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When do firms rely on their knowledge spillover recipients for guidance in exploring unfamiliar knowledge?

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ABSTRACT

Knowledge spillover occurs when recipient firms combine the knowledge of an originating firm with other knowledge. When recipient firms combine the originating firm's knowledge with knowledge that is unfamiliar to the originating firm, the recipient firms potentially provide insight to the originating firm on the viability of exploring such knowledge. By mimicking its recipient firms, the originating firm reduces the challenge and uncertainty of exploring unfamiliar knowledge domains. We examine the exploration activities of 87 telecommunications equipment manufacturers over a ten-year time period. We argue that those firms that operate in competitive and dynamic market environments promoting conservative risk-taking behavior will value such uncertainty reduction more highly and thus rely to a greater extent on their recipient firms for guidance on where to explore for new expertise. In contrast, firms in high-growth market environments are more likely to look beyond the activities of recipient firms when exploring new technological domains and rely less on mimicking their recipient firms.

1. Introduction

Knowledge spillover is thought to be essential for economic growth (Griliches, 1979), urban development (Arrow, 1962; Romer, 1986), and promoting the growth of high technology industries in certain regions (Saxenian, 1994). Knowledge spillover occurs when recipient firms exploit knowledge that has been originally developed by another firm (i.e., originating firm) (Griliches, 1992). These recipient firms may be alliance partners, direct competitors of the originating firm, or firms from other industrial sectors. Whatever the case, when recipient firms exploit the knowledge of the originating firm, they often combine the originating firm's knowledge with other knowledge to create their own unique innovations (Sorenson, Rivkin, and Fleming, 2006). Although many studies have considered how recipient firms absorb and benefit from knowledge spillovers (e.g., Henderson and Cockburn, 1996; Cohen and Levinthal, 1990; Zahra and George, 2002), our understanding of how knowledge spillovers influence originating firms is limited. The conventional wisdom has been that originating firms always lose when knowledge spills out from their boundaries to be used by others (Lippman and Rumelt, 1982; Kogut and Zander, 1992).

However more recent studies suggest that originating firms may benefit when other firms build on their knowledge. For example, firms can strategically promote the copying of their technology to influence industry standards (Spencer, 2003). Firms can proactively shape the collaborative behavior of other firms in their innovation ecosystem by selectively revealing some of their knowledge (Alexy et al., 2013). Aside from strategically motivated spillover, Yang et al. (2010) conceptualize a *knowledge spillover pool* that emerges when an originating firm's knowledge spills over to recipient firms and is subsequently recombined with other knowledge through the innovative activities of recipient firms. Originating firms can potentially learn vicariously from these *knowledge spillover pools* to enhance their subsequent innovation efforts. Yang et al. (2010) showed that originating firms' overall level of subsequent innovation increased the larger their knowledge spillover pool and the more similar it was to their existing expertise. They argue that the originating firm may learn how to further exploit its expertise by observing how other firms are using the originating firm's knowledge in domains that are *familiar* to the originating firm.

However the long term survival and success of firms depend on them being able to discover and use relevant knowledge that

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is *unfamiliar* (March, 1991; Levinthal, 1997). When might recipient firms play a role in guiding originating firms as they search for knowledge that is distant and unfamiliar relative to their existing knowledge? As opposed to exploring how recipient firm activity influences the originating firm's *rate* of innovation as did Yang et al. (2010), we consider how it can influence the *nature* of the originating firm's innovation, i.e., the pursuit of exploration. We also extend the work of Yang et al. (2010) by limiting the knowledge spillover pool to knowledge that is by definition unfamiliar; that is, we focus on knowledge that (1) has been recombined with the originating firm's knowledge by other firms (i.e., recipient firms), and (2) is in technological domains the originating firm has not previously used in their innovative activities.

We contend that if an originating firm can observe how its recipient firms combine its knowledge with knowledge that is unfamiliar to the originating firm, the originating firm's effort and the associated uncertainty in exploring this knowledge will be reduced. For example, an electronics firm (recipient firm) might use a chemical process in its innovation that was originally developed by a chemical firm (originating firm). In turn, by observing the innovation of the electronics firm, the chemical firm may gain some understanding of viable, albeit relatively unfamiliar, knowledge domains in electronics that are worthy of exploring and integrating with its existing repertoire of expertise.

The extent, to which firms mimic the innovative behavior of their recipient firms in such fashion, we argue, largely depends on the environment in which they find themselves. Those firms that operate in highly competitive and dynamic market environments promoting conservative risk-taking behavior will place greater value on such uncertainty buffering and rely more on recipient firms for guidance about where to explore for new expertise. In contrast, firms in high-growth market environments that promote riskier behavior are more likely to look beyond the activities of recipient firms when exploring new knowledge domains and rely less on mimicking their recipient firms.

To test this premise, we track the search activities of 87 telecommunication equipment firms over a ten-year time frame and found a general relationship between environmental context and discovering unfamiliar knowledge through mimicry. While others have considered factors that influence a firm's general propensity for exploring unfamiliar technological domains (March and Shapira, 1992), or the choice between exploring unfamiliar knowledge and exploiting existing knowledge (Benner and Tushman, 2003; Hill and Rothaermel, 2003), we highlight factors that influence *how* firms discover unfamiliar technological domains, specifically how firms can gain insight from their recipient firms.

Firms face a paradox when searching for useful knowledge in unfamiliar technological domains. New capabilities and expertise are especially valuable during times of uncertainty, when the environment is dynamic, and resources are limited (Sirmon et al., 2007). Yet the discovery of valuable, yet unfamiliar knowledge is both cognitively challenging and inherently uncertain (Fleming, 2001; Levinthal and March, 1981; March, 1991). By conceptualizing search behavior within the realm of managerial risk-taking, we show how firms can search for valuable unfamiliar knowledge in a way that reconciles the tension of taking on additional risk in an already uncertain environment. We thus contribute to the literature on knowledge search by identifying a source of knowledge that firms may more easily explore. Finally, our study differentiates the impact of new knowledge domains introduced by the recipients' recombination of originating firm's knowledge spillovers from the overall knowledge domains in this knowledge spillover recombination process (Yang et al., 2010). Our results identify further benefits for the originating firm that may be gained from knowledge spillover (Spencer, 2003).

2. Theory and hypotheses

2.1. The value of recipient firms for exploration guidance

Innovation occurs when knowledge is integrated and recombined with other knowledge (Fleming, 2001). For example, combining physics technology with molecular technology has led to both new electronic devices and new medicines. Firms tend to depend on their existing expertise for input into their ongoing innovation pursuits. Relying on knowledge that is familiar and already resides within the firm is more cost-effective and has a higher probability of success, compared with searching unfamiliar knowledge domains (Fleming and Sorenson, 2001; March and Simon, 1958; March, 1991).

Although relying on existing expertise may seem easy and relatively efficient, it may not be so effective in practice, especially in cases where market environments have changed to the point where a firm's existing expertise is rendered irrelevant. When firms rely only on their existing expertise, they become trapped within their restricted knowledge domains and risk simply perpetuating their own expertise (March, 1991; Levinthal, 1997). To avoid becoming too insular, firms must explore knowledge available outside of their existing expertise.

