Industry and Innovation

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ciai20

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To cite this article: Eunkwang Seo, Jaeyong Song & Chuyue Jin (2023) Heterogeneity of optimal balance between exploration and exploitation:the moderating roles of firm technological capability and industry alliance network position, Industry and Innovation, 30:4, 423-451, DOI: 10.1080/13662716.2022.2036598

To link to this article: https://doi.org/10.1080/13662716.2022.2036598

Published online: 07 Feb 2022.

INDUSTRY AND INNOVATION
2023, VOL. 30, NO. 4, 423–451
https://doi.org/10.1080/13662716.2022.2036598

Heterogeneity of optimal balance between exploration and exploitation:the moderating roles of firm technological capability and industry alliance network position

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ABSTRACT

Although existing ambidexterity literature suggests that firms need to find the optimal balance between exploration and exploitation for superior performance, few studies have empirically examined the heterogeneity of this balance according to firm-specific conditions. Building upon the capability and social network literature, we contend that firms' technological capability and network position within industry alliances determine the optimal balance between exploration and exploitation. Analysing 7-year panel data in the worldwide semiconductor industry from 1994 to 2000, we find support for the following hypotheses: 1) the proportion of exploration has an inverted U-shaped relationship with innovation performance; 2) as firm technological capability increases, the optimal point between exploration and exploitation moves *towards the exploration side*; 3) as network centrality within industry alliances increases, the optimal point moves *towards the exploitation side*. The results offer theoretical insights into the ambidexterity literature as well as managerial implications for firms making resource allocation decisions.

KEYWORDS

Ambidexterity; exploration and exploitation; technological capability; industry alliance network

1. Introduction

To gain and sustain a competitive advantage, firms need to achieve an appropriate balance between the exploration of new possibilities and the exploitation of old certainties (March 1991). If a firm only depends on the exploitation of current knowledge, its technology may become obsolete and it may fall behind 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 gained (Levinthal and March 1993).

On the issue of balance between exploration and exploitation, numerous studies have been conducted, mainly in two streams. The first stream empirically tested whether balancing exploration and exploitation leads to superior firm performance (e.g. He and Wong 2004; Katila and Ahuja 2002). Some scholars have refined and extended this

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stream of research by describing some contingencies under which achieving this balance has a greater effect on performance (e.g. Cho, Bonn, and Han 2020; Jansen, Van Den Bosch, and Volberda 2006; Luger, Raisch, and Schimmer 2018; Suzuki 2019). The second stream focused on how firms effectively achieve the balance between exploration and exploitation. Scholars with this focus have contended that simultaneous pursuit of exploration and exploitation engenders severe tension within firms, and therefore, in order to reap substantial benefits from the exploration-exploitation balance, firms should possess specific mechanisms to resolve that tension. Sequential ambidexterity, structural ambidexterity, and contextual ambidexterity are representative solutions presented by strategy and organisation theorists (e.g. Benner and Tushman 2003; Gibson and Birkinshaw 2004).

Recently, several scholars have pointed out a limitation of many mainstream studies: the balancing issue is examined in a dichotomous way – the balanced versus the imbalanced – and little attention has been paid to the *heterogeneity* of the optimal balance between exploration and exploitation (Birkinshaw and Gupta 2013; Raisch et al. 2009). In reality, there is no universal point of balance that promises the best performance to firms in the entire range of contexts in which they may operate. Under some circumstances, firms may benefit more from an exploration-focused balance (e.g. exploration: exploitation = 6:4), while under other circumstances they may have to invest more in exploitation (e.g. exploration: exploitation = 4:6). According to their specific contexts, therefore, firms must adjust their resource allocation to favour one or the other (Markides 2013). Nevertheless, there has been little empirical investigation into the heterogeneity of the optimal level of balance. As Birkinshaw and Gupta (2013, 295) asserted, 'Suffice it to say that figuring out where on the efficiency frontier (exploration-exploitation) to sit, and under what circumstances, would be a useful question for ambidexterity research to address.' Lavie, Stettner, and Tushman (2010) also called for further research to find the optimal balance between exploration and exploitation under varying conditions.

In this study, we provide a theoretical and empirical answer to the question of how the optimal balance point between exploration and exploitation of technological innovation may vary according to firms' internal and external environments: 1) *firm technological capability* and 2) *industry alliance network position*. Innovation scholars have comprehensively examined innovation activities in firms by considering both internal capabilities and external knowledge acquisition (e.g. Berchicci 2013; Caloghirou, Kastelli, and Tsakanikas 2004; Cassiman and Veugelers 2006). Following their approach, the technological capability of a firm captures the features of the firm's internal ability to innovate within organisational boundaries, while a firm's position within its industry alliance network reflects its external relationships with other organisations. We propose that the optimal point of balance between exploration and exploitation for the best innovation performance is contingent upon both the technological capability of the firm and its network position within industry alliances. We argue that these two seemingly related constructs affect the exploration-exploitation balance in *opposite directions*. That is, an increase in firm technological capability moves the optimal balance point *towards exploration*, while an improvement in network position (centrality) within industry alliances moves it *towards exploitation*. We test our arguments using rich longitudinal data from 55 semiconductor firms over a 7-year period, 1994 to 2000. The results significantly confirm all our hypotheses.

The next section is organised as follows. First, we clearly define the concepts of exploration and exploitation used in this study. Then, we present the traditional ambidexterity hypothesis as a baseline and examine how firm technological capability and network position within industry alliances shape the optimal balance between exploration and exploitation within a given firm.

2. Theory and hypotheses

2.1. Specifications of exploration and exploitation

Since the seminal work of March (1991), many studies in various academic fields have addressed the issues of exploration and exploitation. Notwithstanding the increasing number of publications, discrepancies in defining these two concepts still exist (Gupta, Smith, and Shalley 2006; O'Reilly and Tushman 2013; Raisch and Birkinshaw 2008). Before developing arguments and drawing hypotheses, therefore, we first address three issues involved in defining exploration and exploitation.

We first discuss the domain in which exploratory and exploitive activities take place. In studies ranging in fields from technological innovation to organisational design, various scholars have adopted March's exploration-exploitation framework to study organisational learning. In this paper, we examine exploration and exploitation in the context of technological innovation. More specifically, we define exploration (exploitation) as engagement in R&D activities in pursuit of new (old) technological knowledge. Although organisational learning includes many more different kinds of learning activities than technological innovation, our argument is concrete and testable within a narrow conceptual scope (He and Wong 2004). Since exploration and exploitation are examined in the context of technological innovation, we choose innovation performance as our dependent variable rather than general financial outcomes. Innovation performance can be defined as the extent to which firms generate novel or impactful technologies from their R&D investments (Rosenkopf and Nerkar 2001). Since long and complicated processes are necessary to apply newly developed technologies to new product development and subsequently translate them into actual sales in the market, examining financial performance using variables such as return on assets (ROA) may not be appropriate to assess the outcomes of exploration and exploitation in this context.

