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WHAT DRIVES EXPLORATION? CONVERGENCE AND DIVERGENCE OF EXPLORATION TENDENCIES AMONG ALLIANCE PARTNERS AND COMPETITORS

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Management research has alluded to organizational and environmental conditions that drive firms' tendencies to explore versus exploit. We complement this research by developing theory on vicarious learning to explain how a firm adjusts its own exploration level based on the exploration levels of its alliance partners and competitors. Using panel data on 180 electronics firms publicly traded in the United States, we reveal an inverted U-shaped association between a firm's exploration tendency and the exploration levels of its partners and competitors. Convergence is explained by imitation and legitimation, while divergence is associated with risk perception and specialization in the knowledge domain. We further show how the convergence of the exploration tendency becomes stronger under firm-specific uncertainty but weaker when the exploration patterns exhibited by the firm's partners and competitors are incoherent. Finally, counter to expectations, we show that this convergence is weakened by the technological proximity of the firm's competitors. Our findings inform research on vicarious learning and the antecedents of exploration by underscoring the role of interdependence in firms' exploration tendencies.

The exploration–exploitation framework has gained much scholarly attention in recent years, with its impact extending even beyond the management discipline (Wilden, Hohberger, Devinney, & Lavie, 2018). Nevertheless, "there has been little attempt to uncover why some organizations emphasize exploration while others mostly pursue exploitation" (Lavie, Stettner, & Tushman, 2010: 118). Specifically, what drives a firm's tendency to explore in its knowledge domains? According to research on organizational learning, exploration involves developing knowledge elements that are new to a firm, whereas exploitation entails leveraging and refining the firm's existing knowledge (Levinthal & March,

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1993). By exploring, the firm can avoid obsolescence and remain competitive, while exploitation is essential for its efficiency and for securing its market position (March, 1991). The need to allocate limited resources to these distinct learning activities, which involve conflicting routines, creates inherent trade-offs between them. Accordingly, some scholars have conceptualized these activities as lying on a continuum that ranges from exploitation to exploration (Lavie et al., 2010). Firms vary in their tendencies to explore versus exploit, and adjust these tendencies over time (e.g., Lavie & Rosenkopf, 2006). Still, prior research has mostly focused on the consequences of exploration and on the means by which firms balance exploration and exploitation rather than on the factors that drive these tendencies.

Research on the antecedents of exploration alludes to environmental conditions that can facilitate it, such as resource munificence, technological and market uncertainty, environmental dynamism, and the intensity of competition (Jansen, Volberda, & Van Den Bosch, 2005; Kim & Rhee, 2009; Sidhu, Volberda, & Commandeur, 2004; Voss, Sirdeshmukh, & Voss, 2008). These exogenous factors uniformly shape firms' tendencies to explore in a particular industry, and thus cannot explain heterogeneity in their tendencies. However, some studies have shown that organizational characteristics such as age, size, organizational structure, and culture can explain deviation from the typical exploration tendency in an industry (Jansen, Van Den Bosch, & Volberda, 2006; Sorensen & Stuart, 2000; Voss et al., 2008). Other studies have identified managerial antecedents such as managers' attention to innovation, advice seeking, leadership style, sociopsychological aspects, and adoption of open innovation, which can influence a firm's tendency to explore (Alexiev, Jansen, Van Den Bosch, & Volberda, 2010; Jansen, Kostopoulos, Mihalache, & Papalexandris, 2016; Jansen, Vera, and Crossan, 2009; Khanagha, Volberda, & Oshri, 2017; Li, Maggitti, Smith, Tesluk, & Katila, 2013). But, even though prior research has made progress in understanding heterogeneity in firms' tendencies to explore, it has implied that firms' tendencies are independent or are collectively shaped by industry conditions.