Successful exploration occurs when a firm integrates knowledge into its current innovation from beyond the realm of its existing expertise. To do so, firms often need to hire outside experts or acquire firms that are sources of unfamiliar knowledge (Song et al., 2003). Even after taking these actions, lack of experience and the high cost of a trial-and-error process may cast doubt on whether firms can successfully combine disparate areas of knowledge to create a novel technological contribution (March, 1991).

However, there is an alternative to conducting expensive search into unfamiliar domains and bearing the full uncertainty of combining disparate domains of knowledge. That is, firms can search unfamiliar domains more easily and with less uncertainty by learning from recipient firms which have borrowed knowledge originally created by the searching firm. When recipient firms use knowledge that has spilled over from an originating firm, they often integrate that knowledge with other knowledge to create unique value (Sorenson et al., 2006). Some of the knowledge that is integrated with the originating firm's knowledge by the recipient firms will be relatively unfamiliar to the originating firm.

Drawing on the guidance of recipient firms to identify potentially useful yet unfamiliar knowledge represents a middle ground of sorts in terms of the cognitive challenge and uncertainty of innovation. It will require more effort than simply exploiting familiar knowledge domains that lie within the firm. The firm will still need to cognitively process knowledge in domains which are generally unfamiliar to the firm and lie outside of its technological boundaries. However, drawing on the guidance of recipient firms will not be as costly or uncertain as searching for useful yet unfamiliar knowledge 'cold'; that is, searching for unfamiliar knowledge that has not been associated in any way with the firm's existing knowledge by recipient firms. By mimicking recipient firms in terms of using knowledge from new domains that recipient firms have used in conjunction with the knowledge of the originating firm, the originating firm abbreviates the normally challenging and uncertain search process. Because recipient firms have already established the viability of linking an originating firm's knowledge with the technological domains that are relatively unfamiliar to the originating firm, the risk for the originating firm of doing likewise is reduced (Fleming, 2001; Fleming and Sorenson, 2001).

Furthermore, when knowledge created by the originating firm is recombined with unfamiliar knowledge by other recipient firms, the originating firm will have a unique advantage in learning from these recombinations because it will have been the originator of one of the combinatorial components. The expertise associated with having created a combinatorial component provides the originating firm with some relevant absorptive capacity that will help them understand how unfamiliar knowledge domains introduced by their recipient firms fits with their existing knowledge (Lane and Lubatkin, 1998).

Thus, we suggest a continuum from least to greatest in terms of difficulty and uncertainty: (1) exploiting existing knowledge; (2) searching unfamiliar technological domains drawing on the guidance of recipient firms, and; (3) searching unfamiliar technological domains without such guidance. Because firms are boundedly rational and have limited resources, they are inherently biased toward doing that which is easy, and exploiting existing internal knowledge for their on-going innovation as opposed to exploring new knowledge domains (Hill and Rothaermel, 2003; Stuart and Podolny, 1996).

If a firm's existing expertise is no longer sufficient to enable the firm to thrive, exploring knowledge from domains outside of its bounds may become necessary. The general bias toward doing that which is easier and less uncertain also influences *which* knowledge domains a firm considers searching. All things being equal, originating firms will prefer exploring unfamiliar knowledge that has been already linked to its existing knowledge as compared to unfamiliar knowledge that has not been linked to its knowledge.

When recipient firms combine the originating firm's knowledge with knowledge from domains that are beyond the current expertise of the originating firm, a stock of potential 'recipient-guided' unfamiliar knowledge develops which the originating firm can use during its search activities. This array of recipient-guided unfamiliar knowledge provides the originating firm with a range of efficient ways to complement its existing knowledge with knowledge from outside of its immediate technological expertise. In so doing, the originating firm may be able to gain a unique advantage by drawing on such distinctively blended knowledge in their search (Yang et al., 2010; Barney, 1991).

2.2. Contextual influences on mimicry and guided exploration

Because the external environment influences managerial decisions (Aldrich and Wiedenmayer, 1993), how firms acquire their resource portfolio depends in part on their external environment (Sirmon et al., 2007). The context in which the organization competes influences a willingness to accept risk (Palmer and Wiseman, 1999). Drawing on recipient firms for guidance regarding which new knowledge to explore can buffer the originating firm from the inherent cognitive challenges and uncertainty of exploration. The extent to which firms value such buffering will vary depending on the inherent uncertainty of the market environment. Overall uncertainty associated with a market is a function of competitiveness, growth, and stability in demand (Sirmon et al., 2007). The practice of depicting industrial environment in terms of munificence (i.e., growth), complexity (i.e., competitiveness), and dynamism (i.e., demand volatility) goes back to Dess and Beard's (1984) early work. Keats and Hitt (1988) further conceptualized, measured, and established the construct validity of these three dimensions. We suggest that drawing on the guidance of recipient firms to explore unfamiliar technological domains will be particularly attractive for those firms that operate in markets that have stagnant growth, are relatively volatile in demand, and are intensely competitive.

2.2.1. Market growth

Some markets are growing faster than others in the sense that overall product demand is expanding. General growth in market demand enables organizations to grow (Aldrich, 1979; Dess and Beard, 1984). Such growth also influences innovation and risk-taking in general. When market growth is limited, innovation within the market wanes as conservative behavior becomes prevalent (Miller and Friesen, 1982). When market demand is growing, managers have greater discretion and a wider latitude in the directions their firms may take (Hambrick and Finkelstein, 1987). A growing market provides managers with resources to support riskier decision making. Firms can afford to take more risks and pursue highly novel solutions because they can more easily endure the gambles that don't pay off when there are continued prospects for market growth (Miller and Friesen, 1982). Firms are better able to absorb the high cost of trial-and-error in exploring new technological domains. An expanding market also provides an incentive to pursue highly novel innovation in order to obtain great market share and establish a more sustainable competitive advantage.

The level of growth within a market will influence the manner in which firms explore new technological domains. It is more costly and risky to explore knowledge not previously linked to the originating firms' knowledge. In their attempts to attain new expertise, firms will be more willing to accept the risks associated with exploring new technological domains that have not been previously associated with their knowledge by recipient firms when overall market demand is growing. When growth is limited and risk-taking is blunted, firms will more highly value the buffering provided by the guidance of recipient firms in terms of exploration opportunities.

Hypothesis 1. Originating firms will rely on the guidance of recipient firms in their exploration activities to a lesser extent when markets are growing than when they are stagnating.

2.2.2. Demand volatility

Markets also vary in the extent to which predictions can accurately be made regarding the future. Some markets are inherently more stable and predictable than others. When there is excessive volatility in the demand for the industry's products, such as customers' changing tastes or substitute products from another industry, it becomes difficult for member firms to plan for production, expand in other areas, or determine whether to exit the market sector. New expertise and the opportunity it provides can help firms hedge the uncertainty in volatile markets (Mintzberg, 1973; Miller and Friesen, 1982). Yet the trial-and-error process of exploring unfamiliar knowledge adds further uncertainty at a time when low-risk alternatives would be preferred because of the volatility (Palmer and Wiseman, 1999).