Second, the scale of exploration and exploitation can be considered in terms of *continuity* or *orthogonality*. From the viewpoint of continuity, exploration and exploitation are the two ends of a continuous scale. From the viewpoint of orthogonality, in contrast, they exist on two different and orthogonal scales. As Gupta, Smith, and Shalley (2006) suggested, the choice of which view to adopt depends on the level of analysis and the specific context of the research. In this study, we adopt the viewpoint of continuity for two reasons. First, the view of continuity is more appropriate to our focus on firm-level resource allocation under conditions of limited resources. According to March (1991), inherent trade-offs between exploitation and exploration are primarily due to the fact that exploitation and exploration compete for scarce organisational resources. As such, firms need to decide how much of their scarce resources should be allocated to exploitation or exploration. If more resources are allocated to exploitation, then fewer resources will be left over for exploration, and vice versa. Because this study focuses on firms' choices and their effects on subsequent performance under resource limitations, we adopt the view of continuity, in which both exploitative development and exploratory projects require great investment in R&D, expenses are considerable and resources, such as R&D budgets, research engineers and necessary facilities, are scarce. It is extremely challenging to increase both exploration and exploitation in a single domain, primarily because exploration and exploitation require completely different, often conflicting routines (March 1991). Exploration routines involve experimentation, flexibility and risk-taking, whereas exploitation routines involve consistency, stability and control (Stettner and Lavie 2014). Trade-offs between exploitation and exploration are also 'reinforced by path dependencies when deploying these activities such that investment in one activity drives out the other' (Lavie, Stettner, and Tushman 2010, 116), making simultaneous pursuit of both at a high level and in a single domain all but impossible. Although prior studies showed that firms could achieve an exploration-exploitation balance across multiple domains (Lavie, Kang, and Rosenkopf 2011), because our study focuses on a single domain of ambidexterity (i.e. the technological domain), it is more appropriate to view exploration and exploitation as opposite ends of one continuum, in which the amount of exploration equals the total amount of investment minus the amount of exploitation.

The last issue in defining these two key terms is related to the criterion by which we distinguish between exploratory and exploitive activities. In his paper, March (1991) broadly defined two types of organisational learning: the exploration of *new* possibilities and the exploitation of *old* certainties. To utilise March's framework, a clear-cut boundary that determines what is new and what is known must be specified. In this research, we set the *industry boundary* as the criterion for making this distinction because firms are not totally independent, atomic actors, but are highly embedded in their social contexts (Granovetter 1985; Uzzi 1996). Within industry boundaries, one firm's economic actions can definitely impact the behaviours and performances of other firms. Even internal learning often influences the learning of other collocated competitors through knowledge spillover (Alcácer and Chung 2007; Jaffe, Trajtenberg, and Henderson 1993). Therefore, learning activities cannot be understood comprehensively without considering competitive structure (Levitt and March 1988). Thus, we use the industry boundary to distinguish new knowledge from old knowledge. Specifically, exploration is defined as the pursuit of knowledge that is not known to industry players, whereas exploitation is defined as the utilisation and development of knowledge that is already known to the industry. In a sense, this specification is different from that of prior studies, in which criteria such as organisational boundaries and technological boundaries are used. In our model, even activities involving pursuit of technologically or organisationally distant knowledge are not viewed as exploration if such knowledge is already known to industry players.

2.2. Balancing exploration and exploitation and innovation performance

Based on the specifications outlined above, we now set the following traditional argument as a baseline: balancing exploration and exploitation is superior in terms of innovation performance to focusing on only one of them. The innovation literature has consistently revealed that exploitation has decreasing returns to scale (e.g. Fleming 2001; Katila and Ahuja 2002). As certain knowledge is utilised repeatedly, the pool of possible technological options for recombination is gradually exhausted, and further development based on this knowledge is less and less likely (Levinthal and March 1981). In addition, when it comes to organisational process, excessive exploitation leaves firms with very little flexibility, and they may even disregard potential options that deviate from standardised processes (Leonard–Barton 1992). Therefore, to maintain flexibility and facilitate innovation, it is necessary to engage in exploration to some extent.

Similarly, excessive exploration also reduces a firm's ability to innovate. Newly pioneered technologies are often premature; thus, further elaboration and continuous refinement are mandatory (Zander and Kogut 1995). If follow-up developments are totally neglected, firms may lose important innovation opportunities based on their pioneered technologies. For example, Levinthal and March (1993) pointed out the possibility of falling into a vicious cycle of failure; that is, the failure of an exploratory project leads to a search for other experimental projects that are also likely to fail. In this regard, a certain level of exploitation is required to maximise innovation performance.

All of the above arguments point to the superiority of a simultaneous balance between exploitation and exploration. That is, firms achieve better innovation performance when they exploit knowledge circulated within the industry while also exploring new knowledge beyond the industry boundary at the same time rather than only focusing on exploitation or exploration. Gupta, Smith, and Shalley (2006) suggested that if exploitation and exploration are viewed as two ends of a continuum, the correct test for ambidexterity would be to examine if an inverted U-shaped relationship exists between the degree of exploration (or exploitation) and organisational performance variables. Although using a ratio for exploitation or exploration as the independent variable leads to the same result, we follow the way used in previous studies (e.g. Lavie, Kang, and Rosenkopf 2011; Stettner and Lavie 2014) to test for an inverted U-shaped relationship between the exploration ratio and innovation performance.

In sum, this paper predicts beneficial effects of ambidexterity (a balance between exploitation and exploration) from the continuity viewpoint by testing for an inverted U-shaped relationship between the exploration ratio and innovation performance. Hence, we set a baseline hypothesis as below:

Hypothesis 1. An inverted U-shaped relationship exists between the proportion of exploration and innovation performance.

2.3. Heterogeneity of optimal balance between exploration and exploitation

We extend the ambidexterity hypothesis presented above by examining the heterogeneity of the optimal level of balance between exploration and exploitation. The optimal level of balance is defined as the point on a continuous scale between exploration and exploitation that generates the best innovation performance for a given firm. As Birkinshaw and Gupta (2013, 295) pointed out, on this scale in any given firm, some points 'may actually be superior to others, depending on the exact circumstances facing the firm.' In this study, we focus on firms' internal and external circumstances to explain this contingency-dependent effect of balancing exploration and exploitation.

Given that innovation is a process of knowledge recombination, firms search for a wide range of internal and external sources of knowledge to seek for innovation opportunities (Chesbrough 2003; Rosenkopf and Nerkar 2001; West and Gallagher 2006). Both internal and external sources have unique advantages for firms. Using external sources of knowledge and expertise provides the advantage of value creation (i.e. creating more impactful innovations), whereas using internal sources provides the advantage of value appropriation (i.e. capturing more value from created innovations) (Laursen and Salter 2014). Depending on their strategic focus, therefore, some firms (e.g. AT&T, Bell Labs) rely heavily on internal sources, while other firms (e.g. Cisco, Intel, Microsoft) actively tap into external sources to support their innovation processes (Chesbrough 2003; West and Gallagher 2006). Given the distinct roles of internal and external sources in the process of innovation, prior innovation studies have comprehensively examined corporate innovation activities by exploring both internal capabilities and external knowledge acquisition (e.g. Berchicci 2013; Caloghirou, Kastelli, and Tsakanikas 2004; Cassiman and Veugelers 2006).

Researchers writing from the ambidexterity viewpoint have also considered these two types of sources. For example, Hoang and Rothaermel (2010) showed that firms can exploit and explore both internally and externally, but a heterogeneous combination of exploration/exploitation and internal capability development/external alliance partnership will affect the outcomes of R&D projects differently. Similarly, Rothaermel and Alexandre (2009) also posited that a firm's technology sourcing strategy is formulated based on a mix of internal/external sources and the balance between exploration and exploitation. In fact, the interplay of exploration and exploitation via different modes (e.g. internal organisation, alliance formation, and acquisition) and achieving balance across such modes have become hot topics in the ambidexterity literature (Stettner and Lavie 2014). Following these studies, we examine how different conditions of internal and external learning modes affect the optimal balance between exploration and exploitation. Specifically, we propose two moderating factors in this study: one based on the *internal* technological capability of a firm and the other on its *external* alliance network position.

