경영학석사학위논문

Dynamics of Optimal Balance Between Exploration and Exploitation

: In the View of Capability and Embeddedness

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Abstract

Although existing ambidexterity literature suggests that firms need to balance between exploration and exploitation for superior performance, few studies have empirically examined the dynamic change of a firm's optimal balance between exploration and exploitation. Building upon the capability and embeddedness perspectives, this research investigates how the varying level of a firm's technological capability and network position within industry alliances affects the location of the optimal balance point of the firm. Analyzing 7-year panel data in the worldwide semiconductor industry from 1994 to 2000, I find support for the following hypotheses: 1) the proportion of exploration has an inverted-U-shaped relationship with innovation performance; 2) as a firm's technological capability is enhanced, its optimal point between exploration and exploitation moves *toward the exploration side*; 3) as a firm's network position within industry alliances is central, the optimal point moves *toward the exploitation side*. The results offer theoretical insights into the dynamic nature of ambidexterity as well as the managerial implications for resource-allocation decisions.

Keywords: exploration-exploitation, innovation, technological capability, network position, ambidexterity.

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I. INTRODUCTION

To achieve and sustain a competitive advantage, firms need to achieve an appropriate balance between exploration of new possibilities and exploitation of old certainties (March, 1991). If a firm only depends on the exploitation of current knowledge, the firm may suffer from technological obsolescence and finally fall behind in the competition. In contrast, a firm that explores new knowledge to the exclusion of exploitation may fail to reap substantial benefits from the knowledge already explored (Levinthal & March, 1993).

On the issue of exploration-exploitation balance, a great number of studies have been conducted, mainly in two streams (O'Reilly & Tushman, 2013; Raisch & Birkinshaw, 2008). The first stream empirically tests whether the balance between exploration and exploitation actually leads to the superior performance of a firm (e.g., He & Wong, 2004; Gibson & Birkinshaw, 2004; Katila & Ahuja, 2002). Some scholars have refined and extended this stream of literature by proposing some contingencies under which the balance has a greater effect in performance (e.g., Jansen, Van den Bosch, & Volberda, 2006; Kyriakopoulos & Moorman, 2004; Rothaermel & Alexandre, 2009; Yamakawa, Yang, & Lin, 2011). The second stream focuses on how firms effectively achieve the balance between exploration and exploitation. Scholars in this stream contend that simultaneously pursing exploration and exploitation engenders severe tension within a firm, and therefore, in order to reap substantial benefits from the exploration-exploitation balance, the firm must possess specific mechanisms to resolve the tension. Structural ambidexterity and contextual ambidexterity are representative solutions presented by strategy and organization theorists (e.g., Andriopoulos & Lewis, 2009; Benner & Tushman, 2003; Tushman & O'Reilly, 1996).

Recently, a group of scholars have pointed out a limitation of the mainstream study – it pays little attention to *the dynamic nature of ambidexterity* (Rasich, Birkinshaw, Probst, & Tushman, 2009). That is, previous studies that examine the balancing issue in a dichotomous way – the balanced versus the imbalanced – do not offer a sufficient explanation for the temporal change of a firm's optimal balance point. This is important both theoretically and managerially, because in reality there is no universal point of balance that promises the best performance to the entire range of contexts that firms face over time (Raisch & Birkinshaw, 2008). Indeed, as internal and external contexts change, firms should strategically allocate their scarce resources into two distinct activities, not just strive for a fifty-fifty balance. From this perspective, sequential ambidexterity, or temporal cycling between exploration-focused and exploitation-focused periods, has been presented by strategy and organization researchers. Nevertheless, how those temporal transitions occur over time still remains to be explored (Raisch et al., 2009).

Following the aforementioned line of thought, this study aims to extend the ambidexterity literature by examining the underlying mechanisms of the temporal changes of a firm's optimal balance between exploration and exploitation. Building upon *capability perspective* and *embeddedness perspective*, I focus on two firm-specific contexts: (1) technological capability and (2) network position within industry alliances. While the technological capability captures the aspect of a firm's abilities to innovate as accumulated within the organization, the alliance network position addresses social aspects inherent in relationships with other organizations. In turn, the specific research question of this paper is *to which direction* a firm's optimal balancing point moves when its technological capability, or network position, is enhanced. I argue that a high level of technological capability moves the optimal balance point *toward the exploration side*. This implies that, when a firm develops technological capability, it should gradually increase the proportion of exploration for higher innovation performance. On the other hand, I predict that a high level of network position in industry alliances moves the optimal point *toward the exploitation side*. This indicates that, when a firm moves into a central position, it can enhance innovation performance by increasing exploitation and decreasing exploration. I confirmed the hypotheses using a fixed effects panel negative binomial regression on the 7-year panel data of 55 semiconductor firms from 1994 to 2000.

II. LITERATURE REVIEW

Over the past two decades, the idea of exploration and exploitation has become one of the most popular topics in strategy and organization research (Raisch et al., 2009). March (1991) proposed that *exploration* refers to activities associated with "search, variation, risk taking, experimentation, and discovery," whereas *exploitation* indicates notions such as "refinement, efficiency, selection, and implementation." He further contended that both excessive exploration and excessive exploitation yield destructive consequences, and therefore firms should achieve an appropriate balance between the two distinct activities. Since then, great academic attention has been given to balancing exploration and exploitation. Research on this issue has been conducted in two streams: (1) empirically testing the superiority of the simultaneous pursuit of exploration and exploitation and (2) discovering mechanisms of pursuing both exploration and exploitation with less internal tension (O'Reilly & Tushman, 2013).

In the first stream, a large number of scholars have attempted to find empirical evidence that balancing exploration and exploitation is associated with higher firm performance. Their strategy has been to show that exploration and exploitation are complements rather than substitutes. For instance, through both quantitative time-series analysis and in-depth qualitative case study, Knott (2002) demonstrated that exploration (improvements in product quality) and exploitation (learning curve) coexist in Toyota's product development, which implies that combining exploration and exploitation is a viable solution. Some other scholars provided more generalized results through large-sample analysis. Katila and Ahuja (2002) studied 124 industrial robotics companies and found that exploration has a positive interaction effect with exploitation on new product development. In the context of technological innovation, He and Wong (2004) surveyed 206 manufacturing firms in diverse industries and demonstrated both that exploratory innovation strategy has a positive interaction with exploitative innovation strategy on sales growth rate and that the absolute difference between the two is negatively associated with sales growth rate. All of the above studies confirmed the argument about the superiority of a simultaneous balance between exploration and exploitation.

Since then, several scholars have gone one step further by unearthing boundary conditions that moderate the effect of the exploration-exploitation balance. From the analysis on 340 Dutch business units in the food processing industry, Kyriakopoulos and Moorman (2004) found that market orientation positively moderates the relationship between the balancing strategy and financial performance. This result implies that, for firms with low market orientation, the exploration-exploitation balance may harm performance. In the view of resource endowments, moreover, Ebben and Johnson (2005) stressed the fact that, as compared to large firms, small firms lack sufficient slack resources necessary to pursue exploration and exploitation simultaneously. They found empirical evidence that small companies, which have less than $20 million in sales, benefit more from a one-sided orientation than from mixed strategies. In addition to internal factors, environmental contingencies have also been explored as significant moderators. For instance, Jansen, van den Bosch, and Volberda (2006) investigated 283 organizational units in 115 branches of a large European financial services firm and demonstrated that, under dynamic environments units benefit from exploratory innovation, whereas they benefit from exploitative innovation under competitive environments. Also, Raisch and Hotz's (2010) research showed that balancing exploration and exploitation is not fitted to hostile environments.

Meanwhile, significant academic attention has been given to severe tension inherent in simultaneously pursuing exploration and exploitation and managerial solutions for resolving the tension. First of all, the topic of *sequential ambidexterity*, or temporal cycling between the exploration-focused period and the exploitation-focused period, has been examined by several scholars (e.g., Cyert & March, 1963; Brown & Eisenhardt 1998; Nickerson & Zenger 2002; Puranam, Singh, & Zollo, 2006; Siggelkow & Levinthal 2003). The central argument of this idea is that, by temporally separating two distinctive activities, firms can avoid the challenges of coordinating contradictory organizational routines. The majority of ambidexterity research, however, defines ambidexterity as the *simultaneous* pursuit of exploration and exploitation, and thus most academic attention has been paid to organizational mechanisms to reconcile two distinct activities (Raisch et al., 2009). *Structural ambidexterity* and *contextual ambidexterity* are representative organizational solutions for a simultaneous balance. Structural ambidexterity is achieved by the structural differentiation between exploration-oriented tasks and exploitation-oriented tasks. The separation of business units specialized in exploration from those focused on exploitation provides the benefits of both exploration and exploitation while minimizing conflicts between the two unblendable activities (Benner & Tushman, 2003; Duncan, 1973; Tushman & O'Reilly, 1996). The structural differentiation, nevertheless, does not completely resolve the tension, because the integration between exploration and exploitation must be conducted somewhere. Accordingly, the success of structural ambidexterity significantly rests on the coordination ability of senior-level managers (Jansen, Tempelaar, van den Bosch, & Volberda, 2009; Lubatkin, Simsek, Ling, & Veiga, 2006). On the other hand, contextual ambidexterity resolves the exploration-exploitation tension at the individual level by establishing appropriate organizational contexts (Gibson & Birkinshaw, 2004). In this view, if individual employees make their own judgments about how to best allocate their time, even a single business unit can effectively conduct both exploration and exploitation, thus reconciling conflicting demands. The literature of contextual ambidexterity, therefore, emphasizes the importance of organizational processes and cultures that encourage sufficient authority to lower-level employees (Markides, 2013; Simsek, Heavey, Veiga, & Souder, 2009).