During times of uncertainty, there is comfort in numbers. Mimicking others' proven methods provides some legitimacy and assurance to the mimicking firm that its actions are viable. Indeed, a common response to uncertainty is either to maintain the 'status quo' (Milliken, 1987), or to mimic the actions of other legitimate organizations (DiMaggio and Powell, 1983). Mimicking how recipient firms integrate new knowledge domains with the originating firm's knowledge decreases the uncertainty and increases the likelihood that the originating firm will be successful in exploring similar knowledge. Such buffering against the uncertainty of exploration will be particularly valued by firms operating in environments where the future is uncertain due to market volatility.

Hypothesis 2. Originating firms operating will rely on the guidance of recipient firms in their exploration activities to a greater extent when market demand is highly volatile than when it is stable.

2.2.3. Market competitiveness

High levels of competition can also create a complex and highly uncertain environment (Palmer and Wiseman, 1999). When there are many competitors with varying competencies, the direction of the industry becomes difficult to predict. Industry players are unable to anticipate the actions and responses of their rivals (Zajac and Bazerman, 1991). A greater number of rivals increase the possibility for relatively novel reactions. Under such conditions the likely outcomes of a firm's strategic moves become highly uncertain. When there are fewer industry players, stable norms of interaction more easily develop. Industry players will have an easier time monitoring and understanding a relatively limited number of rivals, and the responses and actions of these rivals will be more predictable.

While exploring new domains of knowledge can be an effective way for a firm to distinguish itself from a large array of competitors (D'Aveni, 1994; Baum and Singh, 1996; Delacroix et al., 1989), the uncertainty resulting from intense competition may influence how firms explore new knowledge domains. Innovating by exploring new knowledge domains is relatively uncertain compared with exploit existing knowledge. The uncertainty of exploration is increased further when rival behavior becomes generally unpredictable due to their large number. Not only is there uncertainty surrounding the exploration process, substantial uncertainty exists regarding competitive responses to that exploration.

One means of buffering overall uncertainty is pursuing exploration through the guidance of recipient firms. By observing how recipient firms combine the know-how of an originating firm with knowledge domains that are unfamiliar to the originating firm, the uncertainty of exploring these unfamiliar knowledge domains is reduced for the originating firm. This mimicry may be particularly valuable to those firms operating in a highly competitive environment that is relatively unpredictable. When competition is more restrained and competitive responses more predictable, firms are more willing to accept additional uncertainty such as exploring knowledge domains without the guidance of recipient firms.

Hypothesis 3. Originating firms will rely on the guidance of recipient firms in their exploration activities to a greater extent when competition is intense than when it is less so.

3. Methods

To test our hypotheses, we first conducted some initial qualitative research by interviewing 11 engineers/inventors and R&D managers to ground our archival data analysis. We then examined the knowledge spillovers and exploration activities of a sample of firms using patent citations. We built on a large body of research which uses patents and patent citations to proxy for knowledge flows and exploration (see Almeida, 1996; Hagedoorn and Cloodt, 2003; Hoetker and Agarwal, 2007; Jaffe et al., 1993). Although knowledge spillovers can occur through a host of mechanisms (e.g., technical publications, conferences, reverse engineering), patents and their citations represent observable knowledge flow regardless of the diffusion mechanism (Jaffe et al., 1993, 2002).

Inventions and the patents that protect them reflect an organization's knowledge creation activities (Trajtenberg, 1990). Patents provide a measure of novel invention that is externally validated through the patent examination process (Griliches, 1990). Because obtaining and maintaining patent protection is time-consuming and costly, patent applications may be seen as a positive expectation by the inventor for the economic significance of the invention (Griliches, 1990). Although patents reflect a codifiable portion of a firm's technological knowledge, they correlate with measures that incorporate tacit knowledge, such as ratings by experts on the technical competencies of firms (Narin et al., 1987) and the introduction of new products (Brouwer and Kleinknecht, 1999).

Patents contain citations to prior patents. These citations represent the technological components that were combined in a novel way in order to yield the patented invention (Basalla, 1988). Patent applicants are required by law to list relevant citations in their applications and are given incentives to do so (Griliches, 1990). Ultimately, the patent examiner reviewing the application is responsible for the citations contained in the granted patent. As such, patent citations have been found to be valid indicators of actual knowledge flows (cf., Jaffe et al., 2002; Duguet and MacGarvie, 2005).

3.1. Empirical context, sample and data sources

We used a sample of firms from the global telecommunications equipment manufacturing industry (SIC 3661, 3663, 3669). Such manufacturers produce and market the hardware and software that enable the transmission, switching and reception of voice, images, and data over both short and long distances using digital, analog, wire lines, and wireless technology. Because it is technologically intensive with a high rate of innovation, and member firms actively patent their innovations, the telecommunications equipment industry was an ideal setting for our study (Griliches, 1990; Levin et al., 1987). Patents associated with these technologies diffuse more rapidly than those from other technologies, are cited sooner and more often, and cite a relatively large number of other patents (Hall et al., 2001). Hagedoorn and Cloodt (2003) found that patents are a particularly good measure of innovation activities in this industry. Finally, the broader telecommunication equipment industry provides variance in terms of narrow and specific sectors (i.e., satellites, antennas, television transmitting equipments) and variance over time in their associated characteristics including demand volatility, growth, and competitiveness.

To control for unobserved sources of firm differences in terms of exploration, we used time-varying data on the same set of firms. To minimize left and right censoring in collecting patent data and to ensure access to firm financial data, we limited the sample period to 1987–1997. Because some of our measures required a ten-year window of patent data prior to each firm-year observation, we needed to collect data on patents applied for as early as the mid-1970s (the beginning of our patent data sources). Furthermore, collecting financial data on many international firms prior to 1987 proved difficult. Given the lag between the application for a patent and its eventual granting, we ended the sample in 1997. Doing so allowed adequate time to elapse between the end of the sample and the end of our patent data collection to assess whether the patent application had been granted. Nearly all patent applications are reviewed and decided by the USPTO within seven years of application (Hall et al., 2001). To minimize survivor bias, we selected the final sample of 87 firms by rank-ordering them by industry sales at the beginning of the sample period.

We obtained U.S. patent data from Delphion and the NUS Patent Database for the period 1977–2005. Using patents from a single country insures consistency, reliability, and comparability across firms (Griliches, 1990). U.S. patents are a very good data source because of the rigor and procedural fairness used in granting them, the strong incentives for firms to obtain patent protection in the world's largest market, the high quality of services provided by the USPTO, and the U.S.'s reputation for providing effective IP protection (Pavitt, 1988).

We took significant care in aggregating patents across subsidiaries to the firm level. Using *Who Owns Whom* and *The Directory of Corporate Affiliations*, all divisions, subsidiaries, and joint ventures of each firm in the sample as of 1976 were identified. Each firm's history in terms of name changes, division names, divestments, acquisitions, and joint ventures was traced to obtain information on the timing of these events. This process yielded a master list of entities which we used to identify all patents belonging to sample firms during the period of study.

