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So Near And Yet So Far? Corporate Venture Capital, External Knowledge Search, and Knowledge Recombination Across Geographic And Technological Distance

Sheryl Winston Smith
Temple University
Strategic Management Department
swsmith@temple.edu

Ahreum Lee
Temple University
Strategic Management Department
ahreum.lee@temple.edu

Abstract

In their quest for competitive advantage, organizations engage in intentional knowledge search that spans both technological and geographic space. However, organizations often suffer from liability of distance ? i.e., an inherent trade-off between technological and geographic distance. In this paper, we investigate organizational learning in the medical device industry through the theoretical lens of recombinant search. Building on the external knowledge search and organizational learning literature, this paper proposes that CVC investments enable incumbents to overcome such technological and geographical constraints, thereby enhancing recombination of external knowledge generated by start-ups with their existing knowledge base to generate new knowledge. We hypothesize that CVC investments can significantly enhance organizational learning, i.e., exploitation and exploration, by investing in a set of start-ups that have diverse spectrum of technological knowledge base and locate in various geographical regions. The empirical setting is the medical device industry, typified by fast innovation cycles, well-defined intellectual property rights, and significant CVC investment. We test our hypotheses with novel, hand-collected panel data on 1,405 matched patent dyads between citing (i.e. incumbent) and cited firms (i.e. start-up) in the global medical device industry over the period 1978-2010. Our results show that multinational enterprises engage in both exploitation and exploration through CVC investment, but that these two types of knowledge search are situated distinctly along technological and geographic distance from the incumbent.

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ABSTRACT

In their quest for competitive advantage, organizations engage in intentional knowledge search that spans both technological and geographic space. However, organizations often suffer from liability of distance – i.e., an inherent trade-off between technological and geographic distance. In this paper, we investigate organizational learning in the medical device industry through the theoretical lens of recombinant search. Building on the external knowledge search and organizational learning literatures, this paper proposes that CVC investments enable incumbents to overcome such technological and geographical constraints, thereby enhancing recombination of external knowledge generated by start-ups with their existing knowledge base to generate new knowledge. We hypothesize that CVC investments can significantly enhance organizational learning, i.e., exploitation and exploration, by investing in a set of start-ups that have diverse spectrum of technological knowledge base and locate in various geographical regions. The empirical setting is the medical device industry, typified by fast innovation cycles, well-defined intellectual property rights, and significant CVC investment. We test our hypotheses with novel, hand-collected panel data on 1,405 matched patent dyads between citing (i.e. incumbent) and cited firms (i.e. startup) in the global medical device industry over the period 1978-2010. Our results show that multinational enterprises engage in both exploitation and exploration through CVC investment, but that these two types of knowledge search are situated distinctly along technological and geographic distance from the incumbent.

INTRODUCTION

Organizations engage in innovation to gain and retain competitive advantage over their rivals. However, no single firm has all relevant knowledge in-house to keep up with technological change in the market (Arora & Gambardella, 1990; Levin, Klevorick, Nelson, Winter, Gilbert, & Griliches, 1987). It is well established that firms face difficulties in generating innovations solely based on internal R&D (Henderson, 1993; Tushman & Anderson, 1986). Therefore, firms often span their boundaries of knowledge search to explore new insights and develop expertise (Rosenkopf & Nerkar, 2001). Particularly for access to early stage knowledge, large corporations often engage in corporate venture capital (CVC) investment, the practice of established firms taking equity investments in young, legally independent companies that are technologically innovative in general and that exhibit high growth potential (Maula & Murray, 2001) to enhance their own innovative output (Dushnitsky & Lenox, 2005a; Rothaermel, 2001).

While firms actively search for external knowledge, the effective integration of internal and external knowledge components requires organizational learning (Kogut & Zander, 1992). The current literature on CVC identifies numerous strategic benefits of CVC investments (Benson & Ziedonis, 2009; Dushnitsky & Lenox, 2005b; Winston Smith & Shah, 2013). CVC is posited as facilitating exposure to new markets and technologies, identification of acquisition targets, and market extension possibilities (e.g., Siegel, Siegel, & MacMillan, 1988; Sykes, 1990). However, less attention has been paid to the nature of organizational learning that occurs through CVC investment. This is particularly notable in comparison with the literature on equity alliances. Indeed, the current literature on equity investment such as joint ventures and M&As notes organizational learning in the form of exploitation as well as exploration depending on the degree of relatedness of technological knowledge of both parties (e.g., Beckman, Haunschild, &

Phillips, 2004; Rothaermel, 2001). Furthermore, the literature remains relatively silent on specific mechanisms through which corporate investors can gain competitive advantage. Importantly, firms search across multiple dimensions, i.e., across technological distance and across geographic distance, in their quest for solutions to problems (Phene, Fladmoe-Lindquist, & Marsh, 2006; Rosenkopf & Almeida, 2003). What is not clear, however, is how search behavior, i.e. exploitation and exploration, is impacted by tradeoffs along these two distinct dimensions. An important question is thus: When firms engage in external knowledge search through CVC investment, how do technological and geographic distance impact the exploitation-exploration continuum?

Finally, although deeply concerned with international sources of technological advantage and the sourcing of technological capabilities through international organizational relationships including R&D subsidiaries (Castellani, Jimenez, & Zanfei, 2013; Phene & Almeida, 2008), international acquisitions and international alliances (Yu, Subramaniam, & Cannella Jr, 2013) the international business literature remains surprisingly quiet regarding the search for early stage knowledge—and the competitive advantage that accrues to it—through external knowledge search and CVC investment. Indeed, recent considerations of IB theory recognize that the external linkages of MNEs are key components of knowledge sourcing and transfer (Cantwell, 2009; Cantwell, 2014; Teece, 2014). In this paper, we address the external knowledge search activities of MNEs through a particularly effective means of accessing early stage knowledge with high innovation potential: namely, CVC investment.

In the medical device industry, the context of this study, CVC investment is particularly prevalent. Dominant firms such as Boston Scientific, Guidant, J&J, and Medtronic operate in virtually all therapeutic market segments such as cardiovascular, neurological, spinal, and orthopedic domains, and they face fast product cycles and intense pressure to gain competitive advantage over their rivals through constant search for new innovation. The relatively low resource commitment of CVC investments (Rind, 1981) enables firms to invest in multiple start-ups with diverse set of technologies, thus increasing the likelihood of quick access to novel, emerging technologies and rapid adaptation to market and technology shifts.

