchanges between organizations including search costs, contracting costs, monitoring costs, and enforcement costs (Williamson, 1989), trust can eradicate the need for formal contracts that incur costs (Barney & Hansen, 1994; Dyer & Chu, 2003). For instance, a firm may reduce search costs and contracting costs of finding a desirable partner, negotiating, and making a valid contract agreement by selecting the same partner via a repeated alliance (Dyer and Chu, 2003; Gulati, 1993). Besides, a firm can reduce monitoring costs of the partner's processes, systems, and routines as they have trust and familiarity spawned by prior ties (Zollo et al., 2002).

Combining relational embeddedness perspectives and transaction cost economics, repeated alliance implicates aggrandizement of innovation performances via collaborative know-how and routines, partner-specific knowledge, integration, trust, and cost minimizations. Repeated alliance engagements over time appear to contribute to the development of an alliance management capability, which the firm can then leverage to enhance the performance in subsequent alliances (Dyer and Singh, 1998; Ireland et al., 2002). Within this context, I expect a startup that has formed repetitive ties with an incumbent would better coordinate with interorganizational routines and know-how in the subsequent, repeated alliance because most startups tend to be lacking in organized, set routines and managing systems (Baum et al., 2000; Eisenhardt, 1996; De Groote & Backmann, 2020). Thus, I hypothesize a startup and an incumbent forming multiple, repeated alliance ties would lead to positive innovation outcomes after the subsequent alliance,

Hypothesis 2a: The number of repeated alliance experiences between a startup and an incumbent is positively related to the quality of joint innovation performance.

2.4 Disadvantages of Repeated Alliance: Prior Alliance Experience with the Same Partner

(1) Exploitation Trap

In organizational learning, bountiful literature has examined the balance between exploitation and exploration (March, 1991; Gupta et al., 2006). Defined as "refinement and extension of existing competencies, technologies, and paradigm (March, 1991)," exploitation has been increasingly discussed in repeated alliance literature (Lewis et al., 2005; Skilton & Dooley, 2010; Zheng & Yang, 2015). Specific to technology-intensive industries with a strong IP regime, the role of inventors is especially crucial for a firm's innovation outputs. Thus, a repeated collaboration of overlapping inventors may be detrimental to a firm' s innovative performance. When two firms repeat partnerships, it is more likely that inventors would repeat cooperation. According to prior research, repeated cooperation implies more shared time between inventors, implying the rise of opportunity costs (Uzzi, 1997; Goerzen, 2007; Toth et al., 2021). In these cases, the increasing overlap of knowledge bases may lead a firm to an exploitation trap by continuously utilizing existing knowledge that can be redundant (Toth et al., 2021). As a consequence, such an exploitation trap may precipitate the decline of the patent quality when two firms continuously repeat partnerships and overlapping inventors exploit existing knowledge.

To further illustrate the constraints of repeated collaborations, prior research has also demonstrated how stability built by repeated collaborations may lead two associated firms to become less creative and innovative (Skilton & Dooley, 2010), and March (1991) has described these phenomena as firms being "trapped in suboptimal, stable equilibria." Under multiple, repeated interactions between two firms, there exists a risk of filtering out novel ideas and the risk of becoming path-dependent (Zheng & Yang, 2015; Lewis et al., 2005). As a consequence, firms' inertia relying on existing routines and knowledge can reduce the rate of innovation activities (Zheng & Yang, 2015). For example, two firms with strong information exchange systems and settled routines built by prior relationships tend to use existing technologies and knowledge onto their new alliances which may obscure novelty and lead firms to be path-dependent (Lewis et al., 2005; Skilton & Dooley, 2010).

With regard to an asymmetric alliance between a startup and an incumbent, startups who relatively lack experience learn how to routinize, distribute, and commercialize their innovative activities when collaborating with incumbents (Gao & Zhang, 2008). While such learnings are crucial for startups to build their capabilities, however, heavily relying on partner incumbents through repeated partnerships and relying on existing routines may generate unfavorable performance as they may repeatedly exploit existing knowledge and routines. In an incumbent perspective, an incumbent who strives for radical or disruptive innovation through partnering with a startup would likely to repeat an alliance with the same startup partner when their prior alliance outcome is positive. However, such dependence on the past collaboration experience may lead incumbents to rely more on the past success, leading to an exploitation trap (Cohen et al., 2000; Katila et al., 2008). Incorporating theoretical perspectives of opportunism and exploitation trap in repeated alliances, this study holds assumptions that there can be unsatisfied consequences in the repeated alliances between startups and incumbents in contrast to Hypothesis 2a. Competing with Hypothesis 2a, I hypothesize a repeated alliance experience between the two asymmetric firms would be negatively related to their innovation performance.

Hypothesis 2b: The number of repeated alliance experiences between a startup and an incumbent is negatively related to the quality of joint innovation performance.

3. Methods

3.1 Data and Sample

I have tested hypotheses using U.S. strategic alliance data from 2000 to 2008 with both firms headquartered in the U.S. and U.S. co-patent data after alliance formations. The study has retrieved alliance data from the SDC Platinum database and gathered 5 types of strategic alliances including research and development (R&D), technology transfer, marketing, licensing, and manufacturing. The study has first collected strategic alliances between two firms in which at least one firm possesses high-tech industry codes determined by SDC Platinum or at least one belongs to E-business including industries of software, business services, computers, electronics, and telecommunications, listing them with Standard Industrial Classification (SIC) codes 7372, 7389, 3674, 7371, and 4812. I have collected strategic alliance information including alliance types, alliance formation dates, participants, participant CUSIP codes, industry SIC codes, and some alliance termination dates. Because SDC Platinum does not track all alliance termination dates, I have used Factiva and Lexis-Nexis, searchable full-text databases of newswires, newspapers, business periodicals, and trade journals, to track alliance termination dates of the remaining alliance data (Xia, 2011; Park & Ungson, 1997; Hohberger et al., 2020).