On the one hand, the capability literature views companies as bundles of firm-specific abilities enabling them to perform productive activities, the behavioural outcomes of which are significantly shaped by these abilities (Helfat and Peteraf 2003; Hoopes and Madsen 2008; Jacobides and Winter 2012). From the social network viewpoint, on the other hand, economic actions are affected by the social context in which they are embedded such as the position of actors in social networks (Granovetter 1985; Gulati and Gargiulo 1999). These two perspectives are distinct in that capability captures the features of a firm's own ability, whereas network position reflects opportunities inherent in inter-firm relationships beyond organisational boundaries (Song, Asakawa, and Chu 2011). In this study, we investigate how firm technological capability and network position within industry alliances affect the optimal combination of exploration and exploitation.

In the theoretical development, we assume that both moderators (i.e. technological capability, network position) are given (exogenous) variables to firms. In the long run, both variables are endogenous variables determined by firms' choice. According to the resource-based view, however, these strategic resources take considerable times to develop and change (e.g. Dierickx and Cool 1989). Allocation of resources between exploration and exploitation, on the other hand, could be determined and changed by managers annually. In a given year, therefore, we could reasonably assume that technological capability and network position are given (exogenous) variables that could moderate the choice of exploration and exploitation. Thus, in this study, we examine how these two moderators influence the outcome of firms' search behaviours (i.e. increasing the proportion of exploitation or exploration).

2.3.1. Firm technological capability and the optimal balance of exploration and exploitation

Not all firms benefit from the same amount of exploration and exploitation. Depending on internal conditions, their potential to reap benefits from exploration or exploitation may vary. From the viewpoint of capability, we argue that the optimal point of balance between exploration and exploitation varies significantly depending on the technological capability of the firm.[1] The literature on organisational learning has suggested that firms lacking sufficient technological capability are less successful in exploratory activities (Lavie, Stettner, and Tushman 2010). Whether firms can achieve desired innovation outcomes from exploration depends on their ability to recognise the potential value of new, external knowledge and utilise it in the creation of new knowledge. Such ability is often referred to as absorptive capacity, which is primarily a function of a firm's prior related knowledge developed through internal R&D activities (Cohen and Levinthal 1990; Zahra and George 2002). Also, in terms of knowledge recombination, firms with a small knowledge base tend to create fewer new linkages between newly explored knowledge and existing knowledge. They are likely to be one step behind in their explorations as compared to firms with deep knowledge embedded in their core technologies.

On the other hand, less competent firms may gain greater benefits from refining technologies already pioneered by competitors in their industry rather than exploring untouched areas beyond the industry boundary. Katila and Chen (2008) discovered the presence of followers' advantages in technological competition by analysing patent data of the industrial automation industry. Their research showed that a head start in new knowledge areas is positively associated with the innovation frequency of industry competitors. This finding implies that firms can obtain some clues regarding which technologies are viable and timely in the market from their competitors because others' pioneering search activities help to resolve the uncertainty around new knowledge. Therefore, a good strategy for firms with lower technological capability is to exploit relatively promising technologies that have already been explored by other firms until they accumulate sufficient technological capabilities to benefit from exploration on their own.

As a firm accumulates capability through ongoing success in internal R&D development, it gradually becomes more capable of utilising new, external knowledge. The accumulation of expertise in certain areas enriches a firm's knowledge reservoir and

[1]Following Helfat and Peteraf (2003), we define technological capability of a firm as the firm's ability to perform a coordinated set of R&D tasks in specific technological fields, utilising organisational resources, for the purpose of achieving a particular end result. According to this definition, in order for the performance of an activity to qualify as a capability, the capability must have been routinised to work in a reliable manner. That is, technological capability is primarily developed by repetition of and accumulated experience with specific R&D tasks.

increases the likelihood of knowledge creation through recombination. Nevertheless, the strategy literature has suggested concrete reasons for such firms to reduce the proportion of exploitation and enter into exploration gradually. According to Leonard–Barton (1992), core capabilities and core rigidities are two sides of the same coin; as employees' skill sets, organisational systems, and cultures become established as a result of a series of successful experiences, search activities and subsequent innovations deviating from the established ways are curtailed. In a similar vein, Christensen (1997) also argued that incumbents successful in the mainstream market are likely to be disrupted by competitors' innovations because they neglect low-performance, high-potential technologies. Thus, as a firm accumulates experience and its innovation activities become standardised and routinised, the proportion of exploration of knowledge beyond the industry boundary should be increased.[2] Start-up firms are at relatively low risk of rigidity in their innovation processes; for these firms, exploitation of known industry knowledge allows them to accumulate technological capability rapidly (Lee and Lim 2001). In contrast, incumbent firms that continue to exploit existing technologies and current competencies are likely to lose innovation opportunities, particularly in rapidly changing environments of technological competition. Taking all these points together, we hypothesise as follows:

Hypothesis 2. As the technological capability of a firm increases, the optimal point of balance on the continuum between exploration and exploitation shifts towards the exploration side.

2.3.2. Network position within industry alliances and the optimal balance of exploration and exploitation

Firms are not totally independent actors, but entities highly embedded within competitive and social environments (Granovetter 1985; Powell, Koput, and Smith-Doerr 1996). Hence, exploratory efforts made by a few firms can benefit their competitors since they can further exploit and utilise the knowledge that was explored by others (Moreira and Tae 2019). However, not all firms can take advantage of competitors' explorative efforts, since such technological information is often proprietary or kept secret. Among various types of relationships in the corporate world, the social relationships established through strategic alliances facilitate valuable information exchange and knowledge spillover (Inkpen and Tsang 2005). Various empirical studies support this idea by showing that when two entities are connected by an alliance tie, they both have a greater chance of receiving information from the other than entities without such ties (e.g. Mowery, Oxley, and Silverman 1996).

A firm occupying a central position has established direct and indirect social ties with competitors. Firms standing at the centre of an industry alliance network are able not only to access knowledge distributed in the alliance network, but also to learn effective

[2]In this theoretical development section, we do not distinguish between exploration-related and exploitation-related capabilities, but focus on aggregated technological competence developed by repetitive activity and accumulated experience of specific R&D tasks in firms. However, it is entirely possible that some capabilities could be more related to exploitation than exploration. For instance, routines established for consistency, stability, and control are related to exploitation (Stettner and Lavie 2014). According to our theory and definition of technological capability, even the accumulation of *exploitation*-related capabilities shifts the optimal balance point towards the *exploration* side, largely because continued exploitation is likely to lead to core-rigidity problems, as outlined by Leonard–Barton (1992) and Christensen (1997). That is, firms should shift their focus to exploration to improve performance in innovation.

ways of utilising that knowledge (Borgatti 2005; Gulati and Gargiulo 1999; Inkpen and Tsang 2005; Shipilov 2009). Accordingly, central firms can detect new technological trends in their industries faster without engaging much in exploration. They achieve the same innovative outcome with less exploration because they use their advantageous position in the network to access knowledge newly explored by others. At the same time, they can invest the resources that saved them from exploration into exploitation instead, further enhancing their innovation performance.

Occupying a central position, however, may hinder the performance of exploration. As Perry-Smith and Shalley (2003) suggested, individuals or organisations in central positions face pressures to conform to conventions taken for granted in the network. Hence, the explorative search of central firms is likely to be constrained by industry norms. That is, central firms have to pursue exploration in conformity to the norms and conventions of their industries. Peripheral firms, on the other hand, are relatively free from the influence of norms and standardised practices in the network and thus can freely search beyond industry boundaries and conduct experiments that are uncommon within their industries, which could potentially lead to novel outcomes (Cattani and Ferriani 2008). Seen from this perspective, occupying a central position could increase constraints on explorative innovation and ultimately decrease its performance for firms.

Therefore, central firms can improve performance by focusing on exploiting knowledge that is already known within the industry alliance network rather than engaging in more exploration beyond the industry boundary. Therefore, we predict as below:

Hypothesis 3. As a firm occupies a more central position in its industry alliance network, the optimal point of balance on the continuum between exploration and exploitation shifts towards the exploitation side.