We test our hypotheses with novel, hand-collected panel data on matched patent dyads between citing (i.e. corporate investor) and cited firms (i.e. start-up) in the global medical device industry over the period 1978-2010. Our theory and results expand the literature on CVC investment by incorporating a deep inside the firm consideration of the relationship between CVC investment and the potential for recombinant fruits of external knowledge search. To the best of our knowledge, this is the first study to combine the insights from knowledge recombination and CVC investing. The findings in this paper also have important implications for managers. As an extensive survey of CEOs globally indicates, external relationships are increasingly important for innovation (Pohle & Chapman, 2006). Our results highlight the use of CVC in the medical device industry to gain distinct knowledge and maintain an innovation edge.

The rest of this paper proceeds as follows. The next section provides theoretical background and develops our hypotheses. The following sections provide an overview of our unique patent dyad data. We then describe our empirical methodology. We provide empirical results in the next section and conclude with a brief discussion and conclusion.

THEORETICAL BACKGROUND AND DEVELOPMENT OF HYPOTHESES

Knowledge Search and Recombination

Organizational learning researchers suggest that search in an organization is one part of organizational learning process through which firms attempt to solve problems in an ambiguous world (Huber, 2012). Knowledge search as a firm's problem solving activities involves the creation and recombination of technological ideas (Katila & Ahuja, 2002). This implies that the process of true learning and innovation depends not only on the elements of knowledge, but also on the configuration of different knowledge sets (Nickerson & Zenger, 2004). In support of this perspective, the recombinant perspective of innovation suggests that new knowledge is created by new combinations of existing knowledge elements or combination of new knowledge elements (e.g., Fleming, 2002; Henderson & Clark, 1990).

In their search for solutions to problems, firms span a spectrum from local to distant search or from exploitation to exploration (Katila et al., 2002). Specifically, local search refers to the firm's behavior to search for solutions in the neighborhood of its current knowledge (Stuart & Podolny, 1996), whereas distant search means a firm's conscious effort to move away from current organizational routines and knowledge base (March, 1991). Similarly, exploitation is understood as the use and development of things already known to the firm, whereas exploration as the pursuit of knowledge, of things that might come to be known (Levinthal & March, 1993).

Organizations need to balance exploitation and exploration for long-run adaptation (e.g., Andriopoulos & Lewis, 2009; March, 1991; Rothaermel & Alexandre, 2009). For instance, conceptualizing exploitation and exploration as search depth and search scope respectively, Katila et al. (2002) found that pursuing exploitation and exploration simultaneously facilitates new product development. In a similar vein, through comparative case study, Andriopoulos et al. (2009) emphasizes the benefits of balancing expoitation and exploration and suggest the ways to manage tentions between exploitation and exploration.

While engaging in exploitation can deepen the understanding of established knowledge and enhance firms' ability to identify valuable knowledge elements within it and to combine them in different ways, heavily relying on established knowledge can lead a firm to fall into competency trap (Levitt & March, 1988) or propinquity trap (Ahuja & Morris Lampert, 2001). Firms that develop core competencies in a certain area tend to engage in that activity more frequently, thereby becoming trapped by their own competencies, with potentially self-destructive consequences (Leonard-Barton, 1992). By trapping by their own competencies, firms are more likely to suffer from obsolescence due to technological progress or changes in market demand. This is particularly true in technology-intensive industries where the pace and complexity of technological change create many uncertainties for firms (Wadhwa & Kotha, 2006). Therefore, firms span their boundaries to explore new ideas, insights, and expertise –i.e., exploration, which would increase a set of knowledge components necessary to provide a sufficient amount of choice to solve problems (March 1991) and subsequently the possibility of finding a new useful combination (Katila & Ahuja, 2002).

As the literature suggests, searching for knowledge beyond the firm's organizational and technological boundaries and ultimately integrating and utilizing such knowledge—provides fundamental building blocks of innovation (Henderson & Cockburn, 1994; Von Hippel, 1994). Again, however, relying exclusively on exploration is highly risky since it incurs substantial costs of experimentation without reaping the benefits from it (March, 1991). In practice, innovations with breakthrough technology often fail to find markets to reap profits which are large enough to compensate for the opportunity cost of other alternatives mainly because those innovations are beyond current customers' needs (Allen, 2012; Stevens & Burley, 2003).

Increasingly, exploitation and exploration are characterized along a continuum. In this view, exploitation and exploration can be differentiated based on the amount of previous or new knowledge on which they build rather than on the presence or absence of previous or new knowledge (Gupta, Smith, & Shalley, 2006) [1] From this perspective, for instance, an organizational activity is increasingly exploitative the more anchored it is in existing knowledge and vice versa (Benner & Tushman, 2002). Recent studies on organizational learning increasingly conceptualize them as orthogonal variables such that these types of learning are simultaneously achievable (Gupta et al., 2006). According to this perspective, these types of learning are potentially unlimited (Baum, Li, & Usher, 2000). In support of this perspective, a substantial body of literature on equity investment such as alliances, joint ventures, and M&As suggests that external corporate ventures are often alternative vehicles for inter-organizational learning such that exploitative and explorative learning take place simultaneously depending on the degree of relatedness of technological knowledge of both parties (Beckman et al., 2004; Rothaermel, 2001).

Scope of Knowledge Search across Technological and Geographic Distance

In order to remain competitive, organizations search for knowledge across both technological and geographic space (Phene et al., 2006; Rosenkopf et al., 2003). Firms in general can search knowledge along these two dimensions in the following manner:1) technologically distant, but geographically close knowledge, 2) technologically and geographically distant knowledge, 3)

[1] As Gupta et al. (2006) argue, by March (1991)'s definition, many organizational activities that should be considered as exploitative would instead be viewed as exploratory, and therefore, it is more logical to differentiate between exploitation and exploration based on the amount of previous or new knowledge on which they builds rather than on the presence or absence of previous or new knowledge. According to March (1991), exploitation and exploration are mutually exclusive activities. In other words, exploitation and exploration are fundamentally incompatible and therefore take place in the form of a zero-sum game where they compete for scarce resources and organizational attention (Gupta et al., 2006). The implicit assumption behind this perspective is that exploratory activities refer solely to the use of knowledge that is completely new to the firm. Reflecting this perspective, empirical studies often distinguish between innovations that rely on a firm's existing knowledge and innovations that draw on no previous firm knowledge (e.g., Rosenkopf & Nerkar, 2001).

technologically and geographically close knowledge, 4) technologically close, but geographically distant knowledge.