I have focused on E-business industries because the number of startups in these industries had shown the most increasing rate from the 1990s to 2000s. Moreover, the objective of this study is how an incumbent-startup alliance can spawn joint technological innovation under a strong IP regime that heavily relies on intellectual properties. This enables patent-based measures to be more reliable proxies for innovation performance. Among these alliances, I have only utilized alliances in which both firms possess high-tech industry codes and in which both firms are headquartered in the U.S. Because SDC Platinum does not provide information on whether a firm is a startup or not, I have gathered startup and incumbent firm information from Crunchbase and Pitchbook that offer firm information data. Using these two databases, I have classified firm type, founding years, headquartered location, funding stage by series, and the total funding amount to the date of an alliance formation. To further standardize startup samples, I have only used startup companies that were established in less than 12 years at the time of alliance formation and excluded all subsidiaries from the sample. Among the 29346 strategic alliances, I have filtered out 29002 alliances. In sum, my final sample contains 343 strategic alliances between startups and incumbents headquartered in the U.S. within these selected E-business industries from 2000 to 2008.

Because a firm's patenting activities may directly lead to a firm innovation, the paper regards each co-patent as an innovation and the number of forward citations retrieved by each co-patent as the quality of joint innovation (Katila, 2001; Jaffe et al., 1993; Kim & Song, 2007). In the context of joint innovation measurement, previous studies have proven a citation-based patent measure as a reliable and powerful method to determine the innovation performance of a technology-intensive firm (Kim and Song, 2007; Ahuja and Katila, 2001; Tseng and Wu, 2007; Huang et al, 2016). Collaborative relationships can be observed from the number of inventors or assignees on patents. For instance, multiple inventors indicate several inventors have collaborated to strive toward an invention via patents (Lei et al., 2013).

I have obtained patent data from the PatentsView and Pitchbook as both databases organize patent data retrieved from the United States Patent and Trademark Office (USPTO). PatentsView offers detailed address information of inventors based on the patent grant date and forward citation information of patents. Pitchbook offers detailed patent information including date, citation information, CPC codes, and information about whether a firm's patents have co-inventors including their exact locations. I have collected all co-patents of each firm after an alliance by setting a 9 years observation period. For co-patent information, I have included grant dates, CPC codes, assignees, and inventors and then filtered these patents by inventor location. Among these co-patents of each firm after a partnership, the study has only identified and selected co-patents whose at least one of the joint inventors' locations overlaps with the target firm's headquarter location or R&D lab location.

Then, I have measured citations retrieved by each co−patent by setting a 5−year moving window (Seo et al., 2022).

3.2 Independent Variables

3.2.1. A Startup’ s prior alliance experience

The number of a startup's prior alliance experiences with other firms prior to the date of the startup's alliance formation with its target incumbent is the independent variable in Hypothesis 1. Using the SDC Platinum database, the study has counted each participant startup’ s prior alliances with other firms prior to the date of the alliance formation using each participant startup’ s CUSIP code.

3.2.2. Repeated Alliance Formations between a Startup and an Incumbent

The number of a startup's repeated alliance formations with an incumbent is my independent variable in Hypothesis 2a and 2b. Because the alliance data on SDC Platinum does not reveal whether an alliance is repeated or not, I have proxied a repeated alliance between a startup and an incumbent by summing up the total alliance duration and dividing the number by the average alliance duration period. According to prior studies, the average lifespan for alliances in high−tech, uncertain environments is 3.02 years (Pangarkar, 2003). Thus, I have set the average alliance lifespan as 3 years. For example, if a startup and an incumbent have formed an alliance that lasts for 9 years, their cumulative number of alliance formations would be 3 which indicates that they have formed 2 repeated alliances after their first alliance.

3.3 Dependent Variables

Forward citation measures of each co−patent, the quality of joint innovation, is the dependent variable for all Hypothesis 1, Hypothesis 2a, and 2b. Many prior studies have confirmed how patents can demonstrate a firm’ s innovation in technology−intensive industries (Ahuja & Katila, 2001; Kim et al., 2012; Li et al., 2014). As forward citations indicate the effect on subsequent technological developments, this study focuses on forward citations of co−patents to empirically measure the quality of patent innovation (Seo et al.,2022). Following the study of Kim, Song & Nerkar (2012), I have measured the quality of innovation performance by counting the total number of forward citations received by each co-patent within 5 years from the grant date after an alliance formation date and dividing the number by the firm' s co-patents. Thus, the higher the number of forward citations retrieved by each co-patent, the higher the quality of conjoint innovation performance. Because the impact of an alliance may last for years, the number of patents published and the number of forward citations can be accumulated over time (Kim et al., 2012). For the observation period of co-patent publication, I have set an average co-patent publication date after an alliance formation to 7 years yet collected all data from 5 to 9 years for the sensitivity test. I have also accumulated the number of co-patent citations for 5 years after the date granted with a five-year moving window frame as many prominent works have justified that most knowledge assets lose value within 5 years (Kim and Song, 2007). For Hypothesis 2a and 2b, I have summed up co-patents by each alliance period. When firm A and firm B formed an alliance in 2000 and terminated their partnership in 2006 for instance, I have summed the citation-based measure of co-patents of firm A and firm B from 2000-2009 and 2003-2012.

3.4 Control Variables

Startup firm size has been measured as a control variable. To control startup firm size, I have classified each startup's size by categorizing its funding stage and total funding amount raised to date when an alliance was formed. S*tartup funding stage* has been controlled too. Because startups experience a few or several funding rounds before stepping into the initial public offering (IPO) stage, I have identified each startup's funding stages by Series A to F, later stage, or IPO status to the date of an alliance formation. When a startup reaches a Series D, E, or F, it is assumed that it lacks business success regardless of the funds that have been raised previously. The later stage implies startups are preparing to become public. *Cross-industry alliance* is another variable I have controlled. In my alliance data, some startups and incumbents belong to the same industry while some of them belong to different industries among the five industries in E−business. Thus, I have set cross−industry as one of my control variables by determining whether an alliance is a cross−industry alliance or not. *Startup firm age* is another control variable, and I have measured startup firm age by subtracting the startup's founding year from the alliance formation date. I have controlled the startup firm age because a firm' s age may have a correlation with the alliance effect. Because a specific type of alliance may spawn varying innovation impacts, *the type of strategic alliance* has been controlled as I have identified which alliance belongs to which type of alliance among the 5 types of non−equity strategic alliances including technology transfer, manufacturing, marketing, research and development (R&D), and licensing. Lastly, I have controlled *the number of a startup's prior alliance experience* for Hypothesis 2a and 2b to observe the interaction effect between the number of a startup' s prior alliance experience with other firms and the repeated alliance between a startup and an incumbent.