3. Methods

3.1. Sample and data

We tested our hypotheses using patent data in an analysis of semiconductor firms from all over the world. For several reasons, the semiconductor industry has been utilised in previous studies as a suitable context in which to study firms' R&D activities and subsequent innovation outcomes (e.g. Sorensen and Stuart 2000; Ziedonis 2004). First, this is an innovation-intensive industry in which multiple observations of technological innovations of considerable variation can be obtained. By focusing on this single industry, we can largely avoid the effects of industry-specific environmental conditions in our analysis. More importantly, the high propensity towards patenting among semiconductor firms offers a great opportunity for researchers to measure innovation activities in an objective and reliable manner (Cohen, Nelson, and Walsh 2000; Podolny, Stuart, and Hannan 1996; Song and Shin 2008). U.S. law obliges patent applicants and their lawyers to specify information about new technologies in detail, ranging from information about the inventor to prior innovations leading to current development (Song, Almeida, and Wu 2003). This information provided by patent documents allows us to look inside the black box in terms of the innovation activities of a firm. Thus, numerous studies on innovation include firms in the semiconductor industry in their empirical analyses (e.g. Adams, Fontana, and Malerba 2013; Carnabuci and Operti 2013; Hsu and Ziedonis 2013). In addition, the semiconductor industry provides an appropriate arena for studying industry alliance networks. Semiconductor companies frequently establish strategic alliances with each other to develop new technology jointly or obtain access to complementary assets (Eisenhardt and Schoonhoven 1996; Stuart 1998). We believe that the intensive and frequent formation of alliances in this industry ensures the meaningfulness and reliability of our network variables.

The data utilised in this study are from the years 1994 to 2000. Because we set a 5-year moving window for key variables, including the proportion of exploration, technological capability, and network position within industry alliances, the data that we collected and analysed dates back to 1989. We posit that this 12-year time span is appropriate for this study because this period was marked by vigorous innovation, entrepreneurship, and active inter-firm cooperation within the industry. This is illustrated well in Figure 1, which shows the numbers of semiconductor firms and strategic alliances among them in each year of the study period. Moreover, according to Jiang, Tan, and Thursby (2010), in the early 2000s, a great paradigm transition occurred in semiconductor technology from complementary metal-oxide semiconductor technology to nanotechnology. Therefore, we set the upper time limit in this study to the year 2000 to rule out exogenous effects associated with drastic technological changes.

For the period from 1994 to 2000, we initially identified 192 semiconductor firms classified as SIC code 3674 in the COMPUSTAT database with at least one semiconductor-related U.S. patent. In this identification process, 30 semiconductor-related patent classes proposed by Yayavaram and Ahuja (2008) were used. In total, 108 firms were excluded from the sample due to a lack of important financial data available in COMPUSTAT, such as R&D expenditure and operating income. Moreover, to enhance the validity of our within-firm panel analysis, we additionally excluded 29 firms with records for less than 4 years. In sum, our final sample contains 306 observations of 55 semiconductor firms during the 7 years from 1994 to 2000.

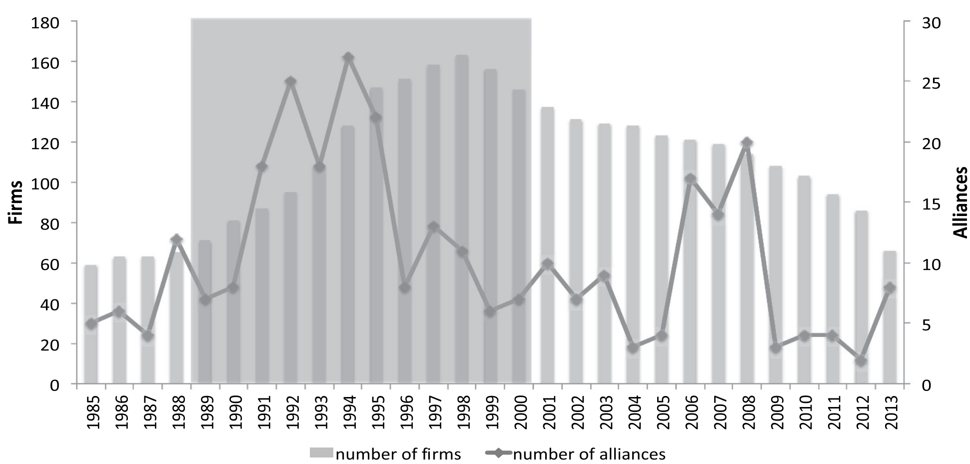

Figure 1. Firms and strategic alliances from 1985 to 2013.

We gathered information from three distinct databases. First, we collected patent data from the United States Patent and Trademark Office (USPTO) to operationalise technology-related variables, including exploration–exploitation-related activities and innovation performance. Patent data has been extensively employed in innovation research because patent documents are systemically compiled with detailed information and are available continuously across sufficiently long periods, which enables longitudinal studies to be conducted (Almeida 1996). Second, we obtained records of strategic alliances from the Securities Data Company database. Since this study focuses on the role of network ties established by inter-firm collaboration as the channel of information flow, all types of strategic alliances established between semiconductor firms were included, such as those based on agreements for the joint development of new technologies and those based on agreements related to manufacturing and marketing. Lastly, general corporate financial data was collected from the COMPUSTAT database.

3.2. Measurement

3.2.1. Dependent variable

Our dependent variable is firm innovation performance and we operationalise it by the number of successful patents filed to the 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 research on knowledge-intensive industries (Ahuja and Katila 2001; Puranam and Srikanth 2007; Rothaermel and Hess 2007). Although not all innovations are patented, semiconductor firms, in general, show a high propensity towards patenting their newly developed technologies (Cohen, Nelson, and Walsh 2000; Kortum and Lerner 2000). Thus, a high number of patent applications can be indicative of great achievement in terms of technological innovation. Of course, simple patent counts do not properly reflect the heterogeneous value of each patent (Griliches 1990; Sampson 2007). We address this heterogeneity by assigning the number of forward citations (citations by later patents) to each patent. Since the forward citations of a patent represent its degree of impact on subsequent technological developments, counting the number of citations has been recognised 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 practice of citation-weighted patent counting captures the innovation performance of a given firm, including both the quantity and quality of technological innovation (Nesta and Saviotti 2005).

3.2.2. Independent variable

Our independent variable is the proportion of exploration. To measure the extent to which a given firm engages in exploration and exploitation activities, we use information about backward citations listed in each patent document of the firm. To apply for a patent to the USPTO, applicants must clearly describe all or any of ‘the prior art’ on which the new technology is based (Song, Almeida, and Wu 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 diverse patterns of firms’ search behaviour. In particular, information about backward citations represents how extensively a firm explored external knowledge that has not yet been utilised by others (Katila and Ahuja 2002; Rosenkopf and Nerkar 2001; Stuart and Podolny 1996).

According to Levinthal and March (1993), exploration refers to activities related to the pursuit of new knowledge. Following this line of thought, Katila and Ahuja (2002) operationalised scope search (or exploration) as the ratio of new citations, which have not been used by the focal firm in the previous 5 years, to the total citations in a given year. We alter this approach to suit our specification of exploration and exploitation in which the industry boundary draws a line between the two activities. We capture exploration using backward citations of patents that had not been used by any other industry players in the preceding 5 years, which we call *new backward citations*. The proportion of exploration is calculated by dividing the number of new backward citations by the total number of backward citations in a focal year. Self-citations are excluded from the count of new backward citations.