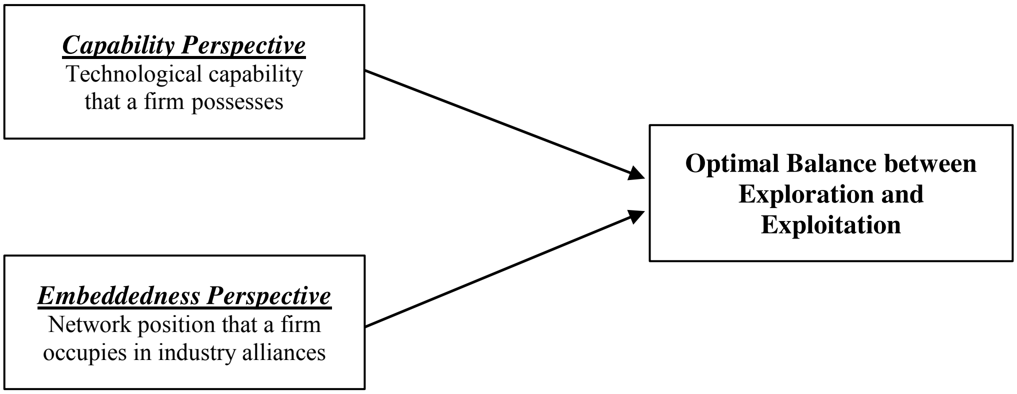
Although the prior research has greatly advanced our understanding of the exploration-exploitation balance, it has a limitation in suggesting which position to take on a specific exploration-exploitation choice set (Birkinshaw & Gupta, 2013).

Balancing exploration and exploitation neither necessarily indicates implementing a fifty-fifty split, nor does it mean that there is a universal, unchanging point that promises the best performance. Under some circumstances, firms may benefit more from an exploration-focused balance (e.g. exploration: exploitation = 6:4), while under other circumstances they may benefit more from an exploitation-focused balance (e.g. exploration: exploitation = 4:6). In turn, varying contexts require a firm to delicately adjust its resource allocation into exploration and exploitation (Markides, 2013). With a similar reasoning, O'Reilly and Tushman (2008) argued that ambidexterity should be viewed as a dynamic capability, which helps a firm continuously reallocate and reconfigure organizational skills and assets to both explore new competencies and exploit the existing ones. Nevertheless, there has been little empirical investigation into the dynamics of the optimal level of balance between exploration and exploitation (Birkinshaw & Gupta, 2013; Raisch et al., 2009).

In this study, I attempt to extend the ambidexterity literature by investigating the dynamic change of the optimal level of exploration-exploitation balance with temporally varying firm-specific conditions. The next section is organized as follows. First, I clearly specify the concepts of exploration and exploitation used in this study. Then, I set the traditional ambidexterity hypothesis as a base line and examine how technological capability and network position within industry alliances affect the specific location of an optimal exploration-exploitation balance. Figure 1 depicts the conceptual research model of this study.

FIGURE 1

Conceptual Research Model



III. THEORY AND HYPOTHESES

3.1. Specification of Exploration and Exploitation

Since the seminal work of March (1991), a large number of studies in various academic fields have addressed the issue of exploration and exploitation. Notwithstanding the increasing number of publications, there are still discrepancies in defining activities of exploration and exploitation (Gupta, Smith, & Shalley, 2006; Simsek et al., 2009; O'Reilly & Tushman, 2013). Before developing arguments and drawing hypotheses, therefore, I first address three definitional issues about exploration and exploitation.

The first issue is specifying the domain of exploratory and exploitive activities.

From technological innovation to organizational design, various fields of studies have adopted March's exploration-exploitation framework to study organization (e.g., Benner & Tushman, 2003; Gupta et al., 2006; He & Wong, 2004; Holmqvist; 2004). This paper specifies exploration and exploitation in the context of technological innovation. More specifically, exploration (exploitation) is defined as R&D activities searching for new (old) technological knowledge. Although organizational learning includes many more different kinds of learning activities than technological innovations, I can make my argument more concrete and testable by narrowing the scope of the concept (He & Wong, 2004). Since exploration and exploitation are limited to activities of technological innovation, I choose innovation performance as my dependent variable rather than general financial outcomes.

Second, the scale of exploration and exploitation should be elaborated upon regarding *continuity* versus *orthogonality*. In the view of continuity, exploration and exploitation are the two ends of a continuous scale. In the perspective of orthogonality, in contrast, they exist on two different and orthogonal scales. The choice of which view to adopt depends on the level of analysis and the specific context of the research (Gupta et al., 2006). This study adopts the view of continuity, since it focuses on firm-level resource allocations under the resource limitation (Barney, 1991; Dierickx & Cool, 1989; Peteraf & Bergen, 2003; Wernerfelt, 1984). For instance, R&D budgets, research engineers, and necessary facilities are unable to be acquired or increased substantially in a short period of time. Given the resource limitation for R&D activities, therefore, an intrinsic trade-off should take place between exploration and exploitation; to invest more in exploratory projects, firms need to reduce some investments in exploitive developments (March, 1991). Thus, this paper regards the exploration and exploitation as the opposite ends of one continuum, in which the amount of exploration equals the total amount minus the amount of exploitation.

The last issue is about the criterion of distinguishing between exploratory and exploitive activities. In his paper, March (1991) broadly defined two types of organizational learning: the exploration of *new* possibilities and the exploitation of *old* certainties. To utilize the framework, studies have to specify a clear-cut boundary that determines what is new and what is known. In this research, I set *the industry boundary* as the criterion. The reason for this decision rests on a central idea of embeddedness study that a firm is not a totally independent, atomic actor, but an actor that is highly embedded in the social context (e.g., Granovetter, 1985; Thompson, 1967; Uzzi, 1999). Under the boundary of industry, economic actions of a firm definitely impact the behaviors and performances of other firms (Chen & Hambrick, 1995; Chen, 1996). Even a firm's internal learning often influences the learning of other collocated competitors through knowledge spillovers (Alcacer & Chung, 2007; Jaffe, Trajtenberg, & Henderson, 1993; Katila & Chen, 2008; Krugman, 1991). Therefore, learning activities of a firm cannot be understood comprehensively without considering competitive structure (Levitt & March, 1988). In this regard, I use the industry boundary to distinguish new knowledge from old knowledge, which is a much more conservative definition. Specifically, exploration is defined as the pursuit of knowledge that is not known to the industry players, whereas exploitation is defined as the utilization and development of knowledge that is already known to the industry. In a sense, this specification is different from that of prior studies, such as organizational boundary and technological boundary proposed by Rosenkopf and Nerkar (2001). In my model, even activities pursing technologically or organizationally distant knowledge are not viewed as exploration if such knowledge is already known to the industry players. This is a particularly important specification in examining a firm's network position as a moderating variable.

3.2. Balancing Exploration and Exploitation in Technological Innovation

Based on the specification, I set as a baseline the traditional argument that balancing exploration and exploitation is superior to focusing on one of them with respect to innovation performance. First of all, innovation studies have consistently pointed out that exploitation has decreasing returns to scale (e.g., Fleming, 2001; Katila & Ahuja, 2002). As certain knowledge is utilized repeatedly, the pool of possible technological options to recombination is gradually exhausted, and in turn, it is less likely to make further development based on that exhausted knowledge (Levinthal & March, 1981). In addition, in the view of organizational process, excessive exploitation renders a firm so rigid as to disregard potential options deviating from its standardized processes (Leonard-Barton, 1992; Levinthal & March, 1993; Hannan & Freeman, 1984). Therefore, to maintain flexibility and subsequently facilitate innovation, it is necessary to engage in exploration to some extent.