3.5 Model Specification

This study has tested hypotheses using a negative binomial regression. Because my independent variables are count variables and my dependent variable is a count variable that contains citation−based patents, the ordinary least squares (OLS) estimates can generate biased and inconsistent results (Seo et al., 2022; Araujo et al., 2019). In these conditions, Poisson or negative binomial distribution would be more suitable for the count−dependent variables to decrease inconsistency (Seo et al., 2022). However, Poisson distribution analysis may generate overdispersion problems due to conditional variance issues, in which the conditional variance is larger than the conditional mean. Therefore, I have selected negative binomial distribution analysis to attain more consistent estimates of the effects as my dependent variable, the number of co−patents weighed by the number of forward citations, is a count variable with over−dispersion (Baltagi, 2008).

4. Results

4.1 Data Description

(insert Table 1 here)

Table 1 presents the descriptive statistics and correlation coefficients among the variables in this study. I have excluded funding series stage, alliance type, and cross–industry status in descriptive statistics as they are not numbers. All correlations are positive. The correlations indicate a repeated alliance experience between the two firms has a weak correlation with the quality of joint innovation. However, the correlation reveals the number of a startup's prior alliance experiences has a moderately strong correlation with the quality of joint innovation.

4.2 Main Findings

(insert Table 2 here)

Table 2 presents the results of the negative binomial regression model to detect Hypothesis 1, proposing whether the number of a startup's prior alliance experiences increases the quality of joint innovation performance from the alliance between the startup and an incumbent. Among the 343 observations, I have used 259 observations because 84 observations lack either startup size information or funding stage information. Table 2 contains 259 observations that have all startup information. The table includes control variables only. Model 2 determines the main effect of Hypothesis 1. In Model 2, the coefficients for the number of a startup's prior alliances are positive and statistically significant (coefficient=0.062, p<0.01), supporting Hypothesis 1. The results in Table 2 support Hypothesis 1, proving the number of a startup's prior alliance experiences has a positive impact on the quality of joint innovation performance when a startup and an incumbent form an asymmetric, strategic alliance.

(insert Table 3 here)

Table 3 exhibits the results of the negative binomial regression model to test Hypothesis 2a and 2b, testing whether the number of repeated alliances between a startup and an incumbent would affect the quality of joint innovation performance positively or negatively. For this table, I have used 172 observations out of the total 343 observations that have all startup size and funding series information used for control variables and the number of repeated alliances information used for independent variables for Hypothesis 2a and 2b. In Table 3, Model 1 includes control variables only. Model 2 determines the main effects of Hypothesis 2a and 2b. The result of Model 2 in Table 3 indicates that both Hypothesis 2a and 2b are not supported. However, I have designed an additional model for Table 2 to test the interaction effect of a startup's prior alliance experience. Model 3 examines the interaction effect of whether a startup with prior experience forming a repeated alliance with an incumbent has a correlation with their joint innovation performances. Interestingly, Model 3 indicates the interaction effect is negative and relatively significant (coefficient=−1.299, $p<0.1$). To specify the result, a startup with no prior experience forming a repeated alliance with its partner incumbent has a positive correlation with the joint innovation performance after the startup−incumbent alliance formation.

4.3 Robustness Check

4.3.1 Sensitivity Tests

(insert Table 4 here)

Because the impact of an alliance may last for years and varies by firm, the number of patents published and the number of forward citations can be accumulated at a different rate of time (Kim et al., 2012; Araujo et al., 2018). Thus, I have conducted a sensitivity test in analyzing the citation ratio of co−patents published after an alliance formation because the time spent to publish patents is not consistent by firms. I set a research period of 7 years from an alliance formation to a patent publication and performed a sensitivity test of citation−based measures of co−patents published after an alliance by observing from 5 to 9 years within my research period.

Table 4 presents the results of a sensitivity test for Hypothesis 1, exhibiting the impact of the number of a startup's prior alliance experience on their joint innovation performance from year 5 to year 9 after an alliance formation indicated as columns (1)-(5). For instance, if an alliance was formed in 2000, I have seen the citation-based measure of co-patents published from 2005 (year 5) to 2009 (year 9). Table 4 includes 259 observations that contain a startup's size and funding series information. The resulting coefficients of Table 4 with columns (1)-(5) are all positive and statistically significant for all five years ($p<0.01$), indicating that the number of a startup's prior alliance experience has a positive impact on the joint innovation performance of a startup-incumbent alliance for all observation periods (5 to 9 years).

(insert Table 5 here)

Table 5 displays the statistical results of a sensitivity test for Hypothesis 2a and 2b. Table 5 consists of 172 observations with all startup information and repeated alliance status information from year 5 to 9 indicated as columns (1)-(5). Although Hypothesis 2a and 2b have not been supported, the sensitivity test results show that the number of repeated alliances has a positive correlation to the joint innovation performance from the year 7 to 9 after an alliance formation, showing statistically significant and positive results (coefficient=1.301 (year 7), 1.390 (year 8), 1.385 (year 9), $p<0.05$).

4.3.2 Additional Tests for Hypotheses using Missing Subsets

(insert Table 2b here)

Because not all of my observations contain full startup information for control variables (startup size or funding series stage) and a repeated alliance status between the two focal firms, I have conducted additional statistical analysis by using the remaining subset observations using a negative binomial regression. Table 2b contains 84 observations that are missing a startup' s total funding amount information or funding series stage information to the date of an alliance formation. In Table 2b, Model 1 examines control variables only, and Model 2 analyzes the main effect of Hypothesis 1. The coefficient is positive and is statistically significant, supporting Hypothesis 1 (coefficient=0.191, $p<0.05$).