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

3.2.3. Moderating variables

Our first moderating variable is firm technological capability. According to Nelson and Winter (1982), a firm's capability is basically developed through the repetition of activities. Building upon this idea, we measure the technological capability of a firm as the cumulative sum of R&D expenditures in the prior 5 years. The extent of R&D investment in a given firm directly represents the scale of the R&D activities in which the firm has engaged during the focal period. Therefore, cumulative R&D experience can be used as a proxy for the technological capability of a firm. Following the practice in prior studies (Hall, Jaffe, and Trajtenberg 2005; McGahan and Silverman 2006), we take into account technological obsolescence and loss of knowledge by depreciating R&D expenditure at 15% per year. This variable is calculated as follows:

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

Our second moderating variable is industry alliance network position. To measure a firm's network position, we first 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 and Zajac 2007), we employ a 5-year window to identify network ties. That is, direct network ties in a given year are calculated based on the strategic alliances established during the preceding 5 years. Then, network position is measured using Bonacich's (1987) centrality measure. In this measurement, centrality in the global network for each node is calculated by the weighted sum of the 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.[3] In this study, tie strength indicates the number of strategic alliances between two firms in the previous 5 years. This variable reflects the effects of indirect ties as well as direct ties. The greater the value of β, the more a node is influenced by its indirect ties. In this study, β is set to 0.995 divided by the maximum eigenvalue, and isolated nodes are given a score of zero. We calculate this using UCINET 6.

3.2.4. Control variables

We rule out inter-industry effects and the impact of technological shifts by examining a single industry within a particular period. Furthermore, our controls include diverse firm-level and alliance portfolio-level variables. Firm-level control variables include*technological diversity*, which is measured by $1 - \sum_{p=1}^{q} \left(\frac{M_p}{N}\right)^2$, 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 degree to which a firm is technology-oriented (Greve 2003), and *ROA* (operating income divided by total assets) is also controlled to eliminate the effects associated with financial performance. Reflecting the findings of prior research in which firms with abundant slack resources tend to engage in exploration more than those with few slack resources (Cyert and March 1963), we include *organisational slack* (retained earnings divided by total assets) in the regression models. Portfolio-level control is the *density of the ego network* (the number of ties between adjacent nodes divided by the total possible number of ties between them) of a focal firm. Also, we take into account alliance-specific variation. Since firms can form either exploratory or exploitative alliances, and this choice affects innovation performance, we control for the *exploratory alliance ratio* (the number of ties established for new product development divided by the total number of alliances). Lastly, to minimise the effects of time-constant and time-varying unobserved heterogeneities, both *firm dummies* and *year dummies* are included in the model.

3.3. Model specifications

Because our 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 such cases, either Poisson or negative binomial distribution can

[3]Isolated nodes are not considered in this calculation and are assigned a value of zero.

be used to model the count-dependent variable. In empirical studies, however, the Poisson regression model is rarely chosen, since the basic assumption underlying it (that the conditional mean of the dependent variable is equal to its conditional variance) is often violated. In the innovation research using patent data, the conditional variance is much larger than the conditional mean, leading to an overdispersion problem (Song, Almeida, and Wu 2003). Since significant overdispersion is evident in our data (G^2 = 3.0e + 0.4, p < 0.001; $G^2 = 2(\ln L_{\mathrm{NBRM}} - \ln L_{\mathrm{PRM}})$), we use the negative binomial model.

To examine the heterogeneity of the optimal balance between exploration and exploitation, we conduct a fixed-effects panel analysis. The inclusion of firm fixed effects explains within-firm variation over time rather than inter-firm variation. The firm fixed-effects model effectively controls for managerial factors that are not readily changed in a short period, such as organisational structure, culture, and long-term strategy. If these 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, we also include year dummies in the negative binomial regression model. Thus, the expected number of citation-weighted patents of firm i in year t, $\lambda_{i,t}$, is specified in the following way:

$$\lambda_{i,t} = \exp\left(\beta_1 PE_{i,t} + \beta_2 PE_{i,t}^2 + X_{i,t}\gamma + a_i + \delta_t\right),$$

where $PE_{i,t}$ indicates the proportion of exploration, $X_{i,t}$ includes all control variables, and a_i and δ_t represent the time-constant effects and year dummies, respectively.

Hypotheses 2 and 3 predict movement of the vertex point of the inverted U curve. To test these hypotheses, we adopt 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 heterogeneous expertise of the firm by examining the interaction between this heterogeneity in expertise and the linear term of the proportion of star individuals. That is, the hypothesis testing of the coefficient of the interaction term confirms in which direction the vertex point moves. Therefore, we designed a model that includes interaction terms between the proportion of exploration and each moderator.[4] The associated equation is specified below:

$$\lambda_{i,t} = \exp\left(\beta_1 PE_{i,t} + \beta_2 PE_{i,t}^2 + \beta_3 PE_{i,t} \times TC_{i,t} + \beta_4 PE_{i,t} \times NP_{i,t} + X_{i,t}\gamma + a_i + \delta_t\right),$$

where $TC_{i,t}$ refers to the technological capability of a firm and $NP_{i,t}$ indicates network position in an industry alliance network. A positive sign of the interaction term supports the movement of the vertex point towards the exploration side, whereas a negative sign confirms its movement towards the exploitation side. STATA version 17 was used to fit the models to the data.

[4]Haans, Pieters, and He (2016) recommended that both interaction terms XZ and X^2Z (X is the independent variable and Z is the moderator) should be included in the model even if only one moderation type (a shift in the turning point or a flattening/steepening of the curve) is hypothesised. However, they also stated that it is appropriate to exclude the interaction term X^2Z only if a shift in the turning point is hypothesised and the coefficient for X^2Z for the full specification is not statistically different from zero. We ran the regression including both XZ and X^2Z, and confirmed that the coefficients for *Proportion of Exploration*^{2} × *Technological Capability* (β = 1.306, p = 0.544) and *Proportion of Exploration*^{2} × *Network Position* (β =0.564, p =0.107) are both non-significant. Thus, these two terms are excluded from our model.

4. Results

4.1. Data description

Table 1 represents the descriptive statistics and correlations of our variables. To check for multicollinearity problems within the model, we conduct the 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, and Price 2000).[5] In the VIF test, including all explanatory variables except the squared term and interaction terms, all scores were lower than 2.60. Therefore, all variables are included in the regression models.

The sample data shows that from 1994 to 2000, each firm had an average of 1.82 partnerships within industry alliances. Although this average is small, large variation across firms is evident. Most had one or two relationships with other firms, but a few firms had up to 16 relationships. Figure 2 depicts the structure of the sample semiconductor alliance network in the year 2000. This distribution is typical of a scale-free network following a power law, in which the probability that a firm will form alliances with k other firms decreases exponentially as k increases (Bae and Gargiulo 2004; Barabasi and Albert 1999). In such a distribution, there is a fundamental asymmetry of information accessibility between central actors highly connected to others and peripheral actors less well connected. In this context, we test how the optimal level of balance between exploration and exploitation varies across firms with varying levels of technological capability and different network positions.

4.2. 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 our theory. Model 2 examines Hypothesis 1, which asserts that the proportion of exploration has an inverted U-shaped relationship with innovation performance. In the model, the coefficient of the *Proportion of Exploration* is revealed to be positive and strongly significant (β= 4.577, p< 0.001), and the coefficient of the *Proportion of Exploration^2* is negative and also strongly significant (β = −4.227, p< 0.001). In support of Hypothesis 1, these results imply that although the increase in the proportion of exploration initially enhances innovation performance, increasing beyond a certain point reduces performance. In our sample data, the optimal balance point (i.e. the vertex point of the inverted U curve) appears when exploration is at 54.14%. Figure 3 illustrates this relationship with 95% confidence intervals. The estimated maximum level of innovation performance (=1.186) is shown to be 51 times greater than its minimum level (=0.023).