Financial data were sourced from Compustat, annual reports, SEC filings for U.S. firms and for non-U.S. firms, from The Japan Company Handbook, Worldscope, and Global Vantage.

The two methodological issues that warranted substantial consideration were unobserved heterogeneity and endogeneity. Exogenous factors may influence the firm's decision to explore in general and explore through the guidance of recipient firms simultaneously, which may cause the correlation of error terms between the endogenous variables. To account for these issues, we pursued a two-pronged research design strategy and used both a longitudinal firm-level panel design employing two-stage methodology, and an experimental design at the patent level of analysis employing the patent case–control method (Agrawal et al., 2006; Almeida, 1996; Almeida and Kogut, 1999; Furman and Scott, 2004; Jaffe et al., 1993; Sorenson et al., 2006). Because each of the designs accounts for the weaknesses of the other, confidence in the empirical findings is enhanced to the extent that the two designs generate consistent results.

3.2. Firm-level panel data design

Patents within the USPTO database are categorized into 470 primary classes at the three-digit level which represent broader technological domains (e.g., chemical process; telegraphy) and can be used to identify the new technological domains that firms explore (Ahuja and Lampert, 2001; McGrath and Nerkar, 2004).

3.2.1. Dependent and independent variables for firm-level panel data design

Reliance on guided exploration$_{it}$ To operationalize the extent to which an originating firm relied on its recipient firms for guidance in its subsequent exploration, we first needed to track the knowledge spillover from our sample firms to their recipient firms. We then had to identify what knowledge was combined by recipient firms with the sample firm knowledge. Finally, we needed to track the subsequent exploration of the sample firms and trace the correspondence between this explored knowledge and the knowledge which recipients firms had previously combined with sample firm knowledge. To do so, we used the following sequential steps:

(1) Spillover process. We initially identified all patents applied for and assigned to firm *i* in the ten years prior to, but not including year $t-1$ (i.e., $t-2$ to $t-11$). We considered these patents as available for spillover from firm *i*. As evidence of spillover, we then identified all patents from other firms (i.e., the recipient firms) and their associated classes that had been applied for in year $t-1$ (and subsequently granted) which had cited any of firm *i*'s stock of patents from years $t-2$ to $t-11$. Finally, we identified all patent citations and their classes contained *within* recipient firms' patents which had also cited firm *i*'s stock of patents. From these recipient firm patents and their associated citations, we generated a list of recipient firm patent classes.

(2) Potential recipient-guided explorable knowledge. We identified all patents applied for and assigned to firm *i* in the ten years prior to, and including year $t-1$ (i.e., $t-1$ to $t-10$). This resulted in a list of patents for the focal firm, each identified with a unique number and associated with a patent class. We also identified all the patent citations for this stock of patents and the associated knowledge classes of these citations. Consistent with Katila and Ahuja (2002), we refer to the combination of firm *i*'s ten-year stock of patents in year $t-1$ with their citations as firm *i*'s knowledge base. From these focal firm patents and associated citations, we generated a list of focal firm patent classes represented in firm *i*'s knowledge base.

At this point, we could compare the list of recipient firm patent classes (step 1) to the list of focal firm patent classes. We eliminated all recipient firm patents and citations identified in step 1 which also appeared on the list of focal firm patent classes. The remaining recipient firm patents and citations were both potentially explorable by firm *i* (i.e., not from a patent class in its existing knowledge base) and had been combined with firm *i*'s patents by recipient firms.

(3) Sample firm exploration. We identified firm *i*'s patents in year *t* and their corresponding citations to determine the knowledge that firm *i* had explored in year *t*. Consistent with Ahuja and Lampert (2001), any patents and their citations of firm *i* in year *t* whose knowledge classes are different from the knowledge classes represented in firm *i*'s existing knowledge base (as determined in Step 2) were considered to be indicative of exploration. A firm's overall exploration is the number of patents and citations whose knowledge classes differ from those found in the firm's existing knowledge base (Ahuja and Lampert, 2001).

(4) Reliance on guided exploration$_{it}$: We compared the list of patents generated in Step 3 to the list of potential 'recipient-guided' explorable knowledge (Step 2) and identified the number of exploration citations in year *t* which also appeared on the list of potential 'recipient-guided' explorable knowledge for year $t-1$. We calculate the percentage of the guided exploration patents over the total exploration patents. This variable is bounded between 0 and 1, and captures a firm's propensity to rely on the activity of recipients firms for exploration guidance versus exploring new knowledge on their own.

To illustrate our operationalization, the following example lays out the various steps described above and is illustrated in Fig. 1. Assume that firm *i* has only one patent available for spillover (patent *a1/class 1*) for the years $t-11$ to $t-2$.

Patent *a1/class 1* is cited by two other firms in their new patents *f2/class 2* and *f3/class 3*, respectively at time $t-1$. In addition to patent *a1*, patents *f2/class 2* and *f3/class 3* cite three other patents: *b1/class 1*, *b4/class 4*, and *b5/class 5*. Thus, the list of recipient firm patent classes includes classes 1, 2, 3, 4, and 5.

In year $t-1$, firm *i*'s knowledge base includes patent *a1/class 1* and its associated citations, *b2/class 2* and *b3/class 3*. Thus, the list of focal firm patent classes represented in firm *i*'s knowledge base includes classes 1, 2, and 3. By comparing the recipient firm patent class list to the focal firm patent class list, we determine the potential recipient explorable knowledge for firm *i*, year $t-1$ includes patent *b4/class 4* and *b5/class 5*. These patents have been connected to the originating firm's existing knowledge base by the recipient firms, and are not drawn from classes represented in the originating firm's existing knowledge base ($t-10$ to $t-1$). Patents from classes 1, 2, and 3 are not potentially explorable because these classes are already represented within firm *i*'s existing knowledge base.

In year *t*, the originating firm develops patent *a2/class 2* whose backward citations are *a1/class 1*, *b4/class 4*, *f1/class4*, *b5/class 5*, *b7/class 7*, and *b8/class8*. In this case, the total exploration of firm *i* in year *t* is 5 (patent *b4*, *f1*, *b5*, *b7* and *b8* from *classes 4*, *5*, *7*, and *8*).

The content from Step 3 (focal firm total exploration) can then be compared to Step 2 (potential recipient-guided explorable knowledge). In the current example, two of the five patents representing firm *i*'s exploration (patent *b4* and *b5* from *class 4* and *5*) derive from the potential recipient-guided explorable knowledge. The reliance on guided exploration for focal firm *i*, year *t* would be .4 (i.e., 2 divided by 5).