(insert Table 3b here)

Table 3b tests Hypothesis 2a and 2b with the remaining missing subsets. Table 3b contains 84 observations that are missing either a startup' s total funding amount information or its funding series stage information. Among these 84 subsets, 44 observations contain data on repeated alliance status. In Table 3b, Model 1 examines control variables only, Model 2 analyzes the main effect of Hypothesis 2a and 2b, and Model 3 observes the interaction effect between a startup's prior alliance experience and the repeated alliance between a startup and an incumbent. Although the results of Table 3 with the main observations do not support both Hypothesis 2a and 2b, the result of Model 2 in Table 3b exposes that the coefficient is positive and statistically significant (coefficient=1.701, $p<0.05$), supporting Hypothesis 2a. Furthermore, Model 3 in Table 3b indicates that the interaction effect is not statistically significant. The results in Table 3b partially support Hypothesis 2a with a positive and statistically significant coefficient. However, both Table 3 and Table 3b reject Hypothesis 2b, suggesting a repeated alliance experience between a startup and an incumbent may have some correlations with their positive joint innovation performance but has no correlation with negative innovation outcomes.

(insert Table 4b here)

I have also conducted an additional sensitivity test for Hypothesis 1 using the missing subsets, Table 4b includes the remaining 84 observations which do not contain startup size information or funding stage information. The main effect results in Table 4b are positive and statistically significant for all five columns ($p<0.05$). Overall, the results of both Table 4 and 4b suggest that when a startup and an incumbent form an alliance, the number of a startup's prior alliance experiences with other firms has positive impacts on joint innovation quality from 5 to 9 years.

(insert Table 5b here)

I have also conducted an additional sensitivity test for Hypothesis 2a and 2b using the missing subsets. Table 5b consists of the remaining 44 observations that do not have startup size information or funding stage information as well as repeated alliance status. Alliance type: R&D is left blank because no R&D alliance has been found among the 44 missing subsets. However, the main effect results in columns (1)–(5) do not statistically support Hypothesis 2a and 2b.

4.3.3 Marginal Effect Analysis

(insert Table 6 here)

Because Hypotheses 2a and 2b have not been supported, I have conducted a marginal effect analysis. To further analyze my hypotheses 2a and 2b, I have separated my samples by the number of repeated alliances which come out to be 0, 1, and 2. Because each group has a relatively small sampling size, I have utilized the parametric bootstrapping method which uses the estimated parameters to estimate the variations. By holding all control variables, the mean of patent citations increases as the number of each group (separated by the number of repeated alliance formations) increases. However, the confidence interval has also increased, implying the uncertainty level is also rising.

5. Discussion

5.1 Contributions

The study observes the impact of two types of prior alliance experience (1) a startup's prior experience with other firms and (2) a repeated alliance experience between a startup and an incumbent who have prior alliance experience on their joint innovation performance, by combining strategic alliance data between two asymmetric firms and their innovation quality through citation-based measures of their co-patents. The study has revisited and substantiated the significance of experience capabilities on a firm's innovation.

For theoretical implications, this paper contributes to an asymmetric alliance, experience capability, and joint innovation literature. This paper investigates how two types of past experience affect the quality of joint innovation in an asymmetric alliance between a startup and an incumbent. In this research, I have distinguished an asymmetric alliance between a startup and an incumbent from other alliances between firms that share similar characteristics, structure, and goals. Moreover, I have questioned whether two types of prior alliance experience of a startup would spawn positive joint innovation outputs. The findings of this study reflect that the number of a startup's prior alliance experiences with other firms has a positive impact on joint innovation quality when a startup and an incumbent form a new alliance, implying that such prior experience is likely to increase alliance management capabilities and absorptive capacity, statistically confirming Hypothesis 1.

While Hypothesis 2a and 2b have been rejected, the result of the interaction effect exhibits how a startup that has prior alliance experience with other firms forming a repeated alliance with the same incumbent may lead to undesirable consequences on their joint innovation performance. This result implies two insights: On one hand, an asymmetric alliance between an incumbent and a startup that has no prior alliance experience may spawn positive joint innovation outcomes in their first strategic alliance. During the alliance period, the incumbent may sense the potential of the startup and repeat collaboration with the same startup partner. On the other hand, a startup that has prior alliance experience with others may simultaneously partner with other incumbents when the startup and the incumbent repeat collaboration, implying that the startup does not solely rely on a single incumbent regardless of repeated collaboration.

With regard to the rejection of Hypothesis 2a and 2b, the study expands ambidextrous understandings of repeated alliances by theoretically illustrating the advantages of relational embeddedness (e.g. know-how, partner-specific knowledge, and trust-building) and transaction cost economics (TCE) and the disadvantages of an exploitation trap. While both Hypothesis 2a and 2b have been rejected, Hypothesis 2a has been partially supported through the additional regression analyses which have used the missing subset groups that do not contain startup size or startup funding stage data. Although trivial, these statistical results may precipitate a possibility that the advantages of repeated alliances such as transaction cost economics (TCE) and relational embeddedness surpass the disadvantages of repeated alliances such as an exploitation trap

5.2 Limitations

This study has several limitations. (1) First, I have only considered the startup's characteristics, experience, age, and size. I have ignored the incumbent's firm size, age, and experience. Some data from my research show partnerships between startups and well-known, giant incumbents such as Microsoft, Oracle, Sun Microsystems, and IBM tend to form more repeated alliances with startups. If I have collected an incumbent's information such as firm size, age, and experience would yield more precise results. (2) Secondly, I have some data constraints in collecting all startup size information and funding stage information, which have been used for my control variables. Among the total 343 observation numbers, I could not track 84 startups' funding series stage or the total funding amount to the date of an alliance formation. Thus, the results for each hypothesis have been separated into two: main observation groups and missing subset groups. Furthermore, I could not find 127 alliance termination date information among the 343 alliances in all three databases, SDC Platinum, Factiva, and Lexis−Uni. (3) Regarding sampling bias, the samples of this study are based on data from both partner firms headquartered in the U.S. Because the number of alliance formation data provided by SDC Platinum is extremely high during the period from 2000 to 2008, I have excluded all alliances, in which at least one firm belongs to a non−U.S. country. Moreover, I have based my industries specific to E−business, in which startups belong to five related SIC codes. If the same study had been done with different industries such as the pharmaceutical industry or the bioscience industry, the result would have been different. (4) In this study, I could not empirically measure and test the trust level or exploitation levels between the two partnering firms. In the future study, I would measure the degree of path dependency by counting backward citations of their co−patents as a part of the exploitation trap. Additionally, I would collect interviews or surveys from employees to estimate the trust level between the two focal firms. These additional data would make my results more convincing. For instance, measuring the level of path dependency by collecting backward citations of each co−patent would provide estimates of the exploitation trap and therefore yield more consistent results. (5) Lastly, although I have filtered and narrowed my alliance data specific to both firms being headquartered in the U.S., I have not considered geographical proximity between startups and incumbents in the U.S. or geographical agglomeration of headquartered locations. Many prominent studies in the past have explored the relationship between geographical proximity or geographical agglomeration and the resulting innovation quality in knowledge and learning literature (Rosenthal & Strange, 2004; Jaffe & Trajtenberg, 1999). In the future study, combining the theories of asymmetric alliances with geographical proximity or geographical agglomeration and testing the innovation quality may further contribute to business and strategic management research.