In Model 3, we test Hypotheses 2 and 3, which both address the heterogeneity of the optimal 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 towards the exploration side. On the other hand, Hypothesis 3 anticipates that for firms occupying more central positions in the industry alliance network, the optimal point of balance between exploration and exploitation moves

[5]The VIF test is performed using the ordinary least squares regression model.

Table 1. Descriptive statistics and correlations.

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9
1. Innovation Performance	1387.28	3545.58	1	27,201									
2. Technological Diversity	0.677	0.214	0	0.933	0.264								
3. R&D Intensity	0.150	0.098	0.011	0.957	−0.118	−0.085							
4. ROA	0.162	0.162	−1.700	0.548	0.060	0.176	−0.274						
5. Organisational Slack	0.147	0.447	−3.784	0.773	0.173	0.297	−0.282	0.599					
6. Ego Network Density	0.116	0.258	0	1	0.180	0.109	−0.012	0.038	0.100				
7. Exploratory-Alliance Ratio	0.215	0.335	0	1	0.113	0.162	−0.037	−0.106	−0.082	0.382			
8. Technological Capability [a]	0.410	1.014	0.001	9.258	0.533	0.337	−0.071	0.165	0.199	0.062	0.168		
9. Network Position	2.860	5.227	0	27.086	0.658	0.343	−0.150	0.098	0.172	0.255	0.299	0.734	
10. Proportion of Exploration	0.585	0.200	0	1	−0.058	−0.056	−0.051	0.026	0.047	−0.188	−0.082	−0.008	−0.020

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

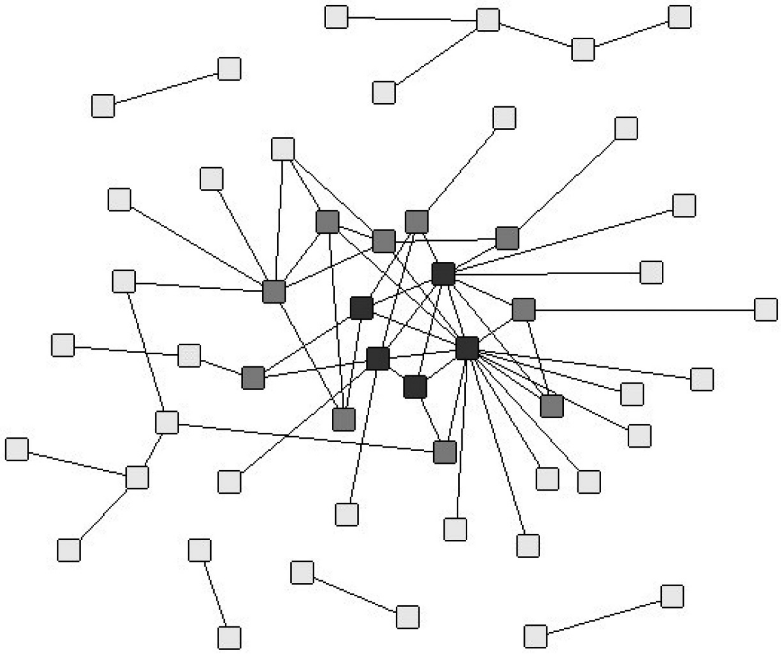

Figure 2. Inter-firm alliance relationships among the sample firms in 2000 [a] Firms that did not participate in an alliance within the industry during 1995 to 1999 are omitted from the figure.

towards the exploitation side. To verify these hypotheses, we include 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 to be positive (or negative) and strongly significant. The results reveal that the coefficient of the *Proportion of Exploration* × *Technological Capability* is significant and positive (β = 1.730, p= 0.001). This suggests that a high level of technological capability is associated with an optimal point of balance located at a higher level of exploration (a lower level of exploitation), which confirms Hypothesis 2. Figure 4 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 accumulate more technological capability to maintain a higher proportion of exploration. Moreover, the coefficient of the *Proportion of Exploration* × *Network Position* is shown to be negative and strongly significant (β= −0.058, p= 0.019), which supports Hypothesis 3. This outcome implies that the optimal point of balance is positioned at a higher level of exploitation (a lower level of exploration) when a firm is in a central position. Figure 5 illustrates the predicted innovation performance for different network positions within industry alliances. It is evident that the vertex point of the curve moves to the left side as network centrality increases. This reaffirms the assertion that it is better for a firm to increase the proportion of exploitation when it occupies a more central position.

Table 2. Fixed-effects panel negative binomial regression models [a].

Variable	Model 1	Model 2	Model 3
Constant	−0.670*	−1.480***	−1.399**
	(0.260)	(0.395)	(0.404)
Technological Diversity	0.663**	0.574*	0.503†
	(0.269)	(0.263)	(0.269)
R&D Intensity	0.574	0.787	0.777
	(0.603)	(0.533)	(0.539)
ROA	−0.233	−0.063	−0.053
	(0.299)	(0.305)	(0.304)
Organisational Slack	0.153	0.093	0.077
	(0.174)	(0.177)	(0.177)
Ego Network Density	0.274	0.175	0.225
	(0.185)	(0.191)	(0.191)
Exploratory-Alliance Ratio	−0.028	−0.123	−0.130
	(0.180)	(0.182)	(0.181)
Technological Capability	0.016	0.019	−0.709**
	(0.053)	(0.052)	(0.227)
Network Position	0.071***	0.066***	0.162***
	(0.016)	(0.015)	(0.041)
Proportion of Exploration		4.330***	4.452***
		(1.041)	(1.067)
Proportion of Exploration ^{2}		−4.031***	−4.106***
		(0.902)	(0.923)
Proportion of Exploration × Technological Capability			1.603**
			(0.509)
Proportion of Exploration × Network Position			−0.200**
			(0.071)
Firm Fixed Effects	Included	Included	Included
Year Fixed Effects	Included	Included	Included
Log likelihood	−1566.06	−1554.80	−1550.39
Wald χ^2	294.90	328.96	414.96
Prob > χ^2	0.000	0.000	0.000
Number of Firms	55	55	55
Number of Observations	306	306	306

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

4.3. Robustness checks

To ensure the robustness of our results, we conduct additional analyses with different measures for network position. In addition to Bonacich's centrality, three different measures are 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 are intended to reflect actors in central positions of a given network, but each measure reflects a different property of network positions (Wasserman and Faust 1994). Degree centrality captures the size of the ego network of an actor. Betweenness centrality is defined as the degree to which a focal actor is located on the shortest paths connecting other actors, while closeness centrality is defined as the sum of the length of the shortest paths from a focal actor to all other actors. The use of these different measurements permits us to check whether our argument can be applied to different positional contexts. In the analysis, we find consistently negative moderating effects for 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 is negative as predicted, but not statistically significant (β= −36.403, p= 0.651). This may be due to the fact that betweenness centrality is based on

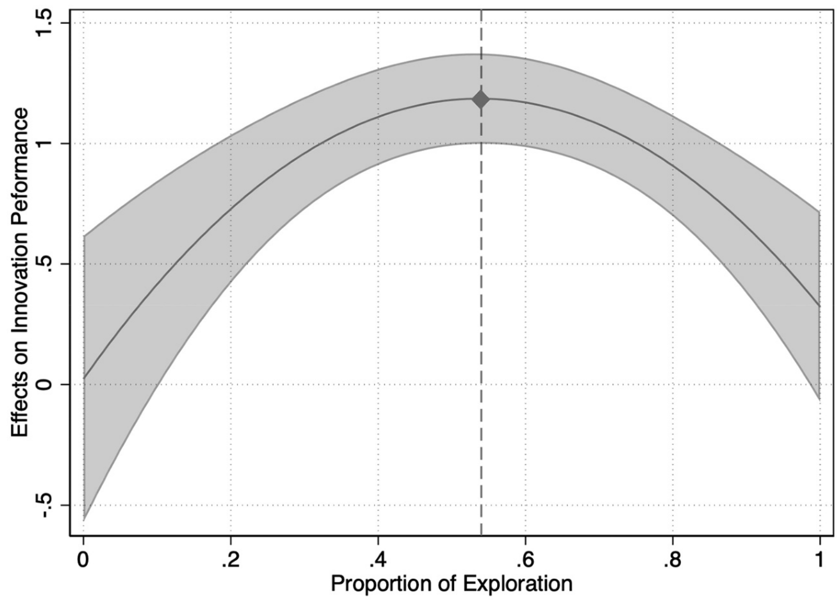

Figure 3. Relationship between proportion of exploration and innovation performance (with 95% confidence intervals).