At the same time, excessive exploration also reduces the possibility to innovate. Newly pioneered technologies are often premature, and thus, further elaboration and continuous refinement is required (Katlia & Chen, 2008; Zander & Kogut, 1995). If follow-up developments are totally neglected, firms may lose enormous innovation opportunities from the pioneered technologies. Moreover, organization scholars alarmed the possibility of falling into a vicious cycle of failure; that is, the failure of an exploratory project leads a firm to seek another experimental project that is likely also to fail (Levinthal & March, 1993). In this regard, a firm is required to maintain a certain level of exploitation to maximize its innovation opportunities.

All of the above arguments boil down to the superiority of simultaneous balance between exploration and exploitation. That is, in my specification that views exploration and exploitation on a continuous scale, the optimal allocation point is located at the middle of the scale. Hence, I set a baseline hypothesis as below:

Hypothesis 1. *The proportion of exploration has an inverted-U-shaped relationship with innovation performance.*

3.3. Dynamics of Optimal Balance between Exploration and Exploitation

This research extends the ambidexterity hypothesis presented above by examining the dynamic change of the optimal level of balance between exploration and exploitation. Building upon both the capability and embeddeness perspectives, I focus on two distinctive firm-specific contexts: (1) technological capability and (2) network position within industry alliances. On the one hand, the capability literature views a firm as a bundle of firm-specific abilities to perform productive activities and proposes that the behavioral outcomes of the firm are significantly shaped by these abilities (Hoopes & Madsen, 2008; Teece, Pisano, & Shuen, 1997; Winter, 2000). In the view of embeddedness, on the other hand, economic actions are affected by the social context in which they are embedded and by the position of actors in social networks (Granovetter, 1985; Gulati, 1998). These two perspectives are complementary in that capability captures the aspect of the firm's own ability, whereas embeddedness addresses opportunities inherent in inter-firm relationships. Indeed, many innovation studies have often used both perspectives to draw key determinants (Song, Asakawa, & Chu, 2011). For instance, Tsai (2001) investigated the positive interaction between absorptive capacity and network position to innovation. Frost and Zhou's (2005) study also suggested that both technical and social dimensions play a key role in the process of knowledge integration. Moreover, a firm's capability and network position dynamically change over the life cycle of business (Baum, Shipilov, & Rowley, 2003; Helfat &

Peteraf, 2003; Powell, White, Koput, & Owen-Smith, 2005). The joint consideration of the two complementary constructs, therefore, provides a comprehensive understanding on the dynamics of the exploration-exploitation balance.

3.3.1. Technological Capability

Not all firms benefit from the same amount of exploration and exploitation. Depending on the external or internal conditions, firms possess heterogeneous potential to reap benefits or losses from exploration or exploitation. Building upon capability perspective, I argue that the optimal exploration-exploitation balance point of firms is contingent upon their technological capability. Specifically, I propose that, as the level of a firm's technological capability increases, the optimal balancing point moves toward the exploration side.

First of all, firms lacking sufficient technological capability may not be less successful in exploratory activities (Cohen & Levinthal, 1990; Lavie, Stettner, & Tushman, 2010). By definition, target knowledge of exploration is unknown and strange to both competent and incompetent firms, and thus it is equally difficult for them to create meaningful inventions from the knowledge. As compared to leading firms, however, incompetent firms possess scant knowledge reservoirs, which determines the potential of recombination and accordingly are likely to encounter difficulties identifying innovation opportunities from the external, unknown knowledge. Even if they catch the potential, moreover, the firms may not realize the creation of new technologies due to the lack of necessary internal routines (Todorova & Durisin, 2007; Zahra & George, 2002).

On the other hand, the incompetent players would gain greater benefits from refining technologies already pioneered by competitors rather than exploring untouched areas. A number of scholars in the field of strategic management have pointed out the late mover's advantages in that the early mover's actions significantly resolve the uncertainty of late movers' subsequent actions (e.g., Kalish & Lilien, 1986; Lieberman & Montgomery, 1988; Mitchell, 1989). From this point of view, competitors' R&D efforts can provide some clues regarding which technologies are viable and timely in the market. Katila and Chen (2008) empirically showed that the focal firm's head-start searches for untouched knowledge positively affect competitors' innovation frequency. The result implies that a pioneer's search activities significantly reduce the uncertainty in the target knowledge. For firms with lower technological capability, therefore, it would be a better strategy to exploit relatively promising technologies that have already been explored by other firms until they accumulate considerable technological capabilities enough to benefit from exploration on their own.

As a firm accumulates capability through ongoing success in internal R&Ds, it gradually becomes able to tap into new, external knowledge (Cohen & Levinthal, 1990). The accumulated expertise in certain areas enriches the firm's knowledge reservoir, and consequently the likelihood of knowledge creation through recombination is increased to a significant extent. However, the literature suggests that a high level of technological capability is a double-edged sword with respect to innovation activities. According to Leonard-Barton (1992), core capabilities and core rigidities are two sides of the same coin; that is, employees' skillsets, organizational systems, and cultures established by a series of successful experience act as a drag on search activities and subsequent innovations deviating from the established ways. In a similar vein, Christensen (1997) argued that incumbents successful in mainstream features are likely to be victims of disruptive innovations because of negligence regarding low performance but high-potential technologies. Thus, as a firm accumulates experience and its innovation activities are gradually standardized and routinized, it needs to reduce the proportion of exploitation to some extent. Start-up firms face relatively little risk of rigidity in their innovation process; rather, the exploitation would present an opportunity to accumulate capability in technology at a fast speed (Lee, 2001). If incumbent firms stick to exploiting existing technologies and current competences, in contrast, they are likely to lose innovation opportunities in rapidly changing environments (Teece, Pisano, & Shuen, 1997). Taken together, I hypothesize as follows:

> ***Hypothesis 2.*** *As the technological capability of a firm increases, the optimal point of balance between exploration and exploitation moves toward the exploration side*.

3.3.2. Network Position within Industry Alliances

Firms are not atomic actors that are totally independent of others, but entities highly embedded within competitive and social environments (Granovetter, 1985; Powell, Koput, & Smith-Doerr, 1996; Uzzi, 1999). Hence, it is possible for a firm to exploit knowledge that was explored by its competitors. However, not all firms can take advantage of competitors' explorative search, since such technological information is often proprietary owned or is treated as corporate secrets. Among various types of relationships, social relationships established through strategic alliance involve valuable information exchange and knowledge spillover (Inkpen & Tsang, 2005). Various empirical studies support the idea by showing that, when connected by an alliance tie, two entities have a greater chance of receiving information from the other (e.g., Mowery, Oxley, & Silverman, 1996). Drawing on the embeddedness perspective, I argue that the optimal level of balance between the points of exploration and exploitation is significantly affected by the position at which a firm stands in the industry alliance network. I predict that, in direct opposition to technological capability, the optimal point of central firms, as compared to that of peripheral firms, is located toward the exploitation side.

First of all, firms at the center of the industry network have inherent advantages in exploiting known knowledge. Network research demonstrates that central firms are better able to access a variety of knowledge and resources that reside in the network (Borgatti, 2005; Gulati & Gargiulo, 1999; Koka & Prescott, 2008;

Shipilov, 2009; Tsai, 2001). That is, central positions confer a great opportunity to innovate by recombining knowledge circulating in the industry network. The use of knowledge received from alliance partners may be seen, in a sense, as exploratory if it is the first time of use for the firm. Under my specification, in which exploration is defined as pursuing knowledge not utilized by any industry players, however, such activities are labeled as exploitation, because receiving firms can access information about the prior use of the knowledge in the industry. From this point of view, firms standing at central positions within the industry alliance network are more likely to generate quality innovations from exploitative activities.

Because of the power of central firms, peripheral firms are constrained to achieve outstanding innovations from such known technologies. By standing at the fringe of the network, however, they enjoy particular advantages in exploratory searches beyond the industry boundary, because peripheral actors are relatively free from the influence of norms and standardized practices in the network. Embeddedness research has revealed that firms at the periphery of the network are more open to embrace alien knowledge and new experimental ways of research (e.g., Cattani & Ferriani, 2008). The results of Song, Almeida, and Wu's empirical study (2003) also imply that the assimilation and the utilization of foreign knowledge essential for exploratory activities actively occur in peripheral areas rather than in core areas within a firm. In this regard, a low network position can be seen as a good place for active exploratory activities.