Tables

Table 1. Descriptive Statistics and Correlations.

Variables	Mean	SD.	Min	Max	(1)	(2)	(3)	(4)	(5)
(1) Startup Age	6.33	2.88	0	11	1				
(2) Startup Size	48.19	85.45	0.06	874	0.08	1			
(3) The Number of Startup' s Prior Alliance Experiences	3.53	7.12	0	49	0.26	0.17	1		
(4) Repeated Alliances	0.48	0.61	0	2	0.22	0.1	0.47	1	
(5) Quality of Joint Innovation	5.85	12.34	0	122	0.1	0.1	0.51	0.27	1

Table 2. Hypothesis 1: The impact of a startup's number of prior alliance experiences on the quality of joint innovation performance

	Dependent variable:	
	The Quality of Joint Innovation Performance	
	(1)	(2)
The Number of Prior Alliance Experience		0.062^{***}
		(0.018)
Startup Size	0.0005	0.0003
	(0.001)	(0.001)
Startup Age	−0.008	−0.026
	(0.047)	(0.046)
Series A	−0.506	−0.629
	(0.416)	(0.404)
Series B	−0.538	−0.454
	(0.399)	(0.386)
Series D	−0.203	−0.104
	(0.520)	(0.504)
Series E	−0.523	−0.423
	(0.704)	(0.682)
Series F	1.469^{**}	1.239^{*}
	(0.672)	(0.659)
Series Late Stage	0.197	−0.091
	(0.536)	(0.523)
Series IPO	0.777	0.316
	(0.495)	(0.523)
Alliance Type: Manufacturing	−0.216	0.107
	(0.987)	(0.956)
Alliance Type: Tech Transfer	0.104	0.259
	(0.618)	(0.600)
Alliance Type: Marketing	0.698	0.438
	(0.590)	(0.577)
Alliance Type: R&D	0.941	1.329
	(1.143)	(1.108)
Alliance Type: Licensing	0.359	0.622
	(0.870)	(0.841)
Cross Industry	0.028	0.001
	(0.256)	(0.248)
Constant	1.581^{**}	1.391^{*}
	(0.776)	(0.753)
Observations	259	259
Log Likelihood	−659.152	−653.396
theta	0.271^{***} (0.031)	0.291^{***} (0.034)
Note: Table 2		*p**p***p<0.01

Table 3. Hypothesis 2a and 2b: The impact of the number of repeated alliance experiences on the quality of joint innovation performance

	Dependent Variable: The Quality of Joint Innovation Perf.		
	(1)	(2)	(3)
The Number of Repeated Alliances		0.244	1.342**
		(0.223)	(0.645)
A Startup's Prior Alliance Experience	2.167***	2.162***	2.730***
	(0.352)	(0.354)	(0.449)
Startup Size	0.0002	−0.00002	0.0003
	(0.001)	(0.001)	(0.001)
Startup Age	0.049	0.037	0.024
	(0.052)	(0.052)	(0.052)
Series B	0.286	0.389	0.514
	(0.436)	(0.436)	(0.437)
Series C	0.905**	0.895**	0.867*
	(0.445)	(0.451)	(0.452)
Series D	0.136	0.164	0.291
	(0.556)	(0.557)	(0.555)
Series E	−0.171	−0.025	0.097
	(0.702)	(0.699)	(0.710)
Series F	1.832***	1.636**	1.923***
	(0.638)	(0.654)	(0.661)
Series Late Stage	0.606	0.740	0.753
	(0.554)	(0.552)	(0.551)
Series IPO	0.964**	1.009**	1.158**
	(0.490)	(0.493)	(0.492)
Alliance Type: Manufacturing	0.078	0.152	0.133
	(0.958)	(0.957)	(0.953)
Alliance Type: Tech Transfer	−0.341	−0.271	−0.195
	(0.583)	(0.581)	(0.581)
Alliance Type: Marketing	0.676	0.721	0.916*
	(0.538)	(0.536)	(0.541)
Alliance Type: R&D	0.528	0.685	0.484
	(1.304)	(1.306)	(1.300)
Alliance Type: Licensing	−0.593	−0.488	−0.369
	(0.824)	(0.826)	(0.826)
Cross Industry	−0.328	−0.382	−0.281
	(0.274)	(0.274)	(0.275)
The Number of Repeated Alliance x Prior Alliance Experience			−1.299*
			(0.688)
Constant	−0.529	−0.651	−1.271
	(0.755)	(0.755)	(0.811)
Observations	172	172	172
Log Likelihood	−458.319	−457.712	−456.475
theta	0.408*** (0.058)	0.412*** (0.058)	0.417*** (0.059)
Note: Table 3			*p**p***p<0.01