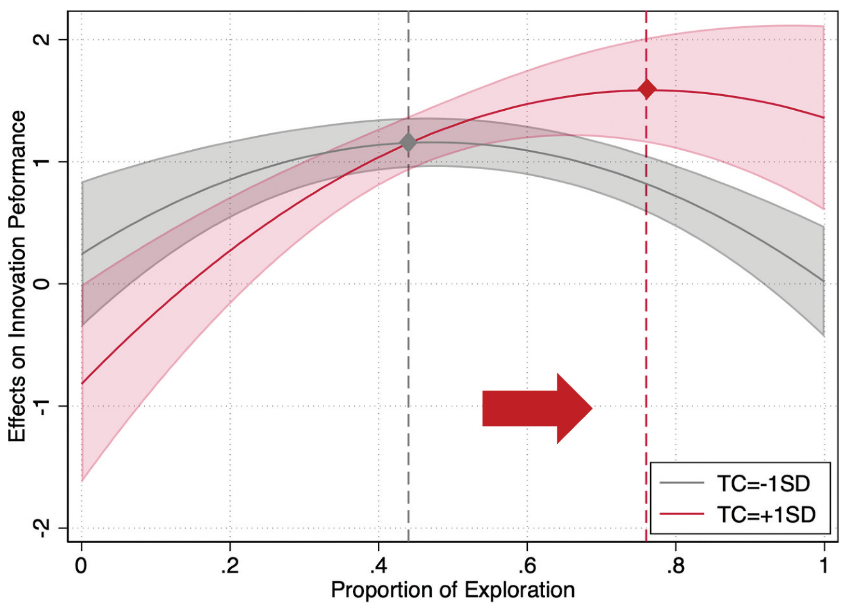

Figure 4. Moderating effect of technological capability on the optimal balance point (with 95% confidence intervals).

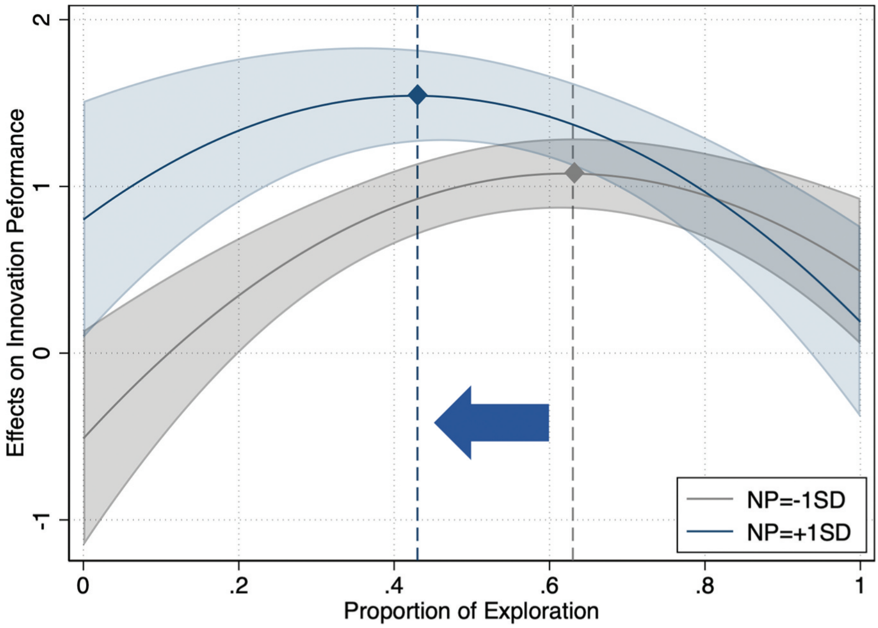

Figure 5. Moderating effect of network position on the optimal balance point (with 95% confidence intervals).

a particularly unique assumption that information literally moves or transfers from node to node only along the shortest paths, rather than simultaneously diffusing via all paths (Borgatti 2005). This may not apply to the setting of strategic alliances, in which information flowing through established ties is duplicable and the flow is not limited to particular paths.

We also check the robustness of our findings using a different regression model. We rerun our regression analyses using log-linear models (i.e. ordinary least squares regression with the natural logged dependent variable)[6] with robust standard errors. As shown in Models 2 and 3 of Table 3, we find results consistent with those of the negative binomial regression analysis. These results give us more confidence about our findings in that it allows for unconditional fixed effects and robust standard errors.

5. Discussion and Conclusion

In this study, we highlight the heterogeneity of the optimal balancing point between exploitation and exploration. Building upon prior research, we argue that the optimal balance differs significantly across various levels of technological capability of a firm and network position within industry alliances. Specifically, we hypothesise that the optimal exploitation-exploration balance point that maximises innovation performance moves towards the exploration side when a firm exhibits a higher level of technological capability, while it moves to the exploitation side when the firm occupies a more central position in an industry alliance network. Our empirical analysis of 7-year panel data from firms in the semiconductor

[6]One is added to the dependent variable before the log transformation.

Table 3. Robustness checks using log-linear models [a].

Variable	Model 1	Model 2	Model 3
Constant	3.919***	3.076***	2.576**
	(0.366)	(0.816)	(0.744)
Technological Diversity	−0.101	−0.098	0.047
	(0.485)	(0.472)	(0.471)
R&D Intensity	2.284**	2.347**	2.329**
	(0.760)	(0.800)	(0.767)
ROA	−0.451	−0.321	−0.248
	(0.284)	(0.277)	(0.262)
Organisational Slack	0.182	0.116	0.150
	(0.186)	(0.217)	(0.231)
Ego Network Density	0.298	0.224	0.213
	(0.290)	(0.235)	(0.258)
Exploratory-Alliance Ratio	−0.695*	−0.789**	−0.891**
	(0.313)	(0.266)	(0.259)
Technological Capability	−0.140	−0.114	−0.823*
	(0.114)	(0.120)	(0.318)
Network Position	0.049†	0.052†	0.237***
	(0.026)	(0.028)	(0.062)
Proportion of Exploration		3.972†	5.110**
		(2.123)	(1.866)
Proportion of Exploration ^{2}		−3.589*	−4.270**
		(1.535)	(1.367)
Proportion of Exploration			1.266†
× Technological Capability			(0.746)
Proportion of Exploration			−0.321**
× Network Position			(0.099)
Firm Fixed Effects	Included	Included	Included
Year Fixed Effects	Included	Included	Included
R^2 (within)	0.587	0.604	0.618
F-statistic	27.63	31.79	32.99
Prob > F	0.000	0.000	0.000
Number of Firms	55	55	55
Number of Observations	306	306	306

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

industry confirms both that the proportion of exploration to exploitation has an inverted U-shaped relationship with innovation performance, and that the vertex point moves in predicted ways as technological capability increases and firms become more central within their networks. The results are robust to different measures and estimation techniques.