Market growth$_{it-1}$: We used industry sales growth as a time-varying measure of industry growth for firm *i* in year $t-1$. Following Keats and Hitt (1988), we calculated average growth rate in industry sales for years 1987–1996 using a five-year moving window. From the U.S. Census Bureau Annual Survey of Manufacturers, we acquired total sales for each industry based on four-digit SIC codes, and log transformed these totals. We used quasi-time series regressions with time serving as the independent variable. The antilogs of the resulting regression slope coefficients served to

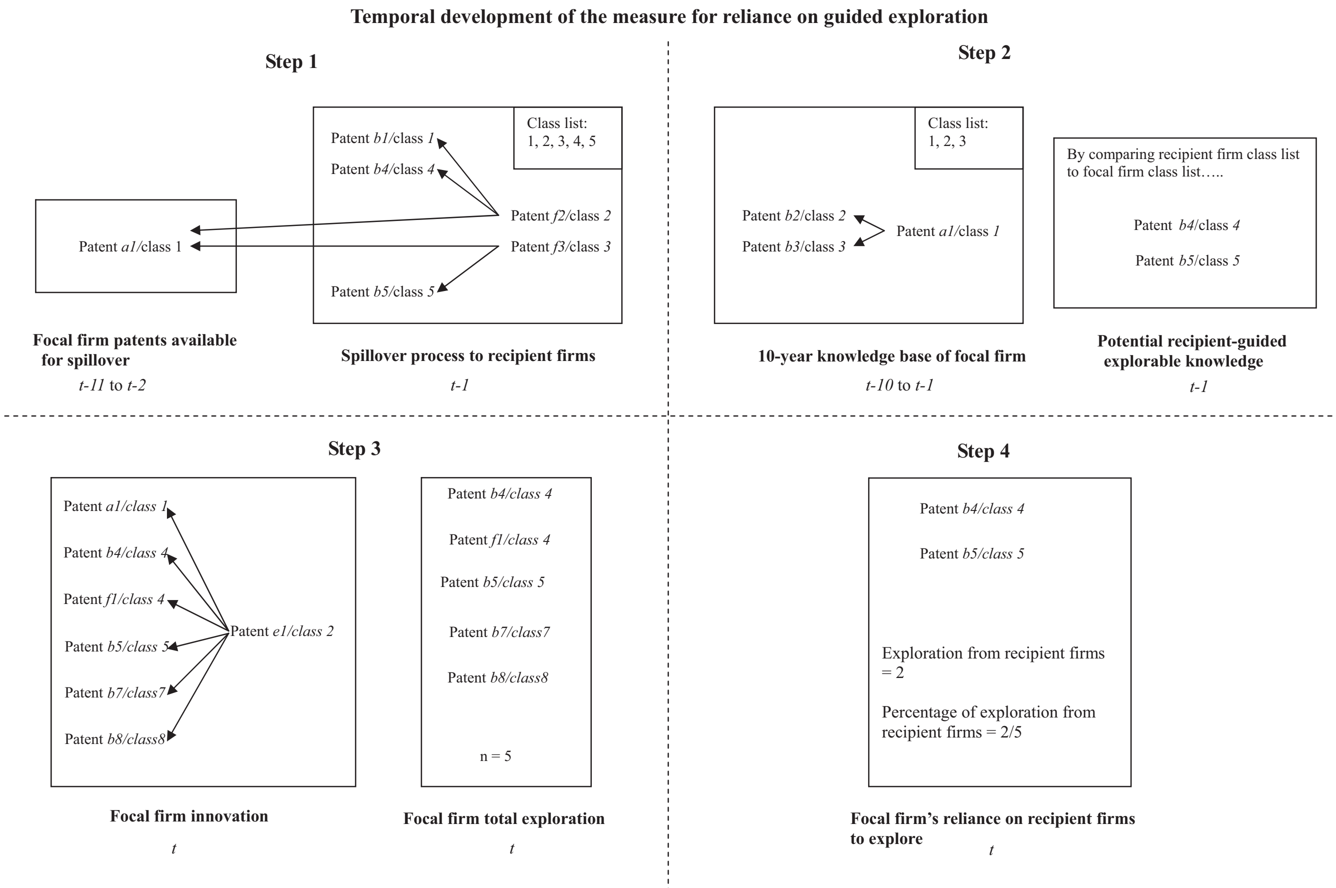

Fig. 1. Temporal development of the measure for reliance on guided exploration.

capture industry growth. We used the firm's primary four-digit SIC to assign its industry.

Demand volatility$_{it-1}$: We used variance in industry sales as a time-varying measure of demand volatility for firm *i* in year *t* – *1* (Keats and Hitt, 1988). The same procedure employed in generating the growth measure was used to calculate the market uncertainty variable. We computed the antilog of the standard errors of the quasi time series regressions to measure variability in industry growth rates (Keats and Hitt, 1988).

Market competitiveness$_{it-1}$: Industries with firms that have relatively equal market share tend to highly competitive (Scherer and Ross, 1990). We used the inverse of the top four companies' market share of firm *i*'s primary four-digit SIC sector for a time-varying measure of competitive intensity for firm *i* in year *t* – *1*.

3.2.2. Control variables for firm-level panel design

General exploration$_{it-1}$: The extent to which firms either explore based on the guidance of their recipient firms or explore on their own depends on their tendency to explore in general. We control for general exploration citations as a percentage of the firm *i*'s overall citations in year *t* – *1*.

Size of potential guided explorable knowledge stock$_{it-1}$: The extent to which firms rely on guided exploration may depend on the amount of knowledge at risk for being explored in this fashion. The size of potential guided explorable knowledge stock is a time-varying variable and equals the total number of the unique patents in *t* – *1* that have been connected to firm *i*'s existing patent stock by recipient firms, and are not represented in the firm *i*'s existing knowledge base (*t* – *10* to *t* – *1*). This variable was log-transformed due to skewness.

Technology opportunity: The potential to advance technologies in different technological and industrial fields differ across time (Jaffe, 1986; Silverman, 1999). Availability of opportunities in a firm's area of expertise directly affects its risk preferences for venturing into new areas. We follow Patel and Pavitt (1997) to control for firm-specific differences in technological opportunity in year *t* – *1* as follows:

$$\text{Technological opportunity}_{it-1} = \sum_{j=1}^{J} [Patents_{jt-1} * P_{jit-1}],$$

We use P_{jit-1} to measure the proportion of firm *i*'s patents applied for and subsequently granted in class *j* in year *t* – *1*. $Patents_{jt-1}$ represents the number of patents granted in the U.S. in patent class *j* in year *t* – *1*. We used the weighted distribution of firm *i*'s patents in different technology classes to measure the overall technological change in those areas where firm *i* might catch up (Patel and Pavitt, 1997). We then divided this variable by 1000 to reduce its scale and ease its interpretation.

R&D intensity$_{it-1}$: A firm's past history of risk taking may influence its present risk-taking behavior (Bromiley, 1991; Palmer and Wiseman, 1999). R&D intensity (R&D/Sales) has been used to measure prior risk propensity of firms (Hoskisson et al., 1993; Palmer and Wiseman, 1999). We thus controlled for the influence of R&D intensity for firm *i* in year *t* – *1*.

Patent stock$_{it-1}$: To capture the path-dependent aspect of innovation, scholars often consider the stock of granted and unexpired patents as an important factor of firm innovation and exploration (Cockburn and Henderson, 1994; Stuart, 2000). We measure the knowledge stock for firm *i* in year *t* – *1* using a ten-year, time-varying window for a count of patent stock and adjust for age using a 10% straight-line annual depreciation. We divided the variable by 1000 to reduce its scale.