Table 4. A Sensitivity Test for Hypothesis 1

	Dependent variable:				
	Year 5	Year 6	Year 7	Year 8	Year 9
	(1)	(2)	(3)	(4)	(5)
The Number of Prior Alliance Experience	0.073***	0.060***	0.062***	0.059***	0.058***
	(0.024)	(0.021)	(0.018)	(0.018)	(0.018)
Startup Size	0.002	0.001	0.0003	0.0002	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Startup Age	0.001	−0.009	−0.026	−0.005	−0.002
	(0.060)	(0.053)	(0.045)	(0.045)	(0.045)
Series A	−0.862	−0.631	−0.633	−0.653	−0.673*
	(0.532)	(0.467)	(0.402)	(0.398)	(0.398)
Series B	−1.257**	−0.679	−0.459	−0.591	−0.597
	(0.513)	(0.448)	(0.384)	(0.381)	(0.381)
Series D	−0.222	−0.268	−0.110	−0.112	−0.167
	(0.663)	(0.584)	(0.501)	(0.495)	(0.496)
Series E	−0.890	−0.395	−0.412	−0.455	−0.474
	(0.901)	(0.786)	(0.678)	(0.671)	(0.671)
Series F	0.239	0.762	1.235*	0.973	0.970
	(0.875)	(0.766)	(0.655)	(0.648)	(0.648)
Series Late Stage	−0.391	−0.092	−0.095	−0.101	−0.081
	(0.689)	(0.605)	(0.520)	(0.514)	(0.513)
Series IPO	−0.898	−0.332	0.312	0.135	0.120
	(0.695)	(0.609)	(0.520)	(0.514)	(0.514)
Alliance Type: Manufacturing	0.522	0.494	0.109	0.185	0.224
	(1.259)	(1.102)	(0.951)	(0.938)	(0.938)
Alliance Type: Tech Transfer	0.418	0.272	0.258	0.179	0.205
	(0.793)	(0.693)	(0.597)	(0.589)	(0.590)
Alliance Type: Marketing	0.402	0.630	0.438	0.408	0.443
	(0.762)	(0.666)	(0.573)	(0.567)	(0.567)
Alliance Type: R&D	2.303	1.676	1.328	1.367	1.416
	(1.464)	(1.283)	(1.101)	(1.088)	(1.088)
Alliance Type: Licensing	0.296	1.050	0.619	0.517	0.515
	(1.116)	(0.970)	(0.836)	(0.827)	(0.827)
Cross Industry	0.107	−0.075	−0.003	0.047	0.029
	(0.330)	(0.288)	(0.247)	(0.245)	(0.245)
Constant	0.943	1.179	1.399*	1.306*	1.282*
	(0.995)	(0.871)	(0.749)	(0.740)	(0.740)
Observations	259	259	259	259	259
Log Likelihood	−508.961	−577.878	−654.746	−641.282	−640.928
theta	0.165*** (0.022)	0.215*** (0.027)	0.294*** (0.034)	0.302*** (0.036)	0.302*** (0.036)

Note: Table 4 *p**p***p<0.01

Table 5. A Sensitivity Test for Hypothesis 2a and 2b

	Dependent variable: The Quality of Joint Innovation Performance				
	Year 5	Year 6	Year 7	Year 8	Year 9
	(1)	(2)	(3)	(4)	(5)
The Number of Repeated Alliance	0.754	1.019	1.301**	1.390**	1.385**
	(0.823)	(0.736)	(0.641)	(0.633)	(0.633)
Startup's Prior Alliance Experience	2.151***	2.404***	2.679***	2.640***	2.637***
	(0.564)	(0.502)	(0.448)	(0.446)	(0.446)
Startup Size	0.001	0.001	0.0003	0.0003	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Startup Age	0.083	0.032	0.024	0.038	0.040
	(0.068)	(0.060)	(0.052)	(0.051)	(0.051)
Series B	0.865	0.649	0.499	0.514	0.525
	(0.567)	(0.503)	(0.435)	(0.427)	(0.427)
Series C	1.418**	1.128**	0.782*	0.821*	0.844*
	(0.580)	(0.516)	(0.448)	(0.439)	(0.439)
Series D	−0.264	−0.123	0.235	0.251	0.232
	(0.735)	(0.647)	(0.551)	(0.539)	(0.540)
Series E	0.190	0.497	0.052	0.127	0.141
	(0.908)	(0.796)	(0.703)	(0.688)	(0.688)
Series F	1.010	1.408*	1.880***	1.572**	1.594**
	(0.867)	(0.764)	(0.655)	(0.642)	(0.642)
Series Late Stage	1.086	0.959	0.720	0.778	0.806
	(0.709)	(0.632)	(0.546)	(0.534)	(0.533)
Series IPO	0.885	0.798	1.076**	0.981**	0.991**
	(0.639)	(0.568)	(0.488)	(0.477)	(0.477)
Alliance Type: Manufacturing	1.007	0.922	0.046	0.101	0.148
	(1.226)	(1.089)	(0.943)	(0.919)	(0.919)
Alliance Type: Tech Transfer	−0.386	0.214	−0.242	−0.391	−0.366
	(0.750)	(0.661)	(0.576)	(0.564)	(0.563)
Alliance Type: Marketing	1.086	1.364**	0.906*	0.765	0.803
	(0.699)	(0.614)	(0.536)	(0.526)	(0.525)
Alliance Type: R&D	1.918	1.223	0.481	0.547	0.576
	(1.681)	(1.491)	(1.288)	(1.255)	(1.254)
Alliance Type: Licensing	−0.940	0.783	−0.323	−0.406	−0.398
	(1.076)	(0.925)	(0.820)	(0.804)	(0.804)
Cross Industry	−0.306	−0.335	−0.243	−0.163	−0.171
	(0.355)	(0.315)	(0.272)	(0.266)	(0.266)
Constant	−0.417	−0.722	−1.206*	−1.257*	−1.267*
	(0.879)	(0.786)	(0.684)	(0.674)	(0.674)
Observations	172	172	172	172	172
Log Likelihood	−382.108	−409.974	−457.342	−447.799	−446.718
theta	0.248*** (0.039)	0.315*** (0.047)	0.425*** (0.060)	0.451*** (0.065)	0.451*** (0.065)

Note: Table 5 *p**p***p<0.01

Table 2b: An Additional Test for Hypothesis 1 Test for Missing Subsets

	Dependent variable:	
	The Quality of Joint Innovation Performance	
	(1)	(2)
The Number of Prior Experience		0.191**
		(0.094)
Startup Age	0.200*	0.133
	(0.115)	(0.115)
Alliance Type: Manufacturing	−0.595	−2.993
	(3.057)	(3.133)
Alliance Type: Tech Transfer	24.889	37.594
	(189,334)	(45,978,825)
Alliance Type: Marketing	26.089	38.912
	(189,334)	(45,978,825)
Alliance Type: R&D	−1.530	−0.032
	(231,518)	(66,074,595)
Alliance Type: Licensing	−1.207	−0.623
	(231,240)	(65,810,382)
Cross Industry	0.249	−0.083
	(0.697)	(0.682)
Constant	−25.757	−38.250
	(189,334)	(45,978,825)
Observations	84	84
Log Likelihood	−118.466	−117.497
theta	0.122*** (0.033)	0.130*** (0.036)
Note: Table 2b		*p**p***p<0.01