Peripheral firms that have succeeded in exploratory innovations may have the chance to move into a central position in the industry network (Baum, Shipilov, & Rowley, 2003). The more a firm is embedded in the network, however, the more the firm is restricted in keeping focused on the experimental activities. Indeed, standing at the center of the network, individual firms are pressed to conform to conventions taken for granted in the network (Perry-Smith & Shalley, 2003; Uzzi, 1997). As those firms' mental models are homogenized to industry-standard approaches, as a result, their ability to succeed in exploration, which requires searching beyond the prevailing conventions, is significantly lowered. Nevertheless, at the expense of such an unfavorable condition for exploration, firms entering central positions are given the positional advantages described above: both channels to identify valuable knowledge within the industry network and powers to convert them into new technologies in advance of competitors (Cattani & Ferriani, 2008). That is, the higher network position at which a firm stands, the higher proportion of exploitation firms need to adopt. I propose, therefore, that as a firm jumps into a central position, it would ensure higher innovation performance to gradually shift the focus from exploration to exploitation.

Hypothesis 3*. As the alliance network centrality of a firm decreases, the optimal point of balance between exploration and exploitation moves toward the exploration side*.

IV. METHODS

4.1. Sample and Data

I tested my hypotheses using panel data analysis of worldwide semiconductor firms. The semiconductor industry has been considered as a suitable context in which to study firms' R&D activities and subsequent innovation outcomes (e.g., Sorensen & Stuart, 2000; Ziedonics, 2004). First of all, this industry is so innovation-intensive that we can obtain substantial observations of technological innovations with considerable variation. By focusing on this single industry, therefore, we can rule out a large part of industry-specific environmental conditions. More importantly, the high propensity to patent among semiconductor firms offers a great opportunity for researchers to measure innovation activities in an objective, reliable manner (Cohen, Nelson, & Walsh, 2000; Podolny, Stuart, & Hannan, 1996; Song & Shin, 2008). US law obliges applicants and their lawyers to specify information in detail about new technologies applied, from inventor information to prior art (Song et al., 2003). Therefore, analyzing patent documents allows us to look inside the black box of the innovation activities of a firm. This is why a great number of innovation studies have still been examining the semiconductor industry for their empirical analysis (e.g., Adams, Fontana, & Malerba, 2013; Carnabuci & Operti, 2013; Hsu & Ziedonis, 2013). In addition, the semiconductor industry provides an appropriate arena for the inter-firm network study as well. Semiconductor companies have frequently established strategic alliances with each other in order to jointly develop a new technology or get access to complementary assets (Eisenhardt & Schoonhoven, 1996; Stuart, 1998). Therefore, the intensive formation of alliances in this industry ensures the meaningfulness and reliability of my network variables.

The time frame of data ranges from 1994 to 2000. Since I set a 5-year moving window for some of my variables, including the proportion of exploration, technological capability, and network position, the data that I collected and analyzed dates back to 1989. I posit that this 12-year time span is appropriate for this study because the period is marked by vigorous innovativeness and entrepreneurship as well as active inter-firm cooperation in the industry. Figure 2 illustrates the number of semiconductor firms and that of strategic alliances among them in each year.[1] The increasing numbers demonstrates the suitability of this period as an empirical context of innovation and alliance network. Moreover, according to Jiang, Tan, and Thursby's research (2010), the early 2000s saw a paradigm transition in the semiconductor technology, from complementary metal-oxide semiconductor (CMOS) technology to nanotechnology. Therefore, this time span effectively rules out unobservable exogenous effects associated with drastic technological changes.

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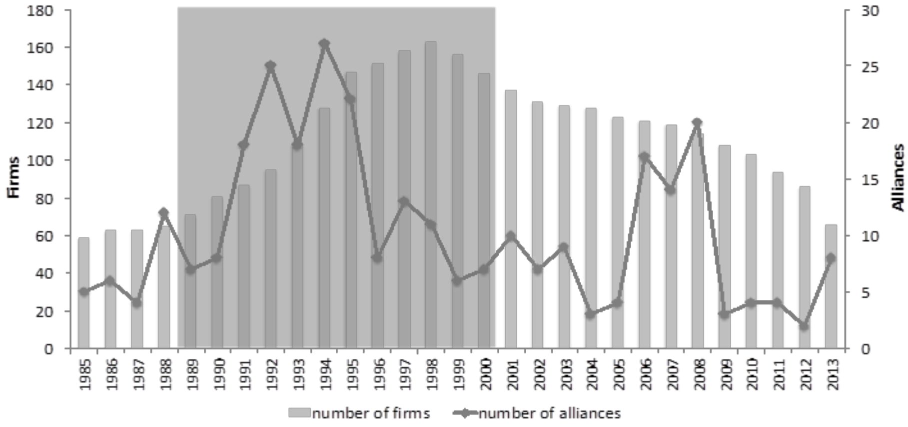
[1] The number of semiconductor firms is based on the data of COMPUSTAT (firms of 3674 SIC), and the number of strategic alliances among the firms is from the data of SDC (alliances among 3674 SIC firms).

FIGURE 2

The Number of Semiconductor Firms and Strategic Alliances from 1985 to 2013



During the period of 1994 to 2000, I initially identified 192 semiconductor firms that are classified as 3674 SIC code in COMPUSTAT database and have at least one semiconductor-related US patent. Table 1 shows 30 semiconductor-related classes used in this identification process. Among the firms, 108 firms were excluded from the sample due to the lack of important financial data available in COMPUSTAT, such as R&D expenditures and operating incomes. Moreover, in order to enhance the validity of my within-firm panel analysis, I additionally excluded 29 firms that had records of less than 4 years.[2] In sum, my final sample contains 306 observations of 55 semiconductor firms during 7 years, from 1994 to 2000.

[2] When the 29 firms were included in the analysis, I found significant results consistent with my predictions.

TABLE 1

Semiconductor-related Classes in U.S. Patents [a]

Class	Description
29	Meal working
148	Metal treatment
174	Electricity: conductors and insulators
250	Radiant energy
257	Active solid-state devices (e.g., transistors, solid-state diodes)
307	Electrical transmission or interconnection systems
323	Electricity: power supply or regulation systems
324	Electricity: measuring and testing
326	Electronic digital logic circuitry
327	Miscellaneous active electrical nonlinear devices, circuits, and systems
330	Amplifiers
331	Oscillators
333	Wave transmission lines and networks
340	Communications: electrical
341	Coded data generation or conversion
345	Computer graphics processing and selective visual display systems
348	Television
361	Electricity: electrical systems and devices
363	Electric power conversion systems
365	Static information storage and retrieval
370	Multiplex communications
375	Pulse or digital communications
427	Coating processes
438	Semiconductor device manufacturing: process
455	Telecommunications
708	Electrical computers: arithmetic processing and calculating
710	Electrical computers and digital data processing systems: input/output
711	Electrical computers and digital processing systems: memory
713	Electrical computers and digital processing systems: support
714	Error detection/correction and fault detection/recovery

[a] This follows the identification of Yayavaram and Ahuja (2008).

I gathered information from three distinct databases. First, I collected patent data from the United States Patent and Trademark Office (USPTO) to operationalize technology-related variables, including exploration-exploitation activities and innovation performance. Patent data has been extensively employed in innovation research, because patent documents are systemically complied with detailed information and are available continuously across time sufficiently to enable me to conduct a longitudinal study (Almeida, 1996). Second, I obtained records of strategic alliances from the Securities Data Company (SDC) database. Since this study focuses on the role of network ties established by inter-firm collaborations as the channel of information flow, all types of strategic alliances established between semiconductor firms were collected, such as agreements for the joint development of new technologies and agreements for manufacturing and marketing. I took into account the heterogeneity of strategic alliances by including exploratory alliance. Lastly, a firm's general financial data was collected from the COMPUSTAT database.

4.2. Measurement

4.2.1. Dependent Variable

Innovation Performance. I operationalized a firm's innovation performance by the number of successful patents filed to USPTO in a focal year, weighted by the number of forward citations of each patent. Patenting frequency is a widely adopted proxy for innovation performance, particularly in the research of knowledge-intensive industries (e.g. Ahuja & Katila, 2001; Puranam & Srikanth, 2007; Rothaermel & Hess, 2007). Although not all innovations are patented, semiconductor firms in general show high propensity to patent their newly developed technologies (Almeida, 1996; Cohen, Nelson, & Walsh, 2000; Kortum & Lerner, 1999). Thus, a firm's high number of patent application can be indicative of great achievement in its technology innovations. Of course, a simple patent counts do not properly reflect the heterogeneous values of each patent (Griliches, 1990; Sampson, 2007). I addressed this heterogeneity by assigning the number of forward citations (citations by later patents) to each patent. Since the forward citations of a patent represent the degree of impacts of the patent on subsequent technology developments, the number has been recognized as a way of assessing the quality of the patent. Empirical evidence shows that the number of forward citations of a patent is significantly associated with the social value of the underlying innovation (Trajtenberg, 1990). Therefore, the citation-weighted patent counting sophisticatedly captures a firm's innovation performance, considering both the quantity and quality of technological innovations (Nesta & Saviotti, 2005).