In this study, we focus on how exploration- or exploitation-focused strategies improve outcomes, offering a detailed framework in which firms can make decisions regarding resource allocation. Prior studies have confirmed some boundary conditions in which an imbalance is preferable to a balanced strategy. In the empirical study of Ebben and Johnson (2005), for instance, small firms lacking slack resources were advised to focus on either exploration or exploitation, although no clear indication is provided as to which one firms should focus on in a given situation. In contrast, the findings of our study can provide guidelines for decision-making. According to our analysis, small firms or start-ups should reflect carefully on their relative strengths, weighing the advantages of technological capability and network position and then making a decision as to focus. If their social networks with other firms are relatively strong, a focus on exploitation will allow them to improve innovation performance, leveraging the relative advantages of their social relationships.

This study contributes to the exploration-exploitation literature that has primarily used technological or organisational boundaries to distinguish exploration from exploitation (Rosenkopf and Nerkar 2001) by providing another criterion – the industry boundary. In this research, we raise the question of whether some R&D activity beyond organisational and technological boundaries may not be classified as exploratory search. When it comes to knowledge spillover and inter-firm dependence of learning, even a knowledge search outside firm boundaries or technologically distant from core expertise should be seen as an exploitative activity if the knowledge has been widely utilised in various ways by other firms in the same industry. For instance, even though technologies A and B may be completely dissimilar, combining these technologies may be a common practice in the industry. Our approach defining exploration as the pursuit of knowledge that is new to the industry effectively accounts for this situation. Under circumstances of strong interdependence among industry players, therefore, it is more appropriate to distinguish between exploration and exploitation based on industry boundaries.

In addition, when we relax our assumption about the exogeneity of our moderators and view technological capability and network position as endogenous variables affected particularly by outcomes of exploration and exploitation, the results of this study expand our understanding of the dynamic nature of ambidexterity and firm growth. Prior research has suggested that exploitation tends to generate competence-enhancing innovations and exploration leads to competence-destroying innovations (Jansen, Van Den Bosch, and Volberda 2006; Kim, Song, and Nerkar 2012) and that firms who succeed in technological exploration are likely to occupy a central position in the industry network (Baum, Shipilov, and Rowley 2003). Given these premises, our framework provides two different paths in which an incompetent, peripheral firm may grow into a competent, central firm, as illustrated in Figure 6. Specifically, after accumulating sufficient capability

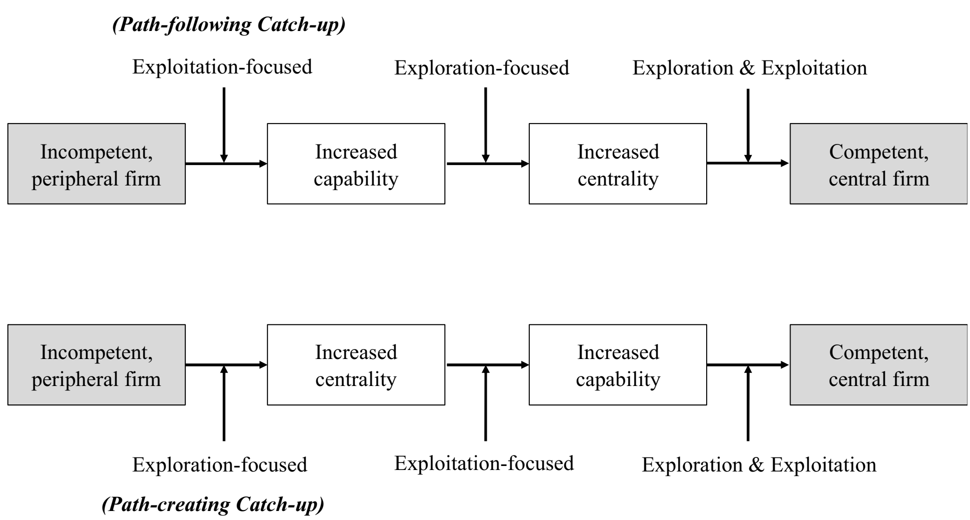

Figure 6. Two sequential paths of growth via exploration and exploitation.

with technology through the exploitation of widely accepted knowledge, a firm can go forward in a central position via exploration of new knowledge based on its accumulated expertise. Alternatively, a firm may initially focus on exploration to shake the existing positional order and then shift its focus towards exploitation to accumulate capability in the pioneer area. In both cases, we can see, at the growth stage, a temporal transition from exploration to exploitation, or vice versa. These models are consistent with the empirical results of prior research revealing that small firms benefit more from a focused strategy than from a balanced one (Ebben and Johnson 2005; Kim and Huh 2013). This study complements these previous studies by providing a foundational explanation of two specific possible directions and their promising sequential paths.

Lastly, the results of this study provide important managerial implications. Our findings suggest that managers should strategically allocate their scarce resources to exploration and exploitation depending on the relative strength between internal technological capability and external network position of their firm. If a firm has a relative strength in internal development over external knowledge acquisition, we suggest that the firm should focus more on exploration over exploitation. Conversely, if a firm's relative advantage is in acquiring knowledge through external connections over internal development, focusing more on exploitation would create more innovation opportunities. For the firms having both strong internal and external competences, their exploration and exploitation should be balanced. As such, this paper could provide a practical framework for strategic decisions for innovation in firms.

Our research has some limitations. The first is the generalisability of the framework outlined herein. To enhance the validity of our empirical analysis, we limit the context of exploration and exploitation to that of technological innovation and restricted our sample to firms in the semiconductor industry. Accordingly, this study's findings may or may not apply to other contexts, such as organisational design, or other industries, such as the pharmaceutical industry. For this reason, we call for future studies to test our framework in other organisational and industrial settings. Second, the potential endogeneity of our moderating variables is another limitation of this study. Although we assume that technological capability and network position are not readily changed in a short period of time due to their nature of resource accumulation (Dierickx and Cool 1989), it is entirely possible that managers might have invested in these resources for many years with a specific intention to increase (or decrease) exploration for their innovation. To the extent that this attempt was related to unobserved factors, our estimates could be vulnerable to omitted variable biases. Although we have included a variety of controls including firm- and year-fixed effects, we might not be able to entirely rule out the possibility of the omitted variable biases. Third, this study addresses only one type of embeddedness in social networks: positional embeddedness. Prior research has revealed other types of embeddedness, including relational embeddedness and structural embeddedness (Gulati and Gargiulo 1999). We suggest that future research should expand our understanding of ambidexterity by theorising and testing other types of embeddedness. Moreover, although we examine exploration and exploitation in R&D activity for technological innovation, we rely primarily on patent data, which only captures the success of upstream technological innovation. The commercialisation of created technology into new products, which is the other significant phase of technological innovation, is not considered. Therefore, the examination of aspects of commercialisation within our framework in future studies will shed further light on the relationship between exploration and exploitation and how firms should choose their emphasis based on the optimal balance point system identified in this study. Lastly, we test our hypotheses using a time span for the same technological paradigm; therefore, our predictions may not apply in environments of drastic change. A paradigm shift in technology can significantly change the whole structure of an industry. For example, in a technological environment of paradigm shift, we often observe that the most successful firms fail to adapt to the changing environment; thus, they suddenly disappear from the industry. An alliance network may also change dramatically due to new entrants to the industry and newly established relationships. In particular, during a period of paradigm shift, the social pressure to conform to previous conventions may weaken, and thus the effect of network position in shifting the optimal point towards exploitation may be minimal. We call for further research to investigate the dynamics among ambidexterity, technological capability, alliance network and industry (technology) evolution.

Acknowledgments

This research has been supported by the Institute of Management Research, Seoul National University.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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