Insert Figure 1 about here

As noted, firms search for knowledge spanning a spectrum from technologically proximate to technologically distant knowledge, thereby broadening their knowledge base. The organizational learning literature suggests that learning is a cumulative activity (Stuart et al., 1996). From this perspective, firms that specialize in a certain technological domain are expected to possess a high level of understanding on technologies belong to that domain. That is, in this case, firms possess a high level of absorptive capacity, the ability of a firm to recognize the value of new, external knowledge, assimilate it, and apply it to commercial ends (Cohen & Levinthal, 1990). Due to the accumulated prior related knowledge, therefore, if firms seek technologically familiar and proximate knowledge, they should be able to better understand the logic behind such knowledge and utilize it effectively to commercial ends.

When searching for technologically distant knowledge, however, firms face difficulty in understanding such knowledge and applying it to new product development process. Difficulty of searching for technologically distant knowledge partly arises from firms' problem-solving cognitive frame, a set of givens, beliefs, or assumptions about which alternatives are worth exploring, the consequences of choosing each alterative, and the expected impact on a problem (Afuah & Tucci, 2012). Such a problem-solving cognitive frame is relatively stable and to a great extent influenced by the experience and history of the firm and the individuals therein (Nelson & Winter, 1982), and therefore, a firm is more likely to better recognize external knowledge close to its existing knowledge base than completely new knowledge to the firm

(Cohen et al., 1990). Acquiring technologically distant knowledge may mean more causal ambiguity, causing confusion. Therefore, when searching for technologically distant knowledge, a firm inevitably faces with more decision elements as to possible alternatives and their consequences (King, 2007). Such a process entails successive trials and experiments (Henderson et al., 1990), suggesting the cost and effort to recombine completely new knowledge increases with technological distance (Weitzman, 1998). Put simply, it will take more time and more effort to understand the causal ambiguities surrounding a new technology.

In addition to technological boundaries, firms can search for knowledge across geographic boundaries. The international business literature suggests that different countries develop distinctive technological competencies by leveraging unique knowledge accumulation patterns (Cantwell, 1989). Likewise, Phene et al. (2006) argue that there are differences in terms of the type of knowledge generated and the manner in which this knowledge is created in different national context. Furthermore, due to the differences in perspectives and cognition, inventors in different national contexts may utilize the same components of knowledge in quite different ways (Phene et al., 2006). Therefore, accessing and acquiring knowledge from a different national context would provide a firm with the increased opportunity set of new components that can be utilized. Current studies on innovation suggest that firms leverage knowledge over a wide range of disciplines by tapping into a diverse set of knowledge in foreign locations, which enables the firm to be in a better position to combine knowledge in a more complicated way (Bierly & Chakrabarti, 1996), thereby creating causal ambiguity which increases the sustainability of competitive advantages (Reed & DeFillippi, 1990). Applying this logic to regional level, as Verspagen and Schoenmakers (2004) suggest, different regions are characterized by different knowledge bases as a consequence of culture, organization of industry, peculiar practices and rules, and scientific, regulatory environments. A substantial body of literature on clusters and regional innovation systems recognize the differences across regions within a country; a group of firms whether from same industry or different industry form a cluster, thereby they share local social as well as regulative context (Maskell & Malmberg, 1999). Tacit knowledge is highly contextual and difficult to codify, therefore, requires direct face-to-face interactions and a shared local context (Feldman, 1999). A certain type of knowledge thus is more likely to stay and be shared among firms within the cluster, reinforcing specialized knowledge within the cluster.

On one hand, seeking technologically distant as well as geographically distant knowledge seems ideal since it would create non-overlapping knowledge bases, thus potentially increasing novel innovations (Phene et al., 2006). However, due to the inherent trade-off between technological and geographical distance, achieving it is not an easy task. Put it another way, external knowledge recombination inherently suffers from liability of distance in terms of technological and geographical distance (Phene et al., 2006). A firm's new knowledge search to a large extent is technologically (Jaffe, Trajtenberg, & Henderson, 1993) and geographically bounded, and as a result, firms are more likely to have difficulty in understanding both technologically and geographically distant knowledge and applying it to their own problem. The difficulty of external knowledge recombination arising from technological distance is further aggravated by the geographical distance. First, geographical distance increases the cost of transferring knowledge (Rosenkopf et al., 2003). Knowledge, particularly in high-tech industries, has a high degree of tacitness, which tends to increase the challenges of understanding. This implies that knowledge cannot be transferred at non-significant costs between individuals or regions, and must be transmitted by close personal interaction, or by a combination of codified sources, experimentation on the receiving end (Verspagen et al., 2004). In support of this, studies on knowledge spillovers find that knowledge spillovers tend to be more intense between parties that are located close to each other in space (e.g., Jaffe & Trajtenberg, 1996; Jaffe et al., 1993). Second, as noted, different countries (Cantwell, 1989) or even regions develop distinctive technological competencies by leveraging unique knowledge accumulation patterns. Such differences or nuance within different countries or regions would pose challenges for a firm such that the firm's ability to access and utilize a large amount of geographically distant knowledge will be limited. Therefore, it is critical to have either technological or physical proximity (Tallman & Phene, 2007). In the case of technologically distant knowledge, geographical proximity becomes critical. Similarly, if a firm wants to access to geographically distant knowledge, then technological proximity has to be ensured.

CVC as a Solution to Knowledge Search and Recombination

The current literature on CVC investment shows that CVC can facilitate incumbents' learning through different knowledge transfer and integration mechanisms; for instance, Dushnitsky et al. (2005a) suggest that CVC investment is conducive to incumbents' learning by promoting their ability to understand the changing dynamics that govern the market, technology and competition and allowing them to interact with start-ups. In a similar vein, Schildt, Maula, and Keil (2005) propose that, compared to non-equity venturing activities, CVC investment is conducive to exploratory organizational learning. Behind the incumbents' learning, there are several knowledge transfer and integration mechanisms at play: first, incumbents can learn from CVC investments through the due-diligence process which allows the incumbent firms to learn about all aspects of a venture such as business plans, technology resources, and proposed products prior to committing capital (Dushnitsky et al., 2005b). Second, they take board seats or board observation rights which provide them with knowledge of the ventures' key technologies (Maula et al., 2001). Third, incumbents can set up specific organizational routines to encourage and funnel learning by utilizing liaisons (Daft & Lengel, 1986), developing joint projects between business units and start-ups, holding face-to-face meetings with top management, and participating in venture fairs (Zahra, Ireland, & Hitt, 2000). Such mechanisms, more or less, enhance the chance of interaction between an incumbent and start-ups that they invest in, which reduces causal ambiguity around the technologies of start-ups and facilitates knowledge transfer (Tsai & Ghoshal, 1998), consequently increasing the possibility of a novel recombination of parts of the incumbent's established knowledge with a start-up's new knowledge and/or combination of a start-up's new knowledge elements.