In the current study, we argue and demonstrate that firms' tendencies to explore are in fact interdependent and associated with the corresponding exploration levels of other firms in their main reference groups. Specifically, we consider how the patterns of exploration exhibited by alters with whom a firm maintains cooperative and competitive ties shape the firm's inclination to explore.[1] By focusing on the firm's motivation to converge or diverge from the exploration levels of these alters, we complement research on organizational learning that alludes to conditions that uniformly shape firms' exploration tendencies in a particular industry.

Convergence with the exploration tendencies in a reference group is far from trivial, because each firm has an idiosyncratic exploration level that is considered desirable (Levinthal & March, 1993) and because the frequency of a behavior does not clearly indicate its efficiency, and thus may be insufficient to encourage firms to follow suit (Gupta & Misangyi, 2018). This is especially the case with exploration, for which the outcomes are unforeseen in the short term (March, 1991). Research on vicarious learning suggests that firms tend to imitate successful behaviors (Greve, 2011), but this learning may be hampered when the success of the behavior is uncertain (Terlaak & Gong, 2008). In turn, our theory suggests that imitation and legitimation facilitate convergence between a firm's tendency to explore and the level of exploration exhibited by its partners and competitors; nevertheless, convergence increases exploration only up to a point, beyond which it is mitigated as a result of aversion of perceived risk. We further propose that, as the exploration level of partners and competitors becomes excessive, the firm diverges from it and shifts to exploitation. Such divergence is explained by efforts to specialize in the knowledge domain. We also expect convergence to intensify when the firm faces increasing uncertainty and becomes more technologically proximate to its partners and competitors. Finally, we suggest that variation in the exploration levels of the firm's partners and competitors weakens convergence.

We test our predictions with panel data on 180 electronics firms publicly traded in the United States. Our findings support our conjectures—with the exception of technological proximity, which does not affect convergence with partners and weakens convergence with competitors as a result of firms' differentiation efforts. Hence, although each

[1] We study the extent of exploration (how much a firm explores) rather than the knowledge domains in which exploration is pursued (where a firm explores). Hence, convergence with the exploration tendencies of the reference group does not necessarily entail entering the same knowledge domains. When the firm's partners and competitors enter new knowledge domains, the firm may invest in exploration that extends its own knowledge domains.

firm is expected to have an idiosyncratic level of exploration that serves its needs, we show that a firm aligns its exploration tendency with the exploration levels of its unique set of partners and primary competitors, at least to an extent. We also reveal that this convergence is subject to boundary conditions, and eventually, as exploration levels become excessive, gives way to divergence of exploration tendencies (see Figure 1).

Our study contributes to research on the antecedents of exploration by explaining some previously unobserved heterogeneity and by uncovering an important antecedent that underscores interdependence in firms' exploration tendencies. We reveal that a firm's tendency to explore is related not only to exogenous industry conditions (e.g., Jansen et al., 2005; Sidhu et al., 2004) and organizational factors (e.g., Greve, 2007; Jansen et al., 2006), but also to the typical exploration levels prevalent in the firm's unique reference groups. This association varies from convergence to divergence, depending on the observed exploration levels. We conclude that firms do not operate in isolation, nor do they uniformly react to changing industry conditions. Rather, their tendencies to explore are interactively constructed in a network wherein firms observe the exploratory behavior of their unique partners and primary competitors and position themselves accordingly. We thus offer a novel explanation for the heterogeneity in exploration tendencies.