Table 3b. An Additional Test for Hypothesis 2a and 2b using Missing Subsets

	Dependent variable:		
	The Quality of Joint Innovation Performance		
	(1)	(2)	(3)
The Number of Repeated Alliance		1.701**	−31.911
		(0.788)	(3,460,631.000)
Startup's Prior Experience	2.108***	0.589	−0.032
	(0.641)	(0.695)	(0.722)
Startup Age	0.035	−0.068	−0.075
	(0.109)	(0.125)	(0.112)
Alliance Type: Manufacturing	−1.642	−3.379	−4.098*
	(2.707)	(2.449)	(2.212)
Alliance Type: Tech Transfer	32.615	30.226	27.850
	(9,809,564.000)	(67,108,864.000)	(6,309,545.000)
Alliance Type: Marketing	34.405	31.713	29.149
	(9,809,564.000)	(67,108,864.000)	(6,309,545.000)
Alliance Type: R&D	−1.189		
	(11,735,657.000)		
Alliance Type: Licensing	−1.449	−6.912	−4.755
	(11,736,497.000)	(94,906,264.000)	(8,895,151.000)
Cross Industry	−0.263	−0.737	−0.771
	(0.643)	(0.736)	(0.679)
The Number of Repeated Alliance x Prior Experience			34.291
			(3,460,631.000)
Constant	−33.465	−29.721	−27.100
	(9,809,564.000)	(67,108,864.000)	(6,309,545.000)
Observations	84	44	44
Log Likelihood	−114.700	−74.679	−71.858
theta	0.159*** (0.046)	0.299*** (0.114)	0.399** (0.164)

Note: Table 3b *p**p***p<0.01

Table 4b. An Additional Sensitivity Test for Hypothesis 1 using Missing Subsets

	Dependent variable:				
	Year 5	Year 6	Year 7	Year 8	Year 9
	(1)	(2)	(3)	(4)	(5)
The Number of Prior Experience	0.354***	0.227**	0.191**	0.220**	0.193**
	(0.125)	(0.108)	(0.094)	(0.094)	(0.096)
Startup Age	−0.102	0.096	0.133	0.129	0.094
	(0.153)	(0.131)	(0.115)	(0.116)	(0.117)
Alliance Type: Manufacturing	−4.571	−3.461	−2.993	−3.331	−2.908
	(4.146)	(3.562)	(3.133)	(3.110)	(3.179)
Alliance Type: Tech Transfer	32.712	30.526	37.594	23.254	34.281
	(54,092,877)	(18,790,085)	(45,978,825)	(442,926)	(67,108)
Alliance Type: Marketing	33.947	32.356	38.912	25.268	36.047
	(54,092,877)	(18,790,085)	(45,978,825)	(442,926)	(67,108,864)
Alliance Type: R&D	−3.398	−6.603	−0.032	−13.953	−3.052
	(71,957,204)	(51,037,899)	(66,074,595)	(47,455,200)	(82,191,237)
Alliance Type: Licensing	−5.640	−7.739	−0.623	−14.984	−3.860
	(70,366,126)	(49,959,966)	(65,810,382)	(45,864,011)	(82,191,237)
Cross Industry	−1.116	−0.501	−0.083	−0.432	−0.277
	(0.904)	(0.776)	(0.682)	(0.686)	(0.695)
Constant	−32.013	−30.982	−38.250	−23.975	−34.704
	(54,092,877)	(18,790,085)	(45,978,825)	(442,926)	(67,108,864)
Observations	84	84	84	84	84
Log Likelihood	−84.096	−104.753	−117.497	−112.206	−114.438
theta	0.074*** (0.025)	0.100*** (0.030)	0.130*** (0.036)	0.131*** (0.038)	0.126*** (0.036)