Notwithstanding the learning benefits from CVC investments in general, current literature has not taken both types of learning simultaneously into account and further did not pay sufficient effort to delineate the underlying mechanism in CVC investment setting. Compared to other types of equity investments such as joint ventures and acquisitions, CVC investment requires relatively low resource commitments (Rind, 1981), which enables incumbents to reach out multiple start-ups all over the place. Start-ups may have diverse spectrum of technological knowledge base, and therefore, to some extent there should be variation in terms of relatedness of technological knowledge between a focal incumbent and start-ups depending on what kind of start-ups that the incumbent invest in. As such, CVC investments can significantly enhance organizational learning-i.e., exploitative and explorative organizational learning (March, 1991) by investing a set of start-ups which have various technological knowledge base. That is, incumbents can balance between the need to harvest existing knowledge by augmenting them with the new technological knowledge gained from the start-ups and the need to explore new technological frontiers that can alter the complexion of the industry they are operating in. For example, consider a firm such as Medtronic. Medtronic's core competency lies in cardiac stimulation. In 2011, Medtronic introduced Activa SC neurostimulator, a device for Parkinson's diseases, essential tremor, and dystonia. Neuro stimulation was not its core competency, but through the investments in start-ups it could not only exploit its existing specialty-i.e., cardiac stimulation in greater depth, but also explore new area with new technology from start-ups – i.e., neurostimulation. In other words, Medtronic could simultaneously engage in a high degree of exploitation and a high degree of exploration.

Exploitation through CVC Investments. Start-ups provide a diverse spectrum of technological knowledge, and incumbents may limit their CVC investments to the start-ups that possess related knowledge base. By investing into related start-ups, incumbents can compare the knowledge they obtain from start-ups and leverage their existing knowledge base by adding complementary insights in their existing understanding about the technologies, industries and markets. In other words, combining related knowledge from start-ups with incumbents' existing knowledge can intensify exploitative learning by allowing them to assimilate preexisting knowledge elements into new syntheses, new patterns, or new configurations (Katila, Rosenberger, & Eisenhardt, 2008). Although a high level of knowledge overlap between an incumbent and start-ups may reduce the possibility to create novel recombinations, it would enhance the ability to understand and absorb the start-ups knowledge (Sears & Hoetker, 2013), ultimately allowing the incumbent to make the most out of its existing knowledge. Hypothesis 1 follows:

Hypothesis 1: CVC investment <u>in technologically close</u> start-*ups facilitates an incumbent's* <u>exploitation</u> of its existing knowledge base, i.e. is associated with less recombination of knowledge elements from the start-up.

In the case of exploitative learning, to leverage existing knowledge base, incumbents would look for new knowledge from start-ups which are located in a relatively geographically distant region. The collocated start-ups within the region where an incumbent is located are more likely to have same or similar manner the knowledge is used in innovation due to institutional factors, culture, organization of industry, and scientific, regulatory environments within the particular region. Therefore, seeking for similar knowledge in a geographically proximate region would not provide much opportunity of learning. However, incorporating geographically distant knowledge would enable incumbents to find new ways of using existing knowledge, thus creating more value. Given the localized nature of knowledge (Jaffe et al., 1993), geographical distance can delay knowledge transfer and acquisition (Freel, 2003). Thus, the knowledge which incumbents are familiar with is less likely to be commonly used in geographically distant locations (Phene et al., 2006). By incorporating knowledge that is geographically distant, incumbents would enhance the likelihood of finding novel ways to use their existing knowledge. That is, geographical distance can revitalize existing knowledge, delay its obsolesce and therefore enhance its value. Hypothesis 2 follows:

> Hypothesis 2: CVC investment in geographically close start-*ups facilitates an incumbent's* exploitation of its existing knowledge base, i.e.is associated with less recombination of knowledge elements from the start-up.

Exploration through CVC Investments. By acquiring broad knowledge about emerging technologies and markets, incumbents establish a foundation for planning their future operations and investments in various emerging technologies. Incumbents learn from exploration by incorporating new knowledge that is unfamiliar and recombining it in novel ways with their current knowledge base (Wadhwa et al., 2006). Investing in a portfolio of start-ups that have dissimilar knowledge provides incumbents with rich insights into changing technological paradigms, and this new knowledge adds to the repertoire that the incumbents can bring to bear on any new problem that they face (Ahuja et al., 2001). In the related context of acquisitions, Sears and Hoetker (2013) argue that the more dissimilar the knowledge between an acquirer and a target, the greater the opportunities for novel recombinations, to the extent that the acquirer has sufficient absorptive capacity. Applying this logic, it is expected that incumbents can learn more from technologically distant start-ups, enhancing the likelihood of generating novel innovation. Hypothesis 3 follows:

> Hypothesis 3: CVC investment in technologically distant start-*ups facilitates an incumbent's* exploration of a relatively new knowledge base, i.e. is associated with greater recombination of knowledge elements from the start-up.

As argued previously, the international business literature suggests that different countries develop distinctive technological competencies (Cantwell, 1989). Phene et al. (2006) argue that there are differences in terms of the type of knowledge generated and the manner in which this knowledge is created in different national context. Furthermore, due to the differences in perspectives and cognition, inventors in different national contexts may utilize the same components of knowledge in quite different ways (Phene et al., 2006). Therefore, accessing and acquiring knowledge from a different national context would provide a firm with the increased opportunity set of new components that can be utilized. Hypothesis 4 follows:

> Hypothesis 4: CVC investment in geographically distant start-*ups facilitates an incumbent's* exploration of a relatively new knowledge base, i.e. is associated with greater recombination of knowledge elements from the start-up.

METHODOLOGY

Research Setting: The Medical Device Industry

The medical device industry is an exceptional target for studying external knowledge search through CVC investment. Incumbent medical device firms are among the largest CVC investors, and the medical device industry is one of the main foci of corporate venture capital investment (PricewaterhouseCoopers, 2006). Incumbents rely on both incremental and breakthrough innovation strategies that require grasping new, often radical, technological and market trends ahead of competitors (Economist, 2000; J.P.MorganSecurities, 2006). As well, intellectual property plays a strong role in this industry (Cohen, Nelson, & Walsh, 2000). Thus, patent-related measures provide strong insights into invention and innovation in this industry.