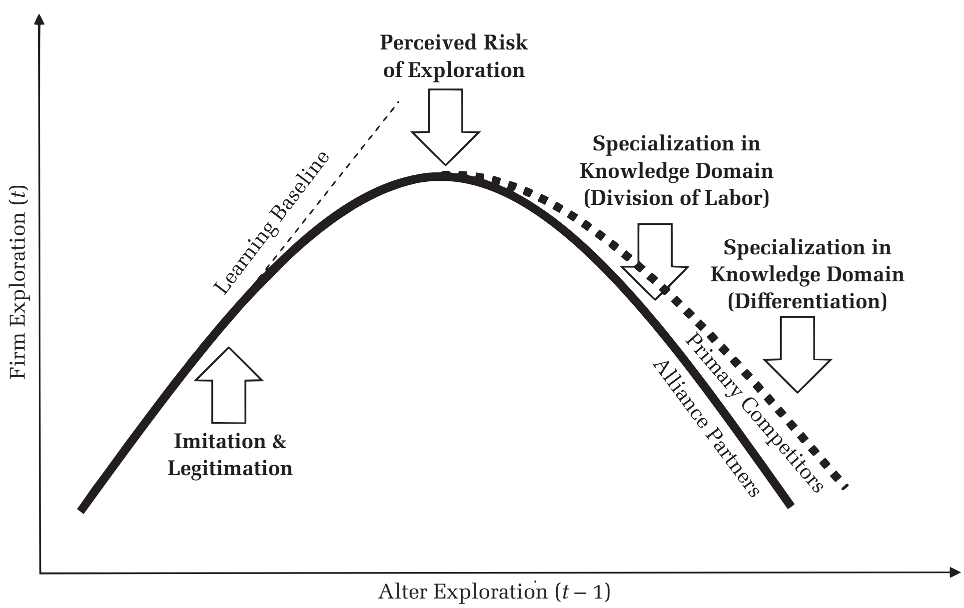
Finally, we advance research on vicarious learning, which has underscored the roles of imitation and legitimation in driving convergence of behaviors (e.g., Haunschild & Miner, 1997; Lieberman & Asaba, 2006), but has paid less attention to boundary conditions that lead to divergent behaviors. We show that imitation and legitimation are offset by risk aversion and efforts to specialize in the knowledge domain when the outcomes of alters' behaviors become unpredictable, thus leading to divergence of behaviors. We further identify firm-specific uncertainty, variance in behaviors, and proximity as important boundary conditions for vicarious learning. Hence, we offer a nuanced perspective on the convergence and divergence of behaviors in reference groups.

THEORY AND HYPOTHESES

Convergence and Divergence of Exploration Tendencies

A firm's exploration tendency is a typical corporate behavior that evolves via experiential and vicarious learning (Baum, Li, & Usher, 2000). In vicarious learning, firms adjust their corporate behavior in response to behaviors prevalent in their reference groups (Srinivasan, Haunschild, & Grewal, 2007). One important reference group that promotes vicarious learning is alliance partners, which directly interact

FIGURE 1
Conceptual Model for Convergence and Divergence of Exploration Levels



with the firm (Powell, Koput, & Smith-Doerr, 1996) and often serve as trendsetters and role models for the firm (Abrahamson, 1996). Besides its partners, the firm's competitors are another important reference group (Fiegenbaum & Thomas, 1995; Porac, Thomas, & Baden-Fuller, 1989). Firms track their competitors' actions and position themselves vis-à-vis competitors (Chen, 1996). They pay most attention to their primary competitors (Clark & Montgomery, 1999) in order to closely monitor them and learn from their behavior (Haunschild & Miner, 1997; Hsieh, Tsai, & Chen, 2015). Hence, vicarious learning from primary competitors complements learning via direct interaction with partners (Baum et al., 2000).

When vicariously learning from partners, a firm can observe its partners' corporate behavior irrespective of the scope and content of its alliances with them (Khanna, Gulati, & Nohria, 1998; Lavie, 2009). Similarly, vicarious learning from primary competitors may encompass corporate behaviors (Miner & Mezias, 1996), as in learning from the failures of competitors, which helps the firm reflect on causal processes and develop its own practices (Kim & Miner, 2007). According to research on vicarious learning from reference groups, a firm is inclined to compare and adopt behavioral patterns that are typical of the population average, which indicates a widely adopted behavior (Hu, Blettner, & Bettis, 2011). Although some firms may rely on a small reference group of leaders that exhibit superior performance (Massini, Lewin, & Greve, 2005), this is unlikely in the case of exploration, for which performance outcomes are unforeseen in the short term.