4.2.2. Explanatory Variables

Proportion of Exploration. To measure the extent of the exploration and exploitation activities of a firm, I used information about backward citations listed in each patent document of a firm. In order to apply a patent to USPTO, applicants should clearly state all or any of "the prior art" that the newly technology is based on (Song et al., 2003). The presence of a third-party inspector in the application process enhances the reliability of citation records in the patent documents. Therefore, by investigating records of patent citations, researchers can examine the diverse patterns of firms' search behavior. In particular, the information of backward citations represents how extensively the firm explored external knowledge that has not been touched by others (Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996).

According to Levinthal and March (1993), exploration refers to activities of pursuing new knowledge. Following this line of thought, Katila and Ahuja (2002) operationalized scope search (or exploration) as the ratio of new citations, which have not been unused *by the focal firm* in the previous five years, to the total citations in a year. I altered this approach to suit my specification of exploration and exploitation, in which the industry serves to draw a line between the two activities. Specifically, I captured a firm's exploration by its backward citations that had not been used *by any other industry players* in the preceding 5 years. After all, the proportion of exploration was calculated by dividing the number of new backward citations by the total backward citations in a focal year.[3]

[3] Self-citations are excluded from the count of new citations.

$$Proportion\ of\ Exploration_{i,t} = \frac{new\ backward\ citations_{i,t}}{total\ backward\ citations_{i,t}}$$

Technological Capability. According to Nelson and Winter (1982), a firm's capability is developed through repetitive prior activities. Building upon the idea, I measured the technological capability of a firm by the cumulative sum of R&D expenditures in the prior 5 years. A firm's R&D investment size directly represents the scale of R&D activities that the firm has performed during the focal period. Therefore, the R&D cumulative experience can be a proxy for the technological capability of the firm. Following prior studies (Hall, Jaffe, & Trajtenberg, 2005; McGahan & Silverman, 2006), I took into account the technological obsolescence and loss of knowledge by depreciating the expenditures at 15 percent per year. The formal definition of this variable is as follows.

$$\begin{aligned} &Technological\ Capability_{i,t} \\ &\quad = R\&D\ expenditure_{i,t-1} + 0.85 \times R\&D\ expenditure_{i,t-2} \\ &\quad + 0.85^2 \times R\&D\ expenditure_{i,t-3} \\ &\quad + 0.85^3 \times R\&D\ expenditure_{i,t-4} \\ &\quad + 0.85^4 \times R\&D\ expenditure_{i,t-5} \end{aligned}$$

Network Position. In order to measure a firm's network position, I firstly set the relationship matrix *R*, in which all main diagonal elements are 0 and each element

r_{ij} equals the number of strategic alliances in which firm i and firm j jointly participated. Following a standard assumption about the duration of alliances (Stuart, 2000; Wang & Zajac, 2007), I employed the five-year window to identify network ties. That is, a firm's direct network ties in a focal year were calculated based on strategic alliances established during preceding 5 years. Then, the network position of a firm was measured by Bonacich's (1987) centrality measure. In this measurement, a node's centrality in the global network was calculated by the weighted sum of centrality of its adjacent nodes. The measure is formally defined as below:

$$c_i(\alpha, \beta) = \sum_j (\alpha + \beta c_j)\, r_{ij},$$

where c_i is the centrality of node i, α is a scaling factor, β is a weighting factor, and r_{ij} represents tie strength between node i and node j.[4] This variable substantially reflects the effects of indirect ties as well as direct ties. The greater the value of β, the more a node is influenced by those indirect ties. As a result, this Bonacich's centrality can effectively capture how much of an opportunity a firm receives a variety of information within the network at a faster speed via both direct and indirect ties. In this study, β was set to 0.995 divided by the maximum eigenvalue, and isolated nodes were given a score of zero. I calculated this using UCINET 6.

[4] Tie strength indicates the number of strategic alliances between two firms in the previous five years.

4.2.3. Control Variables

This study rules out inter-industry effects and the impact of technological shifts by examining a single industry within a particular time period between the shifts. Furthermore, my controls include diverse firm-level and alliance portfolio-level variables. Firm-level control variables include *technological diversity*, which is measured by $1 - \sum_{p=1}^{q}(\frac{M_p}{N})^2$, where N is the total number of patents of firm i, M_p is the number of patents that are classified in technological class p, and q is the total number of 3-digit patent classes covered by the patent stock of firm i. Also, *R&D intensity* (research and development expenditures divided by annual sales) is included to control for the effect of the technology-orientedness of a firm (Greve, 2003), and *ROA* (operating incomes divided by total assets) is also controlled to rule out the effects associated with a firm's financial performance. Reflecting the results of prior research that firms with abundant slack resources tend to engage in exploration greater than those of scant slack resources (Cyert & March, 1963; Greve, 2003), I included *organizational slack* (retained earnings divided by total assets) in the regression models. Portfolio-level control is *the density of ego network* (the number of ties between adjacent nodes divided by the total possible number of ties between them) of a focal firm. Also, I took into account alliance-specific variation; that is, strategic alliances are used both to explore new knowledge and to exploit existing knowledge. Thus, I controlled for the *exploratory-alliance ratio* (the number of ties established for new product development divided by the number of total ties). Lastly, to minimize the effects of time-constant and time-varying unobserved heterogeneities, both *firm dummies* and *year dummies* are included in the model.

4.3. Model Specification

Because my dependent variable is a count variable, the number of patents weighted by the number of forward citations, the OLS model may yield inconsistent and inefficient estimates (Long, 1997). In this case, either Poisson or negative binomial distribution is used to model such a count-dependent variable. In empirical studies, however, the Poisson regression model is rarely chosen, since the assumption of Poisson model that the conditional mean of dependent variable equals to its conditional variance is often violated. Particularly in the innovation research using patent data, the conditional variance shows much larger than the conditional mean, leading to an overdispersion problem (Song et al., 2003). Since my data showed overdispersion at a significant level ($G^2 = 3.0e+0.4$, $p < 0.001$)[5], I used the negative binomial model.

To examine the change of a firm's optimal balance point, moreover, I conducted a fixed-effects panel analysis. The inclusion of firm-fixed effects facilitated the study of individual dynamics by explaining within-firm variation

[5] $G^2=2(\ln L_{\mathrm{NBRM}} - \ln L_{\mathrm{PRM}})$

over time rather than inter-firm variation (Wooldridge, 2002). The firm-fixed effects model effectively controls for some management factors that are not readily changed in a short period, such as organizational structure, culture, and long-term strategy. If such unobservable heterogeneities are correlated to independent variables, regression models omitting the fixed effects yield inconsistent estimates (Johnston, 1984). In addition, to avoid potential endogeneity stemming from year-specific effects, I also included year dummies in the negative binomial regression model. In turn, the expected number of citation-weighted patents of a firm i in year t, $\lambda_{i,t}$, is specified in the following way:

$$\lambda_{i,t} = \exp(\beta_1 PE_{i,t} + \beta_2 PE_{i,t}^2 + \boldsymbol{X}_{i,t}\gamma + a_i + \delta_t + \varepsilon_{it}),$$

where $PE_{i,t}$ indicates the proportion of exploration, $\boldsymbol{X}_{i,t}$ includes all control variables, a_i and δ_t represent the time-constant effects and year dummies, respectively, and ε_{it} refers to an error term.

Hypotheses 2 and 3 predict the movements of vertex point of the inverted-U curve. In order to test the particular proposition, I adopted the approach of Groysberg, Polzer, and Elfenbein (2011). In their research, these authors showed how the optimal proportion of star individuals within a firm varies across the expertise heterogeneity of the firm by examining the interaction between the expertise heterogeneity and the linear term of proportion of star individuals. That is, the hypothesis testing of the coefficient of the interaction term confirms to which direction the vertex point moves. In this regard, I designed a model that includes interaction terms between the proportion of exploration and each moderator. This is specified below:

$$\lambda_{i,t} = \exp\big(\beta_1 PE_{i,t} + \beta_2 PE_{i,t}^2 + \beta_3 PE_{i,t} \times TC_{i,t} + \beta_4 PE_{i,t} \times NP_{i,t} + \boldsymbol{X}_{i,t}\gamma + a_i + \delta_t + \varepsilon_{it}\big),$$

where $TC_{i,t}$ refers to technological capability and $NP_{i,t}$ indicates network position. The positive sign of the interaction term supports the movement of the vertex point toward the exploration side, whereas the negative sign confirms the movement toward the exploitation side. STATA version 12 was used to fit the models to the data.

V. RESULTS

5.1. Data Description

Table 1 represents the descriptive statistics and correlations of my variables. To check whether the model has a multicollinearity problem, I conducted a variance inflation factor (VIF) test. In general, a model is not considered to have a serious problem of multicollinearity unless the VIF value of a variable exceeds 10

(Chatterjee, Hadi, & Price, 2000). In the VIF test with all explanatory variables excepting squared term and interaction terms, all scores showed lower than 2.60. Therefore, all of the variables were included in regression models.