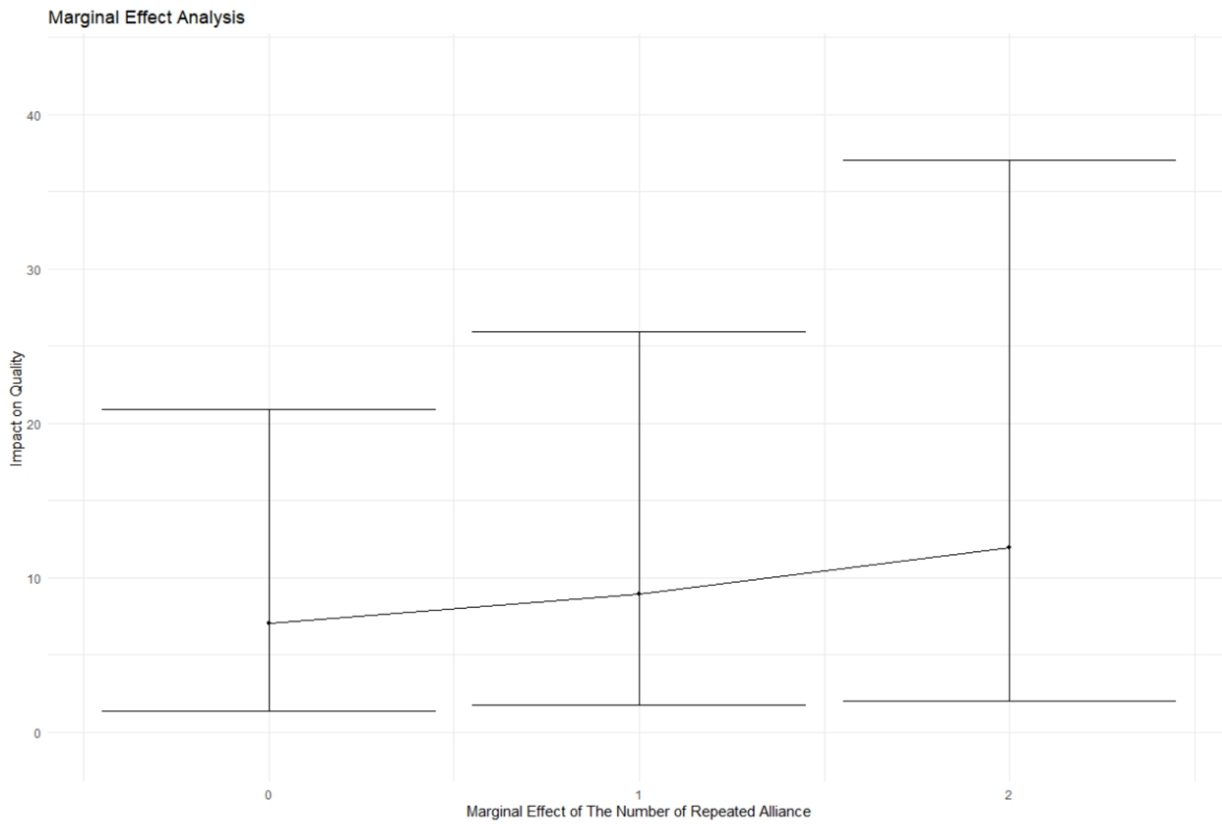
Note: Table 4b *p**p***p<0.01

Table 5b. An Additional Sensitivity Test for Hypothesis 2a and 2b using Missing Subsets

	Dependent variable:				
	Year 5	Year 6	Year 7	Year 8	Year 9
	(1)	(2)	(3)	(4)	(5)
The Number of Repeated Alliance	−33.768	−37.143	−31.911	−36.980	−37.427
	(38,745,321)	(38,745,321)	(3,460,631)	(38,745,321)	(38,745,321)
Startup's Prior Experience	1.508	0.017	−0.032	0.048	−0.186
	(1.006)	(0.945)	(0.722)	(0.748)	(0.772)
Startup Age	−0.538***	−0.112	−0.075	−0.084	−0.117
	(0.199)	(0.147)	(0.112)	(0.117)	(0.119)
Alliance Type: Manufacturing	−7.585**	−3.443	−4.098*	−3.246	−3.332
	(3.062)	(3.002)	(2.212)	(2.276)	(2.386)
Alliance Type: Tech Transfer	29.473	30.624	27.850	32.360	34.346
	(55,901,730)	(67,108,864)	(6,309,545)	(48,692,026)	(67,108,864)
Alliance Type: Marketing	33.106	32.087	29.149	33.855	35.680
	(55,901,730)	(67,108,864)	(6,309,545)	(48,692,026)	(67,108,864)
Alliance Type: R&D					
Alliance Type: Licensing	−6.270	−6.777	−4.755	−4.901	−3.054
	(87,341,875)	(94,906,265)	(8,895,151)	(82,912,684)	(94,906,266)
Cross Industry	−0.948	−1.080	−0.771	−0.856	−0.657
	(0.959)	(0.899)	(0.679)	(0.709)	(0.722)
The Number of Repeated Alliance x Prior Experience	36.806	39.285	34.291	39.057	39.580
	(38,745,321)	(38,745,321)	(3,460,631)	(38,745,321)	(38,745,321)
Constant	−27.548	−29.592	−27.100	−31.636	−33.286
	(55,901,730)	(67,108,864)	(6,309,545)	(48,692,026)	(67,108,864)
Observations	44	44	44	44	44
Log Likelihood	−55.547	−62.977	−71.858	−67.500	−69.786
theta	0.233**	0.206**	0.399**	0.371**	0.334**
	(0.097)	(0.087)	(0.164)	(0.160)	(0.137)
Note: Table 5b					*p**p***p<0.01

Table 6. Marginal Effect Analysis: Parametric Bootstrapping

Repeated Alliance	Prior Experience	Mean Startup Size (million $)	Mean Startup Age (year)	Mean Y	Confidence Level (2.5)	Confidence Level (97.5)
0	1	61	6.3	6.893	1.363	21.342
1	1	61	6.3	8.446	1.695	26.612
2	1	61	6.3	10.959	1.660	41.399



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국문 초록

비대칭적 제휴: 대기업과 스타트업 간의 전략적 제휴에서 경험이 공동 혁신성과에 미치는 영향

박신영

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기업 전략 연구에서 기업 간 동맹 및 스타트업과의 비대칭적 파트너십에 대한 관심이 빠르게 증가하고 있는 것은 기업들이 기술적 불연속성 환경에서 다각적인 협업을 통해 지속적인 혁신을 만들기 위한 전략 방식이라는 것을 반영한다. 이러한 제휴의 성과에 관해서 경험은 동맹 기간 동안 공동 혁신을 촉진하는 촉매제로 작용할 수 있다. 본 연구에서는 (1) 스타트업의 다른 기업과의 사전 제휴 경험 그리고 (2) 사전 제휴 경험이 있는 스타트업과 현직 기업간의 반복 제휴 경험 두 가지 유형으로 경험을 분류한다. 비대칭적 제휴와 경험 역량 문헌을 바탕으로, 이 연구는 이 두 가지 유형의 경험이 스타트업과 현직 기업간의 비대칭적 제휴에 의해 생성된 공동 혁신 성과에 미치는 영향을 조사한다. E-비즈니스 산업에서 2000 년에서 2008 년 사이에 형성된 스타트업과 현직 기업 간의 비대칭 제휴 분석과 특정 관찰 기간 내에 출원된 공동 특허의 인용 기반 조치를 병합하고 분석하며, 본 연구는 스타트업이 새로운 현직 기업과 처음으로 비대칭적 제휴를 맺을 때, 스타트업이 타 기업들과 맺은 사전 제휴 경험 횟수는 두 기업간의 제휴에서 생성되는 공동 혁신 성과의 질과 긍정적으로 관련이 있을 것이다 라는 첫번째 가설을 뒷받침한다. 비록 실증적 통계 결과가 두번째 대립가설을 완전히 뒷받침하지는 못하지만, 스타트업과 현직 기업간의 반복적인 비대칭적 제휴경험이 어떻게 그들의 공동 혁신 성과에 양날의 검이 될 수 있는지에 대한 양손잡이의 통찰력을 제공한다.

주요어: 비대칭적 제휴, 동적 역량, 전략적 제휴, 사전 제휴 경험, 내포된 관계성, 공동 혁신

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