Technology diversity$_{it-1}$: Firms which feature highly diverse technology may have greater experience in recombining across different knowledge domains and integrating new knowledge (Garcia-Vega, 2006). We measured firm *i*'s technological diversity in year *t – 1* using Hall's (2002) Herfindahl index.

$$\text{Technological diversity}_{it-1} = \sum_{j=1}^{N} P_{jit-1}^{2},$$

where P_{jit-1} is the number of patents in technology class *j* of firm *i*'s knowledge spillover pool at year *t – 1* divided by the total number of patents in firm *i*'s knowledge spillover pool in year *t – 1*. This variable may take on values between 0 (no diversity) to 1 (maximum diversity).

Firm size$_{it-1}$: We control for the influence of firm size using firm *i*'s sales in year *t – 1* (in billion $US).

Slack resources$_{it-1}$: Organizations that have significant slack resources may be more eager to participate in exploratory search than their slack-deprived counterparts (Singh, 1986). Such slack may also influence whether firms rely on recipient firms to guide their exploration. We proxy for the slack resources of firm *i* in year *t – 1* using its current ratio (current assets/current liabilities), and use this variable as an instrument.

Spillover$_{it-1}$: Whether firm *i*'s knowledge spilled over to other firms in year *t – 1* is depicted by a dummy variable. This variable indicates the overall attractiveness of firm's knowledge base to other firms and is used as an instrument to predict *general exploration*.

For the firm-level panel design, the dependent variable, *reliance on guided exploration*$_{it}$, is a proportion. Estimation involving a proportional dependent variable presents several challenges to linear regression (Greene, 1997). In accordance with standard econometric practice (Greene, 1997), we transformed this variable using a logistic (i.e., log odds) transformation.[1]

3.2.3. Analysis for firm-level panel design

We employed firm-fixed effects to control for unobserved, temporally stable firm differences. We also included year dummies to control for unobserved systematic temporal impacts. Because the Hausman test indicates rejection of a random effects specification, we use a fixed effects specification for the models. We applied the unconditional fixed effects estimator developed by Allison and Waterman (2002) to more effectively control for all time invariant sources of heterogeneity rather than the more conventional conditional maximum likelihood estimation procedure by Hausman et al. (1984).

One potential threat to the internal validity of our analysis is the endogeneity of the decision to explore unfamiliar knowledge in general, guided or unguided (*general exploration*). However, *general exploration* is a control variable. To the extent that *general exploration* is unrelated to our core exogeneous independent variables (i.e., *market growth, market competitiveness, demand volatility*), its endogeneity and the fact that it may be proxying for deeper unmodeled effects will not adversely bias our coefficients of interest (Stock, 2010). We regressed *general exploration* on our core independent variables and the other control variables in a first stage model (Model 1, Table 2). None of the core variables appear to be significantly related to *general exploration*. We further conducted Wald test to examine the endogeneity of the tendency to explore in general. The Chi-square values generated by Wald test between the tendency to explore in general and two independent variables, market uncertainty and market competitiveness, are 9.56 and 7.28 respectively with two degrees of freedom. However, the Chi-square value about the tendency to explore in general and market growth is 5.36, indicating possible endogeneity.

Therefore, we used two-stage least squares (2SLS) regression models to account for the possible endogeneity of the tendency to explore in general. We first regressed the endogenous variable *general exploration* on all the independent variables, and then regressed our dependent variable, *reliance on guided exploration*, on the predicted value of *general exploration* rather than the observed value of the variable. The instrument variable used was a dummy variable of whether the firm had knowledge spillover for the given year. The *spillover* dummy indicates the overall attractiveness of a firm's technology to others and its desirability. Firms that do not possess desirable technology will likely have greater impetus to explore more generally to develop new capabilities (Levinthal, 1997). However there is little logic linking the desirability of the firm's current technology to its propensity to explore unfamiliar domains using the guidance of its recipient firms. In support of its validity as an instrument, *spillover* is relatively highly correlated with general exploration ($r = -0.52$, $p < 0.01$) and uncorrelated with *reliance on guided exploration* ($r = 0.05$, n.s.) (Table 1).

All explanatory and control variables were lagged one year, reducing concerns of reverse causality and avoiding simultaneity. The panel is unbalanced as some firms were acquired or restructured during the window of observation.

3.3. Matched patent case–control design

In addition to the firm-level longitudinal panel design, we also used an experimental design at the patent level of analysis, employing the patent case–control design (e.g., Agrawal et al., 2006; Almeida, 1996; Jaffe et al., 1993; Sorenson et al., 2006). We wanted to examine how market growth, market uncertainty, and market competition influences the likelihood of a focal firm exploring new knowledge linked to its existing knowledge by recipient firms as compared to exploring new knowledge 'cold', i.e., knowledge not linked by recipient firms to the focal firm's knowledge.

3.3.1. Sample construction and measures for matched patent case–control design

To construct a sample for this analysis, we selected all of the instances of 'guided' exploration for our sample firms where an explored patent was previously linked to the sample firm's knowledge by recipient firms as described above. We designated these 172 observations/patents as our treatment group. We then selected all instances of 'cold' exploration for our sample firms where the explored patent had *not* been previously linked to the sample firm's knowledge by recipient firms. We designated these observations as part of our control sample. We stratified the 'cold' exploration observations by sample firm, primary one-digit technology class, and patent year of issuance. We then randomly matched each of our treatment group observations based on firm, one-digit technology class, and year of issuance to two observations from the control sample (King and Zeng, 2001). By matching control patents to treatment patents in this way, we minimize unobserved heterogeneity. The final sample for our supplementary analysis consisted of 172 treatment and 344 control patents ($n = 516$).

The dependent variable for this analysis, *guided exploration*$_{ijt}$, is a dummy variable. The treatment patents take the value of 1, while the control group patents are 0. The explanatory variables of interest – *market growth*$_{it-1}$, *demand volatility*$_{it-1}$, *Market*

[1] The transformed variable is: ln(Reliance on guided exploration/1 – reliance on guided exploration). Because the transformation is undefined when Reliance on guided exploration equal to 0 or 1, we recoded these values as: 0 = 0.0001 and 1 = 0.9999.

Table 1
Description statistics for firm-level panel analysis.

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	Reliance on guided exploration	0.02	0.10	1											
2	Market growth	1.14	0.18	0.01	1										
3	Market competitiveness	1.34	0.40	0.02	−0.17*	1									
4	Demand volatility	1.05	0.06	0.02	0.49*	−0.18*	1								
5	Technology opportunities	0.86	0.40	0.16*	0.15*	0.04	0.02	1							
6	R&D intensity	0.12	0.80	−0.01	−0.02	0.14*	0	0.08†	1						
7	Patent stock	0.74	1.41	0.12*	0.04	0.06	−0.01	0.12*	−0.04	1					
8	Technology diversity	0.82	0.24	−0.01	−0.09†	0.15*	−0.17*	−0.13*	−0.04	0.31*	1				
9	Size of potential recipient-guided explorable knowledge (log)	5.05	2.14	0.12*	−0.02	0.17	−0.07	0.15*	−0.14*	0.65*	0.54*	1			
10	Firm size	9.3	16.42	0.10*	−0.01	0.39*	−0.03	0.11*	−0.04	0.81*	0.33*	0.63*	1		
11	General exploration	0.13	0.23	−0.02	−0.08†	−0.06	0	−0.05	0.13*	−0.28*	−0.21*	−0.54*	−0.28*	1	
12	Slack resources	2.19	1.30	0.07	0.05	−0.20*	0.12*	0.03	0.09†	−0.25*	−0.44*	−0.38*	−0.30*	0.19*	1
13	Spillover	0.96	0.21	0.05	0.06	0.01	0.03	0.12*	−0.23*	0.11*	0.30*	0.51*	0.12*	−0.52*	−0.22*

$N = 673$ two tailed test.
* $p < 0.01$
† $p < 0.05$

competitiveness$_{it-1}$ – are operationalized as described above for the firm-level panel design.