TABLE 2

Descriptive Statistics and Correlations

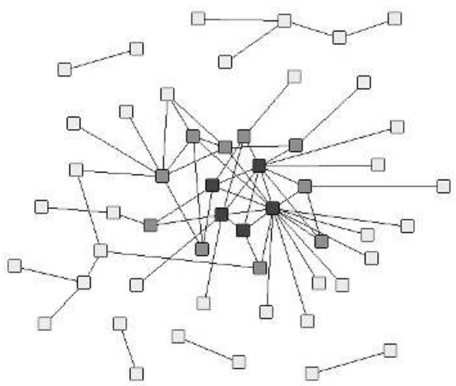
Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Innovation Performance	1387.28	3545.58									
2. Technological Diversity	0.677	0.214	0.264								
3. R&D Intensity	0.150	0.098	-0.118	-0.085							
4. ROA	0.162	0.162	0.060	0.176	-0.274						
5. Organizational Slack	0.147	0.447	0.173	0.297	-0.282	0.599					
6. Ego Network Density	0.116	0.258	0.180	0.109	-0.012	0.038	0.100				
7. Exploratory-Alliance Ratio	0.215	0.335	0.113	0.162	-0.037	-0.106	-0.082	0.382			
8. Technological Capability [a]	0.410	1.014	0.533	0.337	-0.071	0.165	0.199	0.062	0.168		
9. Network Position	8.362	15.764	0.696	0.333	-0.140	0.088	0.172	0.252	0.284	0.763	
10. Proportion of Exploration	0.585	0.200	-0.058	-0.056	-0.051	0.026	0.047	-0.188	-0.082	-0.008	-0.049

[a] One unit of this variable represents 1,000 counts.

Sample data shows that, from 1994 to 2000, each firm had an average of 1.82 partnerships within industry alliances. Although the average is small, there is large variation across firms. Most possessed one or two relationships with other firms, but a few firms had up to 16 relationships. This distribution is typical of a scale-free network following a power law, in which the probability that a firm will have k number of ties exponentially decreases as k increases (Bae & Gargiulo, 2004; Barabasi & Albert, 1999; Powell, White, Koput, & Owen Smith, 2005). In such a distribution, there is a fundamental asymmetry of information accessibility between central actors highly connected to others and peripheral actors less connected. Figure 3 depicts the structure of the sample semiconductor alliance network in 2000.

FIGURE 3

Inter-firm Alliance Relationships of the Sample Firms in 2000 [a]

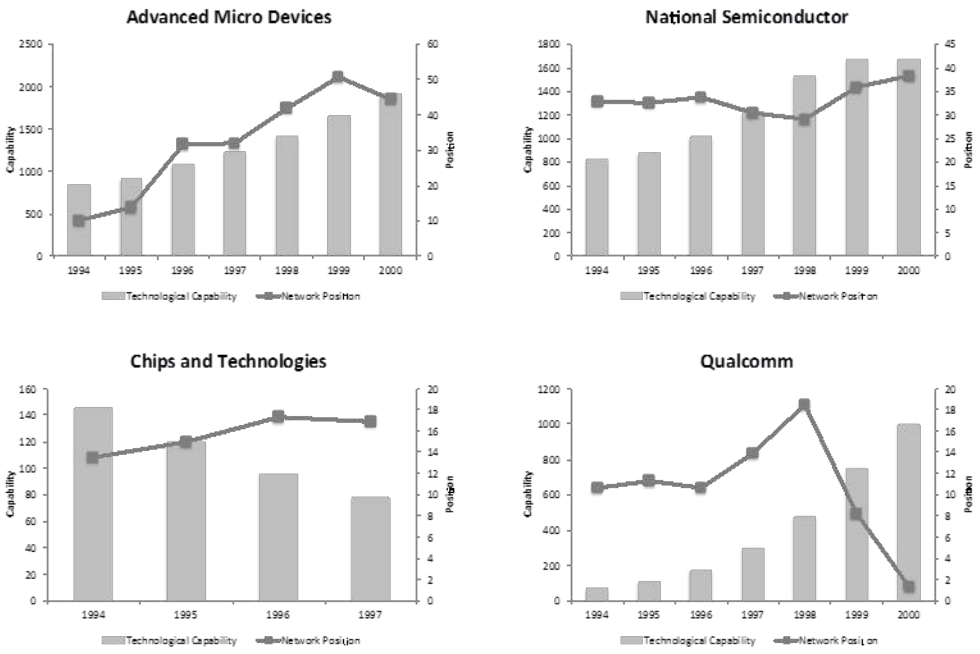


[a] Firms that did not participate in an alliance within the industry during 1995 to 1999 are hidden from the figure.

Moreover, my data shows diverse patterns of temporal change in both the technological capability and network position of a firm. Figure 4 illustrates four sample cases. Qualcomm experienced exponential growth in terms of capability, while Chips and Technologies showed a rapid decline of capability. The network position of Advanced Micro Devices was on an increasing trend, whereas that of National Semiconductor showed a relatively stable pattern. In this context, I tested how a firm's optimal balancing point between exploration and exploitation is affected by changes in its technological capability and network position.

FIGURE 4

Temporal Change of Technological Capability and Network Position
of Four Sample Firms



5.2. Results of Hypothesis Testing

Table 2 shows the results of the fixed effects panel negative binomial regression analysis. Model 1 includes only control variables to serve as a benchmark for the two different models derived from my theory. Model 2 examines Hypothesis 1, which asserts that the proportion of exploration has an inverted-U-shaped relationship with the innovation performance. In the model, the coefficient of the Proportion of Exploration is shown as positive with a strong significance level (β = 4.577, $p < 0.001$), and the coefficient of Proportion of Exploration^2 is shown as negative with a strong significance level as well (β = - 4.227, $p < 0.001$). In support of Hypothesis 1, these results imply that, although the increase in proportion of exploration initially enhances a firm’s innovation performance, further increase exceeding a certain point suppresses it. In my sample data, the optimal balance point (vertex point of the inverted-U curve) appears at 54.14 percent of exploration.

In Model 3, I test Hypothesis 2 and Hypothesis 3, each one addressing dynamics of optimal point of balance between exploration and exploitation. Hypothesis 2 predicts that, as the level of technological capability increases, the optimal point of balance between exploration and exploitation moves toward the exploration side. On the other hand, Hypothesis 3 anticipates that, as the level of network centrality decreases, the optimal point of balance between exploration and exploitation moves toward the exploration side. To verify this, I included interaction terms (Proportion of Exploration × Technological Capability, Proportion of Exploration × Network Position) in Model 3. Hypothesis 2 (or Hypothesis 3) gains support if the coefficient of the interaction term is shown positive (or negative) with a strong significance level. The results reveal the significant, positive coefficient of Proportion of Exploration × Technological Capability (β = 1.730, p = 0.001). This suggests that the high level of technological capability is associated with the optimal point of balance located at the higher level of exploration (the lower level of exploitation), which confirms Hypothesis 2. Figure 5 describes the predicted innovation performance for different levels of technological capability. It shows that the vertex point of the curve moves to the right side as technological capability increases. This information reaffirms the assertion that it is better for a firm to increase the proportion of exploration while accumulating more capability in the technology. Moreover, the coefficient of Proportion of Exploration × Network Position is shown to be negative with a strong significance level (β = - 0.058, p = 0.019), which supports Hypothesis 3. This outcome implies that the optimal point of balance is positioned at the higher level of exploitation (the lower level of exploration) when a firm stands at a peripheral position. Figure 6 illustrates the predicted innovation performance for different levels of network position within industry alliances. It is shown that the vertex point of the curve moves to the left side as the network position increases. This reaffirms the assertion that it is better for a firm to increase the proportion of exploitation while ascending to higher positions.