Sample Selection and Data

We construct the sample from all CVC investments in the medical device industry made by the 4 largest medical device-CVC investors in this industry over the period 1978-2010. The four incumbent device companies in the sample (Medtronic, Boston Scientific, Guidant, and Johnson & Johnson) together account for the majority of CVC investment in the industry and are four of the top ten by sales (Standard and Poor's Corporation, 2007). Firm level financial data on CVC investment are drawn from the VentureXpert database available from Thomson Financial that collects data from the National Venture Capital Association and other sources. VentureXpert has been used in many studies of CVC activity (Benson et al., 2009; Dushnitsky et al., 2005a, 2005b; Dushnitsky & Lenox, 2006).

Our unit of observation is the patent dyad, where each CVC investor patent and each cited startup company patent is a dyad. We collected all patents filed by the four incumbents and the portfolio companies between 1978 and 2010 using the US Patent and Trademark Office (USPTO) database. Patents must cite related prior patents, enabling us to link each incumbent's patents to the start-up companies' patents. We identified 2,620 unique patents in our sample, consisting of 1,637 patents for incumbents and 983 patents for start-ups; 299 start-up patents were not cited by incumbents and thus are not included in the dyads we identified. Since our intent is to investigate the incumbent's learning through investing in start-ups, we limit our sample to the realized investment dyads, resulting in 1,405 citing patent (incumbent)-cited patent (start-up) dyads in total.

Sample Description: Diversity of Patent Technology Classes

Following others in the literature (Fleming & Sorenson, 2001; Yayavaram & Ahuja, 2008), we conceptualize patent technology classes as representing distinct knowledge elements. Under The U.S. Patent Classification System, every patent is assigned to a patent class and subclass by the U.S. Patent and Trademark Office (USPTO) based on the information provided in the patent application (Anand, Oriani, & Vassolo, 2010). Patent classes reflect the technological principals of an invention as well as distinct technological knowledge elements, and as such, have been widely used to access firms' technological capabilities (Jaffe et al., 1993; Penner-Hahn & Shaver, 2005). For instance, Jaffe (1986) captures the technological position of the firm by utilizing patent class data. In a similar vein, a substantial number of studies (e.g., Reuer & Lahiri, 2013; Sampson, 2007) use patent class data to capture firm technological capabilities. From this perspective, patent classes enable us to compare the technological profiles of incumbents and start-ups in detail.

Examination of the technology classes in which incumbents and start-ups patent points to avenues for both exploitation and exploration by incumbents. Overall, incumbents patented in 101 distinct technology classes and start-ups patented in 127 distinct technology classes. The dyads we identified include 684 unique patents with 101 technology classes (patents in 26 classes were not cited by the incumbents at all and thus are not included in the rest of our analysis). The top 10 technology classes for the incumbents and startup patents are presented in Table 1 and 2, respectively, where the ranks are in order of the number of classes included within the patents.

Not surprisingly, the most frequent technology classes within the technological profile of incumbents and start-ups fall within surgery-related technologies, e.g., patent class 600, 604, 606 and 128. However, many other technology classes—beyond those above that are typically thought of as "medical device classes"—occur frequently in both incumbent and start-up patents.

Insert Table 1 about here

Insert Table 2 about here

Notably, the distribution of technology classes inhabited by the incumbents differs from that of the start-ups, suggesting that these two groups—incumbents and start-ups—represent distinct knowledge pools. In Table 3 and Table 4 we further dig into technology classes that represent incumbents' exploitation and exploration, respectively. On the one hand, both start-ups' and the incumbents' patent in many of the same technology classes, indicating incumbents' exploitation of knowledge elements of which they are already in possession. To give an example, technology class 435 accounts for 8.8% of patents among the total number of technology classes in the start-ups' patents, while consisting of 1.2% among the total number of technology classes in the incumbents' patents.

On the other hand, start-ups are patenting in 14 technology classes that are distinct from the incumbents' patents; in other words, these are technology classes in which the incumbents are engaged in exploration. For instance, technology class 96 ranks first in order of the frequency of startup patents, amounting to 0.37% among the total number of technology class in the start-ups' patents, while no incumbents possesses this technological class.

Insert Table 3 about here

Insert Table 4 about here

To visualize the search patterns of incumbents more effectively, we utilize a network analysis approach to map the knowledge structure of each of the incumbents and each of the start-ups. We show here one of the incumbents (J&J) alongside the knowledge structure of two start-ups in which J&J has invested (Wasserman & Faust, 1994).[2] These knowledge maps provide visual intuition into exploitation and exploration search. As seen in Figure 2, J&J is most highly concentrated in technology classes 600, 606, 623, and 264, in that order, where the size of the vertex is proportional to the concentration in that class. Figure 3a and 3b show the knowledge maps of two start-ups in which J&J made CVC investments: Acorn and Cardiovention. Acorn represents a typical example of exploitation. It shows a high level of specialization in technology class 600, in which J&J has biggest concentration of patents. Furthermore, in addition to technology class 600, most of the other technology classes in Acorn's patents also belong to

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[2] Our knowledge mapping procedure is derived from social network analysis, whereby the vertices (in this case technology classes) and edges (co-occurrence of technological classes) represent the "map" of each organization's knowledge space. (Details are available from authors upon request).

technology classes in which J&J focuses. In contrast, Cardiovention represents exploration. Its specialization is technology class 604, a lesser-populated class for J&J. Applying the logic of exploitation and exploration as a continuum, we can see J&J exploring knowledge in this area through investing in Cardiovention. These maps also help provide the intuition for thinking about exploitation and exploration along a continuum rather than as distinct activities. Finally, we note that J&J's learning pattern is consistent with our argument of the impact of technological and geographic distance on the exploitation and exploration continuum. Specifically, in the case of Acorn, its technological and geographic distance are 0.255 and 998 km respectively. In contrast, in the case of Cardiovention, its technological and geographic distance are 0.822 and 2,530 km respectively.

Insert Figure 2 about here

Insert Figure 3a about here

Insert Figure 3b about here

Dependent variable

Knowledge Recombination. Our dependent variable captures the extent to which an incumbent patent recombines technological knowledge from the startup patents that it references (i.e., Recombination) and is conceptually related to measures of knowledge recombination breadth in the literature (Gruber, Harhoff, & Hoisl, 2012).