Firms learn a range of corporate behaviors from their reference groups, such as alters' innovation strategies (e.g., Semadeni & Anderson, 2010), product introductions (e.g., Giachetti & Lanzolla, 2016), international expansion (e.g., Henisz & Delios, 2001), and market entry (e.g., Haveman, 1993), but there is heterogeneity in the extent to which these behaviors are followed (Gupta & Misangyi, 2018). A firm is more likely to track and adopt the corporate behavior of its partners and primary competitors when such behavior is visible (Baum et al., 2000) and entails uncertainty (O'Neill, Pouder, & Buchholtz, 1998; Srinivasan et al., 2007). By definition, exploration is observable yet inherently uncertain, forcing the firm to confront outcomes that cannot be foreseen in the short term (March, 1991). As a result, we expect a firm to engage in vicarious learning that is driven by imitation and legitimation and that leads to convergence with the typical exploration level of the firm's partners and primary competitors.[2]

Specifically, vicarious learning of exploratory behavior is driven by imitation that enables firms to seek adaptive responses to common challenges (Kraatz, 1998). By acquiring knowhow from alliance partners or by scanning their competitive environment, firms are prompted to imitate the observed behavior of alters (Huber, 1991). Imitation is invoked by the perception that the information that is available to alters and that guides their exploration efforts is more valuable than one's own information. Assuming that alters possess superior information or expertise facilitates imitation of their exploration level. As information is revealed about firms that adopt this level of exploration, imitation is further reinforced in the reference group. Aligning the firm's exploration tendency with the exploration level exhibited by alters is thus driven by the desire to overcome information asymmetry (Kraatz, 1998; Lieberman & Asaba, 2006), capitalize on opportunities for expanding the firm's own knowledge domains (Anand, Mesquita, & Vassolo, 2009), and imitate an effective practice that has been tested by others (Greve, 1996, 1998).

Besides vicariously learning proven practices, convergence of exploration tendencies may result from imitation of common practices in a search for legitimacy (Suddaby, Bitektine, & Haack, 2017), which is essential when a corporate behavior entails risk and uncertainty (Lieberman & Asaba, 2006). Indeed, scholars have argued that "legitimacy-based reference groups guide firms in their mimetic behavior" (Barreto & Baden-Fuller, 2006: 1559). Exploration can be considered legitimate when there is a shared perception of its appropriateness. Adopting a behavior that is deemed appropriate and desirable in a social context contributes to the adopter's legitimacy in the eyes of external stakeholders (DiMaggio & Powell, 1983; Suchman, 1995). Firms need to ensure that their exploration tendencies are sufficiently similar to those of alters in their reference groups—for example, primary competitors—in order to signal to their stakeholders that they conform to industry norms. Firms conform to these expectations because

[2] We study the extent of exploration (how much a firm explores) rather than the practice of exploration (how a firm explores). Adjusting a firm's tendency to explore based on its alters' level of exploration is more straightforward than learning the practice, which involves tacit routines for knowledge creation (Brix, 2017; Rosenkopf & Nerkar, 2001).

the external endorsement obtained via legitimacy helps in gaining access to resources and carrying out the firms' exploration efforts. Thus, a firm that adheres to the exploration level of role models can enhance its legitimacy beyond the expected performance gain associated with exploration (Deephouse, 1996; Haunschild & Miner, 1997; Lieberman & Asaba, 2006). In sum, convergence with the exploration level of partners and primary competitors may be driven by vicarious learning in which the firm imitates a popular behavior in a search for legitimacy (Henisz & Delios, 2001; Suchman, 1995).