To control for differences in the underlying quality of each patent from the sample, we included three control variables that were known to be good proxies for invention quality (Lanjouw and Schankerman, 2004). We controlled for the number of claims contained in patent i (*Claims*$_i$), which defines the scope of intellectual property rights this patent claimed for and therefore the value that the patent brings to the firm (Reitzig, 2003). We controlled for the number of backward patent citations contained in patent i (*Backward Cites*$_i$) (Harhoff et al., 2003). The number of forward citations a patent receives is a good indicator of the value or quality of the patented invention (Trajtenberg, 1990). We controlled for the cumulative number of forward citations patent i received as of year t, excluding those made by focal firm j in that year (*Cumulative Forward Cites*$_{it}$). Patents that build on a wide range of technologies may be more novel and therefore more often cited (Trajtenberg et al., 1997; Singh, 2008). We controlled for the originality of patent i (*Originality*$_i$) using Trajtenberg et al.'s (1997) originality measure: $1-\sum s_{ij}^2$, where s_{ij} refers to the fraction of patents cited by patent i that belong to technology class j. To account for the differences of the time that a patent has been at risk of forward citation, we controlled for the age of patent i in year t (*Age*$_{it}$).

3.3.2. Analysis for matched patent case–control design

The unit of analysis is the patent. Because the dependent variable is a binary variable and the events of interest (i.e., guided exploration) are a relatively small portion of the population, standard logit or probit procedures might provide biased results. To address the problem of systematically underestimating the probability of rare events (King and Zeng, 2001), we utilized the Rare Events Logistic Regression (relogit) procedure developed for STATA by Tomz et al. (2002). The same procedure has been used in other studies examining the probability of rare events in the context of venture capital investments (Sorenson and Stuart, 2001) and knowledge sharing in organizations (Hansen et al., 2005).

Table 2
Unconditional two-stage least square fixed effects models for firm-level panel (Stages 1 and 2).

	General exploration	Reliance on guided exploration	
	Model 1	Model 2	Model 3
Market growth	0.19 (0.66)		−0.96† (0.73)
Market competitiveness	−0.10 (1.30)		2.71* (1.45)
Demand volatility	−0.16 (3.09)		8.28** (3.45)
General exploration		0.18 (0.38)	0.26 (0.38)
Technological opportunities	0.62 (0.46)	0.09 (0.55)	0.27 (0.55)
R&D intensity	0.11 (0.14)	−0.01 (0.17)	−0.05 (0.17)
Patent stock	−0.34 (0.29)	0.52 (0.34)	0.54 (0.35)
Technological diversity	2.09* (1.02)	0.33 (1.30)	0.41 (1.30)
Size of potential guided explorable knowledge stock	−0.16 (0.13)	0.36* (0.18)	0.37* (0.18)
Firm size	−0.01 (0.03)	0.02 (0.03)	0.02 (0.03)
Slack resources	0.22* (0.11)	0.09 (0.15)	0.08 (0.15)
Spillover	−1.95** (0.66)		
Constant	−4.29 (3.37)	−11.27*** (2.46)	−21.61*** (4.15)
Year dummies	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes

$N = 673$ Wald test: chi-square = 11.39, $p < 0.01$.
One tailed test for the independent variables, and two-tailed test for the control variables.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
† $p < 0.1$.

Table 3
Descriptive statistics for matched patent case–control design.

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1	Guided exploration	0.33	0.47	1							
2	Market growth	1.15	0.15	0	1						
3	Market competitiveness	1.33	0.38	0.13*	−0.20*	1					
4	Demand volatility	1.05	0.05	0.08	0.57*	−0.13*	1				
5	Originality	0.41	0.29	0.16*	−0.02	0.01	0.01	1			
6	Claims	15.00	18.11	0.14*	−0.05	0.04	0	0.10†	1		
7	Backward cites	1.31	3.56	0.14*	0.05	−0.01	0.01	−0.01	0.04	1	
8	Forward cites	109.34	317.03	0.43*	−0.03	0.07	−0.04	0.10†	0.06	0.20*	1
9	Age	4.84	4.81	−0.19*	0.08	0.02	0.03	−0.14*	−0.15*	−0.15*	−0.07

$N = 522$ two tailed test.
* $p < 0.01$.
† $p < 0.05$.

4. Results

4.1. Results discussion

Table 1 gives descriptive statistics for firm-level panel design variables. Table 2 reports the regression results of the 2SLS unconditional fixed-effects models for our panel. Model 2 includes only control variables. Model 3 introduces the variables of theoretical interest. Hausman tests (1978) for all reported models were significant, suggesting that the fixed effects estimator was more appropriate than random effects. R-squared statistics are not reported for the second stage models because overall model goodness-of-fit is not a consideration for 2SLS models and may decline when a variable is treated as endogenous (Wooldridge, 2003). The result of the Wald test (Chi-square = 11.39, $p < 0.01$) indicates the improvement of the model's goodness of fit. Table 3 provides descriptive statistics for the matched patent case–control design variables. Table 4 reports rare events logistics models for the patent case–control design.

Hypothesis 1 proposed that *market growth* would negatively influence on the firm's *reliance on guided exploration*. Model 3 of Table 2 indicates that the coefficient associated with *market growth* is negative and significant ($p < 0.1$). Similarly Table 4, Model 2 reports the coefficient for *market growth* as negative and significant ($p < .05$) suggesting that this variable distinguishes between guided exploration and exploring without the guidance of recipient firms. Hypothesis 1 is thus supported.

In Hypothesis 2, we suggested that *demand volatility* would positively influence a firm's *reliance on guided exploration*. Model 3 of Table 2 shows that the coefficient associated with *demand volatility* is both positive and significant ($p < .05$). In Table 4, this coefficient is also positive and significant for the matched patent case–control design ($p < .05$). Hypothesis 2 is supported.

Hypothesis 3 suggests that *market competitiveness* would positively influence a firm's *reliance on guided exploration*. The coefficient associated with *market competitiveness* in our panel design (Table 2) is positive and significant ($p < .01$), as is the coefficient in the matched patent case–control design ($p < .05$; Table 4). Hypothesis 3 is supported.