We operationalize our dependent variable in two ways. First, we operationalize exploitation and exploration as a continuum with the dependent variable Recombine. To construct this variable we enumerate the set of patent technology classes unique to each patent dyad and represent each as a unique vector. Given that our firms are all in the medical device industry we incorporate each patent class subclass combination on a patent as a unique knowledge element (e.g., the class-subclass combination 623.11 is distinct from 623.14). We then compare the patent classes spanned by the citing patent relative to the cited patent that it incorporates. We measure this mathematically using the cosine similarity of the vectors (Manning, Raghavan, & Schütze, 2008). Our variable is equal to one minus the patent dyad cosine similarity; thus greater difference between knowledge classes spanned in the dyad reflects higher the knowledge recombination, and thus higher exploration and vice versa.

Second, we consider an alternative conceptualization where we consider exploitation to be the lowest quartile of recombination (Recomb25) and exploration to be the highest quartile of recombination (Recomb75). Drawing on the logic that exploitation and exploration are on continuum, ranging from 0 to 1, we consider exploration if the value is over the lower and upper quartile and vice versa. This is a more conservative measure and makes a clear distinction between these two types of learning.

Focal independent variables

Our focal independent variables are technological distance and geographic distance between the CVC investor and the start-up.

Technological Distance. There are some measures that essentially capture the extent to which how dissimilar pair firms' technological profile is. First, prior studies (e.g., Ragozzino, 2009; Reuer et al., 2013; Rosenkopf et al., 2001) measure technological distance between two firms by Euclidean distance between the pair's portfolios of three-digit technology classes. For instance, Rosenkopf et al. (2001) measure technological distance between each pair of firms, ranging from 0 to 1.4 by aggregating the set of patents for each firm and then summarizing the percentage of assignments in each patent class.

Drawing on this, we created vectors for paired incumbents and start-ups and calculated technological distance using Euclidean distance. For instance, if incumbent and startup vector for each patent dyads are (0, 0, 0, …, 0, 4, 0, 0, 0, 0) and (0, 0, 0, …, 0, 1, 0, 0, 0, 0) respectively, then the Euclidean distance is calculated as following:

Euclidean distance = $\sqrt{(0-0)^2+\cdots+(4-1)^2+\cdots+(0-0)^2} = 3$

Since this measure gives us individual patent dyads, not incumbent-start-up dyads, we aggregated technological distance by each specific incumbent-startup dyad such as Medtronic (incumbent)-3F (startup) dyad etc. and then averaged them.

Geographic Distance. Following previous studies (e.g., Coval & Moskowitz, 1999; Ragozzino, 2009; Reuer et al., 2013), we measure geographic distance between the CVC investor and the start-up by using spherical geometry and applied the Great Circle distance formula[3]. To calculate geographic distance, we collected latitude and longitude coordinates on incumbents and start-ups' locations based on zip codes.

Control variables

In order to control for unobserved heterogeneity or alternative possible explanations, a number of controls were included in the model.

Knowledge Age. In addition to technological and geographical distance, we include age of

[3] Geographic Distance = r × acros[sin ($lat_{incumbent}$) × sin ($lat_{startup}$) + cos($lat_{incumbent}$) ×cos($lat_{startup}$) × cos($lon_{startup}$−$lon_{incumbent}$)], where r is the radius of the earth in miles (r = 3,963), and the latitude and longitude coordinates for both an incumbent and a startup have been converted into radians by dividing by 180/π (Ragozzino, 2009).

knowledge. According to organizational learning literature, it has been widely accepted that a firm's knowledge searching behavior is path-dependent, indicating a firm searches for new solutions close to existing solutions (e.g., Keil, 2004; Leonard-Barton, 1992). From this perspective, it is reasonable to expect that age of an incumbent's knowledge would affect the incumbent's propensity of knowledge recombination such that an incumbent with old knowledge is more likely to exploit such knowledge. We measured age of knowledge by application date of patent. Each patent document includes the date when the inventor filed for the patent-i.e., application date and the date when the patent was granted-i.e., grant date. Since the actual timing of the patented inventions is closer to the application date than to the grant date (Hall, Jaffe, & Trajtenberg, 2001), we rely on application date.

Additional controls. Following prior work (e.g., Dushnitsky et al., 2005a; Wadhwa et al., 2006), we include the number of patents the startup possesses, the number of backward citations from incumbent to start-up and if start-ups are acquired by incumbents as additional control variables. We also include dummy variables to control for incumbent firm heterogeneity.

Model and Econometric Approach

The basic regression model used in the analyses is as follows:

$$\mathrm{Pr}(\mathrm{Knolwedge\ Recombination}) = \beta_0 + \beta_1 Technological\ distance_{ij} + \beta_2 Geographic\ distance_{ij} + Controls + \varepsilon_{ijt}$$

where Pr(Knowledge Recombination) is the incumbent's probability of knowledge recombination; Technological distance $_{ij}$ is the dissimilarity of knowledge between an incumbent i and a startup j; Geographic distance $_{ij}$ is the distance between an incumbent i and a startup j; and a series of controls and the error term complete the specification.

In our first model, our dependent variable Recombine is a continuous variable that ranges between 0 and 1. We estimate it using a Tobit regression model to account for the censored regression (Greene, 2008). Our second two models are based on dichotomous dependent variables, Recomb25 and Recomb75, respectively. We estimate these using Probit regression framework (Greene, 2008). Results are also robust to logit specification.

RESULTS AND DISCUSSION

Means, standard deviations, and correlations are provided in Table 5. We report the results of the Tobit and Probit regression analysis in Table 6.

Insert Table 5 about here

Insert Table 6 about here

Model 1 reports the result of Tobit regression analysis. Model 2 and 3 report the results of Probit regression analysis for the 25 percentile and 75 percentile recombination respectively. Hypothesis 1 posits the exploitation through searching for start-ups that possess technologically similar knowledge, while hypothesis 4 posits the exploration through searching for start-ups which possess technologically dissimilar knowledge. The results in Model 1 and 3 show that technological distance is positive and significant ($p < 0.001$), while in Model 2 technological distance is found to be negative and significant ($p < 0.001$), thus supporting hypothesis 4. This indicates that greater recombination of knowledge elements from the startup-i.e., exploration is enhanced through engaging in external knowledge search for technologically dissimilar knowledge. However, exploitation takes place through investing in start-ups with technologically similar knowledge. Hypothesis 2a, 2b and 4 argue the relationship between geographic distance and exploration. The results in Model 1 and 3 show that geographic distance is positive and significant ($p < 0.001$ and $p < 0.05$ for Model 1 and 3 respectively), whereas in Model 2, it is found to be negative and significant ($p < 0.05$), supporting hypothesis 2a and 4. This indicates that greater recombination of knowledge elements from the start-up-i.e., exploration is enhanced through engaging in external knowledge search for start-ups that are located in geographically distant space. However, exploitation is enhanced through investing in start-ups that are located in geographically close space.