A remaining question is whether firms engage in frequency imitation of common practices or, rather, outcome imitation (Haunschild & Miner, 1997). Because the outcomes of exploration cannot be foreseen in the short term, it is unlikely that exploration merely reflects the firm's intention to do the right thing. Rather, imitation reflects unconscious cognitive processes such as herding in addition to more consciously deliberate processes (Gupta & Misangyi, 2018). Regardless of its underlying cause, imitation facilitates convergence with the typical exploration level exhibited by partners and primary competitors. For both reference groups, imitation is driven by the perceived value and available information. However, for partners with which the firm maintains cooperative relations, information on their exploration level is more readily accessible than for competitors, which may limit the firm's access to information. In turn, information on the exploration level of competitors is more relevant and valuable to the firm that operates in similar domains.

Nevertheless, we expect the convergence between a firm's tendency to explore and the exploration level exhibited by its partners and primary competitors to increase only up to a certain point, beyond which it is mitigated. Operating at high levels of exploration entails exorbitant risk, given that it involves entering several new knowledge domains. Thus, the firm may be unable to support extensive exploration (Uotila, Maula, Keil, & Zahra, 2009). Because the likelihood of successful exploration is lower than that of exploitation (Levinthal & March, 1993), the firm may avoid aligning its exploration level with the excessive exploration levels of its partners and competitors in order to minimize losses from failed exploration. Hence, the firm's aversion to the perceived risk of excessive exploration exhibited by its partners or primary competitors is likely to mitigate the convergence associated with imitation and legitimation.

Whereas perceived risk restricts convergence with the exploration levels of partners and primary competitors, specialization in the firm's knowledge domain prompts divergence from their excessive exploration levels, and thus a tendency to revert to exploitation. Specialization in the knowledge domain fosters experiential learning that counters vicarious learning and deters imitation (Reed & DeFilippi, 1990). Although, for both reference groups, specialization drives divergence, it is ascribed to division of labor with partners, as opposed to differentiation vis-à-vis competitors. Specifically, at high levels of partner exploration, the firm can divide labor with its partners that engage in extensive exploration, while it reverts to internal exploitation in a narrow knowledge domain (Stettner & Lavie, 2014). Whereas, at low levels of partner exploration, the firm must rely on its internal exploration efforts, at high levels of partner exploration, the firm can rely on partners for externally extending its knowledge domains (Rosenkopf & Almeida, 2003). As it increases its reliance on partners for exploration, it can specialize in exploiting the knowledge that it has accumulated internally. Hence, when partners engage in excessive exploration, the firm can rely on their complementary expertise in new knowledge domains. Because of such division of labor, some partners are prone to further increase their exploration level while the firm gravitates toward exploitation (Hess & Rothaermel, 2011). Hence, as partners explore more, the firm can capitalize on their boundary spanning, which, in turn, further restricts its own exploration tendency.

Finally, at high levels of competitor exploration, the firm is likely to diverge from the exploration tendency of its primary competitors and revert to exploitation. This specialization in its existing knowledge domains is due to the firm's intent to differentiate itself from competitors while avoiding increased investments in innovation that can escalate technology races (Deephouse, 1999). When the firm diverges from its competitors' excessive exploration level and concentrates instead on its established knowledge domains, it can reinforce its corporate identity, rely on existing skills and capabilities, enhance its unique value proposition to customers, and defend its industry position. Differentiation explains the firm's reversion to exploitation once its primary competitors turn to excessive exploration. In sum, at high levels of exploration by both partners and primary competitors, specialization in the knowledge domain offsets the vicarious learning associated with imitation and legitimation.

The firm is likely to adjust its tendency to explore per the exploration levels of these alters up to a threshold, beyond which the firm is expected to revert to exploitation.

Hypothesis 1. A firm's tendency to explore exhibits an inverted U-shaped association with the exploration levels of (a) its alliance partners and (b) its primary competitors.

Uncertainty, Variation, and Technological Proximity as Boundary Conditions

Firms vary with respect to the extent to which their exploration tendencies converge with those of their partners and primary competitors. Convergence is contingent on conditions that can influence the firm's motivation and ability to engage in vicarious learning (e.g., Baum et al., 2000; Gioia & Manz, 1985; Haunschild & Miner, 1997) and thus align its exploration tendency with those of alters. These conditions include firm-specific uncertainty, variation in the exploration levels of partners and primary competitors, and technological proximity to these alters.