TABLE 3

Fixed Effects Panel Negative Binomial Regression Models [a]

Variable	Model 1	Model 2	Model 3
Constant	-0.643* (0.266)	-1.523*** (0.395)	-1.372** (0.408)
Technological Diversity	0.722** (0.271)	0.636** (0.264)	0.509† (0.269)
R&D Intensity	0.572 (0.605)	0.806 (0.532)	0.769 (0.538)
ROA	-0.232 (0.303)	-0.053 (0.310)	-0.042 (0.303)
Organizational Slack	0.153 (0.174)	0.095 (0.178)	0.064 (0.176)
Ego Network Density	0.295 (0.186)	0.180 (0.193)	0.231 (0.191)
Exploratory-Alliance Ratio	-0.051 (0.183)	-0.158 (0.185)	-0.123 (0.184)
Technological Capability	-0.001 (0.067)	-0.011 (0.064)	-0.745** (0.227)
Network Position	0.019** (0.006)	0.020*** (0.005)	0.044** (0.013)
Proportion of Exploration		4.577*** (1.047)	4.540*** (1.067)
Proportion of Exploration ^{2}		-4.227*** (0.906)	-4.236*** (0.923)
Proportion of Exploration × Technological Capability			1.730** (0.509)
Proportion of Exploration × Network Position			-0.058* (0.025)
Firm and Year Fixed Effects	Included	Included	Included
Log likelihood	-1569.02	-1556.76	-1552.42
Wald chi-square	273.84	312.64	396.83
Prob > chi-square	0.000	0.000	0.000
Observations	306	306	306

[a] Standard errors are in parentheses. † $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

FIGURE 5

Impact of Technological Capability on the Optimal Balance Point

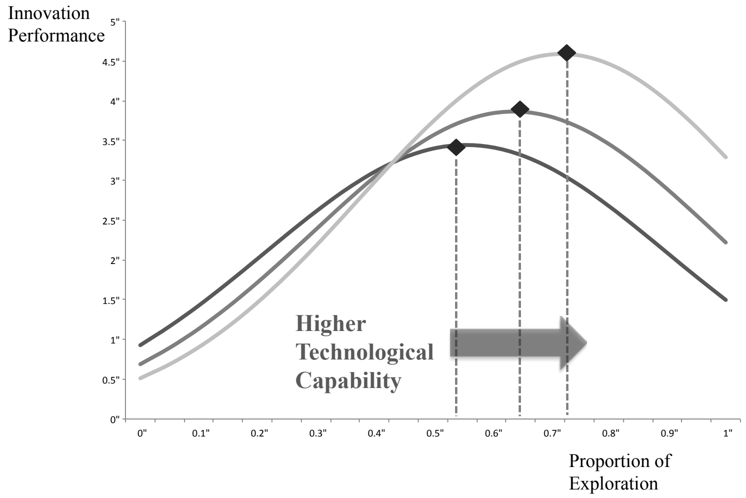
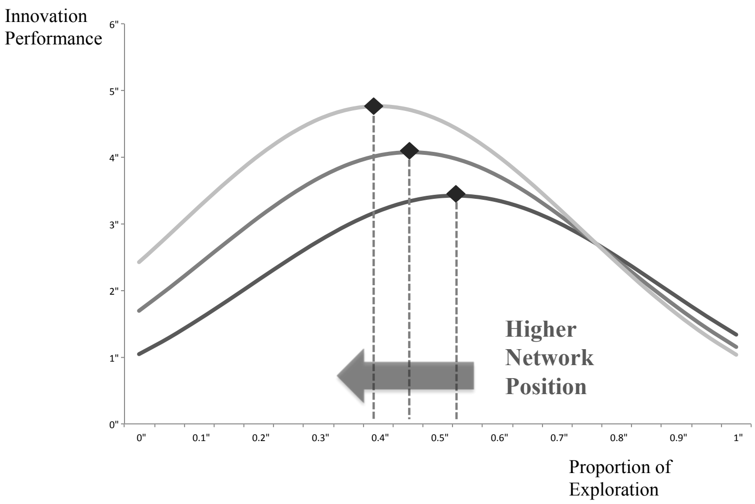


FIGURE 6

Impact of Network Position on the Optimal Balance Point



5.3. Robustness Checks

5.3.1. Different Measures for Network Position

To ensure the robustness of my results, I conducted additional analysis with different measures for network position. In addition to Bonacich's centrality, there are three different measures widely used to capture the centrality of a firm within the industry alliance network: *degree centrality, betweenness centrality,* and *closeness centrality* (Freeman, 1979). All three measures aim to figure out actors in central positions of the network, but each measure employs a different property of an actor's network position (Wasserman, 1994). Degree centrality captures the size of the ego network of an actor. Between centrality is defined by the degree to which a focal actor is located on the shortest paths connecting other actors, while closeness centrality is defined by the sum of the length of the shortest paths from a focal actor to all other actors. Therefore, the use of different measurements permits to check whether my argument can be applied to different positional contexts. From the analysis, I found consistently negative moderating effects in degree centrality (β = - 53.941, $p < 0.001$) and closeness centrality (β = - 12.446, p = 0.001). In the case of betweenness centrality, however, the sign of the coefficient was shown to be negative as predicted, but it was not statistically significant (β = -

36.403, p = 0.651).[6] This may be due to the fact that betweenness centrality is based on a particularly unique assumption that information literally moves or transfers from node to node, and it moves only along the shortest paths, rather than simultaneously diffusing via all paths (Borgatti, 2005). This may not be applicable to the setting of strategic alliances, in which information flowing through established ties is duplicable and the flow is not limited to particular paths.

5.3.2. Two-stage Analysis

Since a firm's technological capability and network position are outcomes of its previous investments and operations, my regression models treating the variables as exogenous may yield biased estimates due to the endogeneity. To handle the potential endogeneity, I conducted additional analysis using a two-stage approach. Following prior research (e.g., Lavie, Kang, & Rosenkorf, 2011), in the first stage I regressed technological capability and network position at time t on technological diversity, ROA, R&D intensity, organizational slack, ego-network density, exploratory-alliance ratio, proportion of exploration, technological capability, and network position at time t – 1 and on year- and firm-fixed effects. The predicted value of technological capability and network position obtained from the first-stage models were entered as independent variables in the second-stage models, where a

[6] In all three cases, technological capability shows significantly positive moderating effects, consistently.

firm's innovation performance was the dependent variable. The results are reported in the Appendix. The results of the second-stage models are consistent with those of my original models at a strong significance level.

VI. DISCUSSION

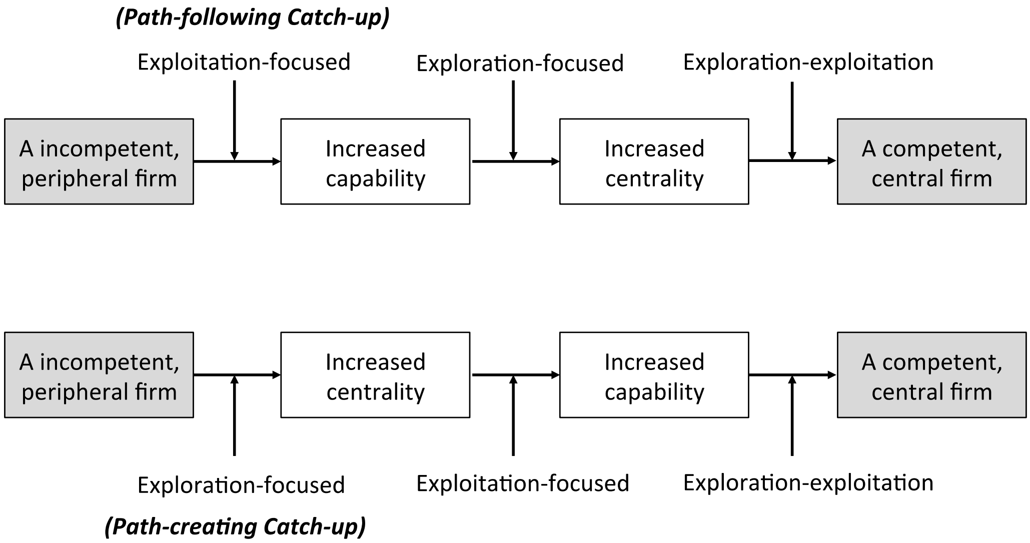
In this study, I sought to understand how the optimal balancing point between exploration and exploitation dynamically changes. Drawing upon capability and embeddedness perspectives, I argue that changes in a firm's technological capability and the network position of a firm shift the location of its optimal balancing point between exploration and exploitation. I hypothesized that the level of technological capability drives the optimal balance between exploration and exploitation toward the exploration side while the level of network position within industry alliances pushes the optimal point toward the exploitation side. My empirical analysis on the 7-year panel data from the semiconductor industry shows both that the proportion of exploration has an inverted-U-shaped relationship with innovation performance and that the vertex point moves in ways I predicted as technological capability and a network position increase. The results are robust to different measures and estimation techniques. From the results, I draw meaningful theoretical and managerial implications as follows.