Overall our regression results show that incumbents search external knowledge in both geographically and technologically distant space, and CVC investment enables incumbents to achieve both exploitation and exploration. In case of exploration learning, in particular, it is possible because CVC investment allows them to overcome the trade-off between technological and geographic distance. Recall 4 types of knowledge search in CVC (Figure 1). Type 2 and 3 represent clear-cut exploration and exploitation respectively. From the results above, we confirm that incumbents enhance exploration by searching for technologically as well as geographically distant knowledge-i.e., type 2. We also confirm that unlike exploration, incumbents exploit their existing knowledge base by searching for technologically as well as geographically close knowledge-i.e., type 3. Conceptually, type 1 and 4 would lie somewhere between type 2 and 3 (two end of the continuum), and since incumbents can achieve both type 2 and 3, it is reasonable to expect that they should be able to achieve type 1 and type 4. That is, incumbents do enhance organizational learning by spanning their knowledge search boundary from exploitation and exploration continuum.

In addition, among the control variables, we found that knowledge age matters for exploration, especially in case of incumbents' knowledge. That is, as seen from Model 1 and 2, incumbent knowledge age is found to be positive for exploration, but negative for exploitation, indicating that as incumbents possess old knowledge, they are more likely to engage in exploitation through CVC investment. This reflects the incumbents' path-dependent learning which is widely supported by current organizational learning literature (e.g., Keil, 2004; Leonard-Barton, 1992).

CONCLUSION

We find that multinational enterprises engaged in CVC investing engage in external knowledge search that spans the exploitation-exploration spectrum. We identify two dimensions along which this knowledge search occurs—technological distance and geographic distance—and identify the relative importance of these two distinct types of distance in exploitation versus exploration behavior. Our findings suggest CVC investing allows these global incumbents to differentially access knowledge that is distant in both technological and geographic space for exploration, while also accessing knowledge that is closer in both dimensions for exploitation purposes. In doing so, we contribute extend the existing frameworks in the alliance literature and in the international business literature to an important activity through which external knowledge search occurs, namely CVC investing. Furthermore, we also contribute to the literature on CVC investing by peering inside the black box of incumbents' learning mechanism-i.e., recombination of external and internal knowledge. In doing so, we explore the implication of CVC investing for incumbents' ability to generate new knowledge and ultimately competitive advantage.

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Type 1 Technologically distant, but geographically close knowledge	**Type 2** Technologically and geographically distant knowledge
Type 3 Technologically and geographically close knowledge	**Type 4** Technologically close, but geographically distant knowledge

Figure 1. Types of Knowledge Search in Geographic and Technological Space

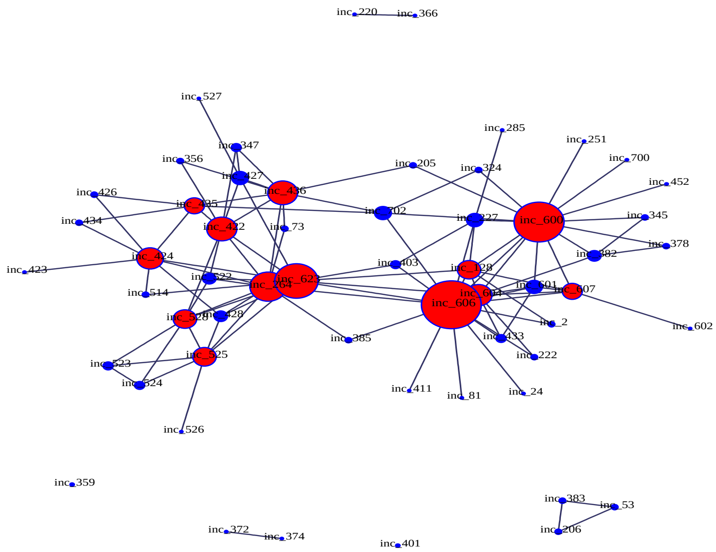

Figure 2. Johnson and Johnson Knowledge Map

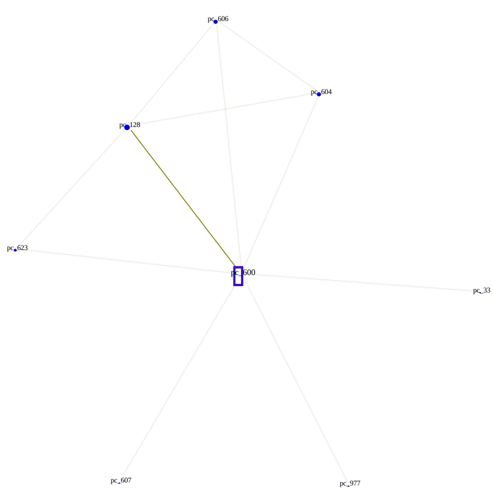

Figure 3a. Acorn Knowledge Map

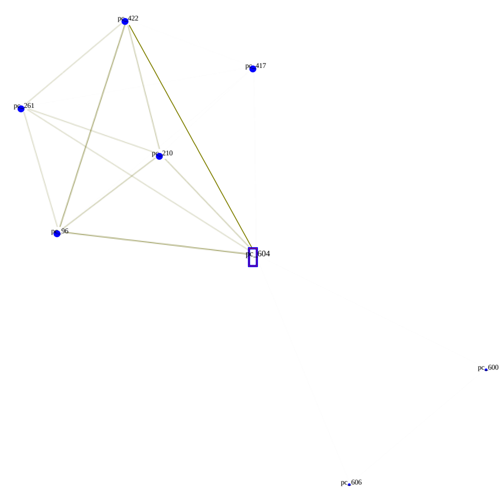

Figure 3b. Cardiovention Knowledge Map

Table 1. Most Frequent Technology Classes, Incumbents

Rank	Technology class	Technology class title	% of incumbent patents that include technology class:
1	606	Surgery	21.87%
2	600	Surgery	14.33%
3	623	Prosthesis (i.e., artificial body members), parts thereof, or aids and accessories thereof	14.29%
4	607	Surgery: light, thermal, and electrical application	11.93%
5	604	Surgery	11.48%
6	227	Elongated-member-driving apparatus	5.75%
7	128	Surgery	1.59%
8	264	Plastic and nonmetallic article shaping or treating: processes	1.32%
9	422	Chemical apparatus and process disinfecting, deodorizing, preserving, or sterilizing	1.28%
10	427	Coating processes	1.28%