A firm's inclination to follow the exploration level of alters depends in part on the uncertainty that it encounters. Firms experience distinctive challenges in predicting future outcomes. They often face market uncertainty (Srinivasan et al., 2007), but some uncertainty remains firm specific (Beckman, Haunschild, & Phillips, 2004). Firm-specific uncertainty refers to a "lack of assurance about the probability and outcomes of corporate decisions" (Gulati, Lavie, & Singh, 2009: 1220). It indicates the difficulty that managers face in predicting environmental trends in light of idiosyncratic internal factors (Beckman et al., 2004), such as the firm's decisions, capabilities, and strategies. Firm-specific uncertainty can be only partially resolved by the firm's actions (Cuypers & Martin, 2010). Although firm-specific uncertainty is defined from the standpoint of managers, it also exposes the firm to potential speculation by external stakeholders (Beckman et al., 2004).

Vicarious learning is likely under conditions of uncertainty, which prompts managers to seek external guidance (Srinivasan et al., 2007). This suggests that convergence increases with firm-specific uncertainty. Convergence with the exploration levels of partners and primary competitors is especially likely under uncertainty, given the nature of exploration. In reaction to the challenge of predicting the outcomes of its exploration efforts, the firm is likely to seek more guidance as firm-specific uncertainty increases. When uncertainty increases, managers become doubtful about the prevalence of opportunities for exploration, the possibility of pursuing these opportunities, and the opportunities' prospects (McMullen & Shepherd, 2006). Firm-specific uncertainty restricts the firm's ability to recognize, assess, and pursue exploration opportunities. As a result, its managers may become hesitant about missing market opportunities or assuming the risk of exploration. The high uncertainty about the outcomes of exploration motivates the firm to learn from the conduct of alters (Greve, 1996; Rosenkopf & Abrahamson, 1999). Moreover, as uncertainty increases, so does the belief that partners and competitors possess more reliable information about exploration opportunities (Haunschild & Miner, 1997; Lieberman & Asaba, 2006). Consequently, the firm is more prone to imitate alters and align its exploration efforts with their exploration level.

Firm-specific uncertainty reinforces convergence with the exploration levels of alters not only because it fosters imitation, but also because it increases the need for legitimacy. As uncertainty increases, convergence with the exploration levels of alters becomes essential for convincing stakeholders that the firm is able to cope with environmental challenges (Kondra & Hinings, 1998). Indeed, alignment with alters' behavior enhances the firm's legitimacy in the eyes of stakeholders (Gimeno, Hoskisson, Beal, & Wan, 2005). Hence, uncertainty reinforces the need for legitimacy and spurs the firm's efforts to converge with the exploration levels of its partners and competitors.

Overall, firm uncertainty reinforces vicarious learning by increasing the need for legitimacy and the reliance on alters for information. This increases convergence of the firm's exploration tendency with that of its partners and competitors at any level of exploration pursued by them.

Hypothesis 2. Firm uncertainty increases the positive association between a firm's tendency to explore and the exploration levels of (a) its alliance partners and (b) its primary competitors.

Although a firm may learn to align its exploration tendency with that of alters, this may not be straightforward when the partners or competitors exhibit varied levels of exploration. Research on vicarious learning suggests that "faced with such streams of inconsistent inputs and with maneuvering limited cognitive capacity, at least some managers are uncertain about the underlying covariation between practice value and the relevant trait" (Terlaak & Gong, 2008: 850). Indeed, incoherent behavior makes it difficult for the firm to identify the typical tendency in the reference group and to align its exploration tendency accordingly. Convergence entails discerning exploration levels, interpreting them, synthesizing this input, and adjusting the firm's exploration tendency. Variation in the exploration levels of partners or competitors inhibits these processes.