Based on the first stage results of our panel design (Table 2, Model 1), other than the instrument variable *spillover*, only the technological diversity of a firm's knowledge base influenced its general level of exploration. It is noteworthy that our core variables, *market growth, market competitiveness*, and *demand volatility* have no influence in our first stage model, while significantly influence the extent to which firm rely on the guidance of recipient firms in their exploration pursuits. This pattern of results is consistent with the notion that relying on recipient firms to guide exploration activities is a means of buffering against market uncertainty and the uncertainty resulting from highly competitive environments. The lack of significance in the first model may be due to the heterogeneity within the dependent variable (i.e., general exploration). In essence, not all exploration is equally difficult or risky. That which is guided by recipient firms is less risky and thus particularly attractive in uncertain and competitive environments.

4.2. Robustness checks

To test the sensitivity of our firm-level panel design models, we ran these models using conditional fixed effects estimators and achieved consistent results. To test the robustness of our matched patent case–control design, we randomly selected control observations using a one-to-one ratio and we obtained similar results in terms of significance and direction.

Table 4
Rare events logistic models for matched patent case–control design.

Independent variable	Guided exploration	
	Model 1	Model 2
Market growth		−2.12* (1.10)
Demand volatility		7.44* (3.28)
Market competitiveness		0.88** (0.31)
Originality	0.52 (0.46)	0.51 (0.47)
Number of claims	0.003 (0.005)	0.001 (0.005)
Number of backward citations	−0.001 (0.04)	0.01 (0.05)
Number of forward citations	0.05** (0.01)	0.05** (0.01)
Age	−0.07* (0.03)	−0.07* (0.03)
Constant	−2.67** (0.60)	−9.39** (3.21)
Year dummies	Yes	Yes

$N = 522$ Wald test: Chi-square (3) = 12.37
Robust standard errors in parentheses.
One tailed test for the independent variables, and two-tailed test for the control.
** $p < 0.01$.
* $p < 0.05$.

5. Discussion

Exploring new technology and developing new capabilities are particularly valuable for firms hedging against the uncertainty that is associated with intense competition, fluctuating demand, and limited growth. However, exploring knowledge domains that lie beyond a firm's existing expertise is also a cognitively challenging and highly uncertain process. Paradoxically, to create a buffer against the inherent uncertainty of their environment, a firm may need to pursue relatively uncertain exploration processes. To resolve this dilemma, we delineated the exploration process to suggest that not all exploration is equal. Exploring some knowledge domains will be easier and less uncertain than exploring others. We argue that the uncertainty and challenge of exploring new knowledge domains for a given firm is reduced when those knowledge domains have been previously linked to the firm's existing knowledge by other firms. We suggest that by mimicking the efforts of their recipient firms, the difficulty and uncertainty of exploring new knowledge can be reduced. Such guided exploration reconciles the tension between a firm's desire to explore new knowledge when operating in uncertain environments and its limited appetite for additional uncertainty in such environments.

We found that firms which operate in environments that are highly competitive or relatively volatile environments in terms of market demand are more prone to rely on recipient firms for guidance as to where to explore for new expertise. In highly competitive markets it is generally more difficult to predict rival responses. Volatile market demand also makes it difficult for firms to predict which products or services will be valued in the future. Such unpredictability renders the outcomes of exploration increasingly uncertain. In such markets, mimicking others can provide some comfort and assurance for the exploring firm. Thus, relying on recipient firms for guidance in exploration is particularly valued in competitive and volatile markets.

We found that firms operating in high growth environments tend to rely on recipient firms for exploration guidance to a lesser degree. In high growth contexts, firms are more willing to pursue higher-risk exploration because gambles that don't pay off will not threaten their survival. The sufficient resources of a high growth environment can mitigate relatively risky exploration.

5.1. Implications

This study contributes to the literature on firm exploration. While previous work has focused on the balance between exploitation and exploration (e.g., Benner and Tushman, 2003; Hill and Rothaermel, 2003), we suggest that not all exploration is equally challenging or risk-laden. A further delineation of exploration in this fashion may provide more fine-grained insight into the antecedents and outcomes of exploration in general. By conceptualizing a new mechanism for exploration beyond that of strategic alliances (Phelps, 2010), corporate venture capital investment (Wadhwa and Kotha, 2006), hiring new engineers (Rosenkopf and Almeida, 2003), and informal social networks (Almeida and Kogut, 1999), we can broaden the alternative whereby firms acquire new knowledge.

Our study also has implications for understanding firm strategies in highly uncertain environments. We suggest that the tension between the firm's desire to explore in an uncertain environment and its limited appetite for the add uncertainty of exploration may be reconciled. Exploration through mimicry is a possible strategy for managers to maintain competitiveness while minimizing risk. When the external environment is highly uncertain, managers and executives alike might find that the new knowledge domains in the firm's knowledge spillover pool provide ideal place to search for effective and efficient solutions to adapt to the changing environment. These results also highlight how originating firms can benefit from knowledge spillovers. Conventional wisdom has it that knowledge spillovers are a net loss for the originating firm since it loses proprietary know-how and possibly monopoly rents. Such losses may be partially offset if the originating firm can subsequently learn vicariously and gain insight into new knowledge domains.

5.2. Limitations and future research

Although our study addresses important issues in firm exploration, it has its limitations. We use patents and patent citations to measure knowledge spillovers and exploration activity. These measures are unlikely to fully capture all firms' exploration activities and knowledge flows (Jaffe et al., 2002). Our findings may also be unique to a particular time period, the sampled firms, and industry context. More evidence using data from different time periods, samples, and industries is needed to further validate this study's findings.

Our research considers the propensity to pursue exploration based on the guidance of recipient firms and how they may combine the firm's knowledge with technological domains that are unfamiliar to the firm. Our work does not address the performance implications of pursuing exploration based on the innovation activities of recipient firms. Scholars have argued for a balance between exploitation and exploration to ensure long-term success (Levinthal and March, 1993). We suggest that exploration may be further demarcated into that which is guided by recipient firms and that which is not. Does one type of exploration dominate the other, or should there be a balance to optimize performance? Does drawing on the guidance of recipient firms limit the possibility of breakthrough innovations? One might expect that the variance and average outcome resulting from exploration based on recipient firm activities would be lower due to the reduction in uncertainty associated with such exploration. Future theoretical and empirical work along these lines should prove enlightening.

In particular, Jansen et al. (2006) found that exploration in general was especially beneficial to firms in volatile environments and where resources were somewhat restrained. One could further speculate whether these results vary depending on whether the explored technological domains are previously linked to the firm's existing knowledge base. Various firm coordination mechanisms such as centralization and formalization (Jansen et al., 2006) and process management activities (Benner and Tushman, 2003) can influence the balance between exploitation and exploration. Such firm differences may also influence how and where a firm explores.

Our industry context was also limited to the various telecommunication equipment sectors. Incumbent firms particularly in mature industries often have difficulties contending with the onset of radical technologies and exploration due to inertia and various strategic inflexibilities (Hill and Rothaermel, 2003). One means of overcoming such inertia is to pursue exploration as guided by recipient firms. Continuing work examining the use of recipient firm guidance for exploration across a broader array of sectors and contexts would most likely be a fruitful avenue for future research.

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