6.1. Theoretical and Managerial Implications

This research extends the literature on exploration-exploitation balance or ambidexterity. From the prior literature we know that making an appropriate balance between exploration and exploitation is the essence of management for a firm to achieve its long-term goal (e.g., March, 1991; Levinthal & March, 1993; Tushman & O'Reilly, 1996). However, the heterogeneity and the dynamic nature of the *appropriate* balancing point still remain underspecified (Raisch et al., 2009). By linking ambidexterity to capability and embeddedness, this study deepens our understanding of dynamic nature of ambidexterity with a framework that allows for exploration-focused (or exploitation-focused) balances, far from just comparing the balanced to the imbalanced. In particular, combining with prior literature proposing that exploitation tends to generate competence-enhancing innovations and exploration is likely to lead to competence-destroying innovations (Baum, Shipilov, & Rowley, 2003; Jansen et al., 2006; Kim, Song, & Nerkar, 2012), this framework can serve to explain an underlying mechanism of sequential ambidexterity. Figure 7 illustrates two different paths in which an incompetent, peripheral firm grows to a competent, central firm. According to my framework, a firm's growth with the sequential exploration-exploitation balance is caused by the underlying dynamics in its capability and network position. For instance, after accumulating sufficient capability in the technology through the exploitation of widely accepted knowledge, the firm can go forward in a central position via exploration of unknown knowledge, based on the accumulated expertise. Otherwise, at first the firm focuses on exploration to shake the existing positional order and then shifts its focus toward exploitation to accumulate capability in the pioneered area. In both cases, we can see at the growth stage the temporal transition from exploration to exploitation, or vice versa. These models are consistent with the empirical results of prior research that small firms benefit from the focused than the balanced (Ebben & Johnson, 2005; Kim & Huh, 2013). This research complements the previous studies by providing foundations to explain two specific possible directions and their promising sequential paths.

FIGURE 7

Two Models of Growth by Sequential Ambidexterity



In addition, this study contributes to the exploration-exploitation literature that primarily uses technology or organization boundary to distinguish exploration from exploitation (e.g., Rosenkopf & Nerkar, 2001; Rothaermel & Alexandre, 2009) by providing another criterion – the industry boundary. In this research, I raised the question of whether some of R&D searches beyond the focal firm's organizational and technological boundaries may not be classified into the category of exploratory search. In the view of knowledge spillover and inter-firm dependence of learning, even a firm's search for knowledge that is outside the firm boundary or is technologically distant from its core expertise should be seen as an exploitative activity if the knowledge has widely been utilized in various ways by other firms in the industry. For instance, even though technologies A and B are significantly dissimilar, it is possible that firms in an industry are substantially aware of the possible application of combining the technologies because of their accumulated experience. In this regard, this research defines exploration as the pursuit of knowledge that is new to the industry. Under the circumstances of strong interdependence among industry players, it would be more appropriate to draw a line between exploration and exploitation based on the industry boundary.

Also, the results of this study provide practical implications for managers in allocating resources into exploratory and exploitative activities. With respect to the exploration-exploitation balance, managers pose a fundamental question about to what extent they should engage in exploration and exploitation, respectively. In this study, I argued that the optimal allocation point is a function of both the technological capability and network position of firm. Specifically, I suggest that a high level of technological capability requires an increase in exploration and a decrease in exploitation, whereas that of network centrality demands the increase of exploitation and the decrease of exploration. These results offer tangible implications. For instance, a firm growing in technological capability can enhance its innovation performance by gradually increasing the proportion of exploration. Moreover, prior literature contends that small start-ups should pursue the imbalanced approach, but it does not offer a specific answer about which one the firm should apply. This research suggests that each firm should practice careful reflection on its relative strengths between technological capability and network position. If a founder of a start-up is not an expert in core technologies but has a broad social network with other firms in the industry, it may have to focus on exploitation leveraging its relative advantage of the social relationship.

6.2. Limitations and Future Research

The first limitation of this research is the generalizability of the framework of this research. To enhance the validity of my empirical analysis, I limited the context of exploration and exploitation only to that of technological innovation and restricted our sample to firms in the semiconductor industry. Accordingly, there still remain questions of whether this study's findings can be applied to other contexts, such as organization design, and other industries, such as the pharmaceutical industry, as they stand. For this reason, I call for future studies to test my framework in other organizational and industrial settings. Second, this study addresses only one type of embeddedness: positional embeddedness. Prior research reveals other types of embeddedness, including relational embeddedness and structural embeddedness (Gulati & Gargiulo, 1999). I believe that this study will definitely expand our understanding of ambidexterity if others are theorized and tested. Lastly, although our study addresses the exploration and exploitation of R&D activities for technological innovations, it has a limitation in that my analysis relied primarily on patent data that only captures the success of upstream technological innovation. The commercialization of created technology into new products, which is the other significant part of technological innovation, was not considered. Therefore, further examination of the commercialization side with my framework will significantly contribute to the literature of exploration and exploitation.

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APPENDIX

Fixed Effects Panel First-stage OLS Models [a]

Variable	Model 1	Model 2
Constant	-0.044 (0.041)	1.771 (2.682)
Technological Diversity$_{t-1}$	0.033 (0.037)	2.171 (2.429)
R&D Intensity$_{t-1}$	0.151 (0.093)	-2.264 (6.102)
ROA$_{t-1}$	0.008 (0.038)	-3.219 (2.525)
Organizational Slack$_{t-1}$	0.030 (0.021)	-0.290 (1.408)
Ego Network Density$_{t-1}$	-0.038 (0.028)	5.027** (1.857)
Exploratory-Alliance Ratio$_{t-1}$	-0.063* (0.027)	-4.092* (1.798)
Technological Capability$_{t-1}$	1.150*** (0.018)	5.347*** (1.199)
Network Position$_{-1}$	0.005*** (0.001)	0.494*** (0.065)
Proportion of Exploration$_{t-1}$	0.011 (0.038)	1.493 (2.522)
Firm and Year Fixed Effects	Included	Included
F-value	668.24	20.58
Prob > F	0.000	0.000
R^2	0.992	0.894
Observations	246	246

[a] Standard errors are in parentheses. † $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$
Model 1: Technological capability is the dependent variable.
Model 2: Network position is the dependent variable.

Fixed Effects Panel Second-stage Negative Binomial Regression Models [a]

Variable	Model 1	Model 2	Model 3
Constant	-1.061** (0.365)	-2.263*** (0.459)	-2.386*** (0.498)
Technological Diversity	0.580 (0.365)	0.556** (0.346)	0.449 (0.352)
R&D Intensity	0.715 (0.566)	0.892† (0.507)	0.915 (0.513)
ROA	-0.347 (0.273)	-0.194 (0.302)	-0.142 (0.300)
Organizational Slack	0.109 (0.190)	0.103 (0.200)	0.081 (0.190)
Ego Network Density	0.200 (0.200)	0.045 (0.210)	0.074 (0.212)
Exploratory-Alliance Ratio	0.070 (0.214)	-0.015 (0.220)	0.038 (0.220)
Predicted Technological Capability	-0.161 (0.129)	-0.197 (0.126)	-1.067** (0.346)
Predicted Network Position	0.039** (0.014)	0.042** (0.013)	0.087** (0.029)
Proportion of Exploration		5.063*** (1.141)	5.493*** (1.264)
Proportion of Exploration ^{2}		-4.328*** (1.006)	-4.523*** (1.062)
Proportion of Exploration × Predicted Technological Capability			2.237** (0.805)
Proportion of Exploration × Predicted Network Position			-0.115* (0.055)
Firm and Year Fixed Effects	Included	Included	Included
Log likelihood	-1225.97	-1214.26	-1211.11
Wald chi-square	189.77	226.02	308.25
Prob > chi-square	0.000	0.000	0.000
Observations	246	246	246

[a] Standard errors are in parentheses. † $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

국문초록

탐색과 활용 최적 균형점의 역동적 변화에 관한 연구

: 기업 역량 및 배태성의 관점에서

서 은 광
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기업의 탐색활동과 활용활동의 정적인 균형에 관한 많은 연구가 수행되어 왔지만, 탐색–활용 최적균형점의 역동적인 변화에 대하여는 상대적으로 이론적 경험적 연구가 부족하였다. 본 논문은 기업의 역량관점과 배태성관점에 입각하여, 기업의 기술적 역량과 산업 내 전략적 제휴 네트워크에서의 위치가 달라짐에 따라 어떻게 탐색–활용의 최적균형점의 위치가 역동적으로 변하는지를 연구한다. 글로벌 반도체 산업의 1994 년 부터 2000 년까지 7 년 간의 패널자료를 분석함으로써 본 논문은 기업의 탐색활동의 비중과 혁신성과 간에 역 U 자형 관계가 있음을 밝힌다. 나아가, 이 관계의 최적균형점이 기업의 기술적 역량을 증가할수록, 제휴 네트워크 내 위치가 낮아질수록 탐색활동의 방향으로 움직임을 제시한다. 본 연구결과는 양손잡이 조직의 역동성에 관한 연구에 이론적 통찰을 제시할 뿐 아니라, 기업의 자원배분 의사결정에 실천적인 시사점을 제공할 것으로 기대한다.

주요어: 탐색과 활용, 혁신, 기술적 역량, 네트워크 위치, 양손잡이 조직
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