Table 2. Most Frequent Technology Classes, Start-ups

Rank	Technology class	Technology class title	% of start-up patents that include technology class:
1	606	Surgery	16.78%
2	604	Surgery	9.21%
3	600	Surgery	9.19%
4	623	Prosthesis (i.e., artificial body members), parts thereof, or aids and accessories therefor	9.16%
5	435	Chemistry: molecular biology and microbiology	8.79%
6	607	Surgery: light, thermal, and electrical application	7.29%
7	422	Chemical apparatus and process disinfecting, deodorizing, preserving, or sterilizing	3.91%
8	436	Chemistry: analytical and immunological testing	2.64%
9	536	Organic compounds	2.64%
10	514	Drug, bio-affecting and body treating compositions	2.13%

Table 3. Evidence of Exploitation, Most Frequent Overlapping Technology Classes

Rank	Technology Classes for Start-ups		Frequency: Start-ups	Frequency: Incumbents	Difference*
1	435	Chemistry: molecular biology and microbiology	8.7893%	1.1989%	7.5904%
2	422	Chemical apparatus and process disinfecting, deodorizing, preserving, or sterilizing	3.9127%	1.2802%	2.6324%
3	381	Electrical audio signal processing systems and devices	1.9563%	0.0610%	1.8954%
4	514	Drug, bio-affecting and body treating compositions	2.1265%	0.3455%	1.7810%
5	436	Chemistry: analytical and immunological testing	2.6368%	1.0364%	1.6004%
6	438	Semiconductor device manufacturing: process	1.2759%	0.0813%	1.1946%
7	128	Surgery	2.0981%	1.5850%	0.5131%
8	361	Electricity: electrical systems and devices	1.2192%	0.7316%	0.4876%
9	424	Drug, bio-affecting and body treating compositions	1.5878%	1.1583%	0.4295%
10	385	Optical waveguides	0.7088%	0.3048%	0.4040%
11	356	Optics: measuring and testing	0.4253%	0.0610%	0.3643%
12	73	Measuring and testing	0.5954%	0.2642%	0.3312%
13	428	Stock material or miscellaneous articles	0.6805%	0.3658%	0.3147%
14	415	Rotary kinetic fluid motors or pumps	0.3402%	0.0406%	0.2996%

* Difference between the frequency in start-ups and frequency in the incumbents

Table 4. Evidence of Exploration: Technology Classes with No Overlap

Rank	Technology Classes for Start-ups		Frequency: Start-ups	Frequency: Incumbents
1	96	Gas separation: apparatus	0.370%	0.0%
2	215	Bottles and jars	0.185%	0.0%
3	250	Radiant energy	0.185%	0.0%
4	261	Gas and liquid contact apparatus	0.185%	0.0%
5	430	Radiation imagery chemistry: process, composition, or product thereof	0.139%	0.0%
6	102	Ammunition and explosives	0.093%	0.0%
7	368	Horology: time measuring systems or devices	0.093%	0.0%
8	546	Organic compounds	0.093%	0.0%
9	977	Nanotechnology	0.093%	0.0%
10	74	Machine element or mechanism	0.046%	0.0%
11	257	Active solid-state devices (e.g., transistors, solid-state diodes)	0.046%	0.0%
12	289	Knots and knot tying	0.046%	0.0%
13	310	Electrical generator or motor structure	0.046%	0.0%
14	544	Organic compounds	0.046%	0.0%

Table 5. Correlations and Descriptive Statistics

Variable	Mean	s.d.	Min.	Max.	1	2	3	4	5	6	7	8	9	10
1. Recombine	0.58	0.21	0	0.92	1.00									
2. Recomb25	0.23	0.42	0	1	-0.84***	1.00								
3. Recomb75	0.26	0.43	0	1	0.56***	-0.32***	1.00							
4. Technological distance	2.54	0.85	0	13.30	0.29***	-0.18***	0.26***	1.00						
5. Geographic distance	6.10	1.85	1.16	8.73	0.05***	-0.07***	0.03†	-0.12***	1.00					
6. Start-up knowledge age	1998.19	4.34	1975	2007	-0.11***	0.09***	-0.07***	-0.15***	-0.29***	1.00				
7. Incumbent knowledge age	2003.22	2.92	1988	2009	-0.01	0.03*	-0.02†	0.01	-0.46***	0.63***	1.00			
8. Cited Before CVC	56.16	76.30	0	266	-0.05***	0.02	-0.02†	-0.12***	0.22***	-0.16***	-0.19***	1.00		
9. Start-up patents	3.32	0.80	0	5.03	-0.02	0.01	0.01	-0.05***	0.06***	0.06***	-0.004***	0.83***	1.00	
10. Acquired by incumbent	0.21	0.40	0	1	-0.10***	0.07***	-0.04**	-0.18***	0.11***	-0.01	-0.08***	0.64***	0.58***	1.00

N=1,405 observations
† p < .10; * p < .05; ** p < .01; *** p < .001. (All two-tailed tests)

Table 6. Regression Results

	(1) Tobit Recombine	(2) Probit Recomb25	(3) Probit Recomb75
Technological distance	0.094***	-0.668***	0.546***
	(4.50)	(-12.71)	(8.72)
Geographic distance	0.026***	-0.114***	0.083***
	(4.20)	(-2.46)	(2.68)
Start-up knowledge age	0.985**	0.099**	-0.070**
	(-2.08)	(2.06)	(-3.14)
Incumbent knowledge age	1.010**	-0.064**	0.037
	(2.32)	(-2.42)	(1.23)
Cited Before CVC	0.00001	-0.001†	-0.002***
	(0.07)	(-0.60)	(-3.73)
Start-up patents	0.026†	-0.013†	0.322***
	(1.92)	(-0.12)	(4.27)
Acquired by incumbent	-0.07†	0.767	-0.157
	(-1.80)	(1.58)	(-1.56)
Medtronic	1.101***	-0.343**	0.253***
	(4.59)	(-3.44)	(14.30)
JandJ	0.069***	-0.090	-0.098†
	(3.61)	(-0.64)	(-1.90)
Boston Scientific	0.074***	-0.040	-0.004
	(3.05)	(-0.18)	(-0.04)
Observations	1,405	1,405	1,405
log pseudolikelihood	-134.1	-671.8	-717.0

Robust z-statistics in parentheses

† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.