Specifically, to learn about the desirable level of exploration, the firm needs to monitor the behavior of its partners and competitors. Such monitoring requires discerning the typical tendency in these reference groups, which becomes more challenging the more dispersed the observed exploration pattern. Hence, convergence of exploration tendencies is impaired by inconsistent information and unclear causal relationships (Gioia & Manz, 1985). Next, convergence involves interpreting information, giving meaning to data, and synthesizing it (Maitlis & Christianson, 2014). When the exploration of partners or competitors reflects coherent tendencies, interpretation and synthesis are straightforward. However, when their exploration levels vary, it is more difficult to make sense of their tendencies and identify the desirable exploration level. As a result, the firm's ability to converge with the exploration levels of its partners and competitors is compromised. Moreover, convergence entails devising organizational routines for adjusting the firm's exploration tendency based on comprehension and interpretation of the learned practice (Nelson & Winter, 1982). However, variation in the exploration levels of partners and competitors makes it difficult to learn a set of routines that enable the firm to follow their exploration tendencies.

In addition, when alters in the reference group exhibit inconsistent patterns of exploration, it becomes more difficult to gain legitimacy by following their exploration tendencies (Henisz & Delios, 2001; Suchman, 1995). Stakeholders may associate such variation with randomness and unreliability of the behavior, and thus perceive it as illegitimate (Rhee, Kim, & Han, 2006). Variation in the exploration levels of alters may preclude consensus among stakeholders about the desirable level of exploration, so that the firm cannot gain legitimacy by conforming to that level (Deephouse, 1999). Indeed, when the firm's partners or primary competitors disagree about the desired level of exploration, the firm's convergence with the typical exploration level does not enhance legitimacy and validation of its exploration endeavors. Without a well-received reference for exploration, convergence with the typical tendency is less likely to be deemed appropriate (Suchman, 1995). Overall, variation in the exploration levels of partners and primary competitors hampers the learning and interpretation of their tendencies, and constrains the firm's ability to imitate their exploration levels while undermining their legitimacy, thus mitigating convergence with the exploration levels of partners and competitors.

Hypothesis 3a. Variation in the exploration level of a firm's alliance partners weakens the positive association between the firm's tendency to explore and the exploration level of its partners.

Hypothesis 3b. Variation in the exploration level of a firm's primary competitors weakens the positive association between the firm's tendency to explore and the exploration level of its competitors.

Whereas variation in exploration levels can impede convergence, technological proximity can facilitate it. Research on vicarious learning suggests that, "for another organization's actions to influence a potential imitator, the organization and its context must be seen as sufficiently similar to the imitator's" (Baum et al., 2000: 775). A key aspect of similarity is technological proximity, which refers to the extent of overlap in firms' technical knowledge domains (Rosenkopf & Almeida, 2003), or "the degree to which their technological problem-solving focuses on the same narrowly defined areas of knowledge" (Makri, Hitt, & Lane, 2010: 606). Prior research has noted that similarity in knowledge domains facilitates knowledge transfer (Mowery, Oxley, & Silverman, 1996; Phene, Fladmoe-Lindquist, & Marsh, 2006; Rosenkopf & Almeida, 2003), but this can also apply to imitation of exploratory behavior. The more proximate a firm to alters, the more relevant their behavior, and the easier it is for the firm to monitor and follow that behavior (Baum et al., 2000). Thus, technological proximity increases the firm's motivation and ability to align its exploration tendency with the tendencies of its partners and primary competitors.

In particular, technological proximity is expected to facilitate convergence of exploration levels because operating in comparable environments and engaging in similar activities affect judgment about the relevance of alters (Greve, 2005). According to the homophily principle, ties to similar alters are considered more significant (McPherson, Smith-Lovin, & Cook, 2001). Technological proximity to alliance partners and competitors thus reinforces the perception that the firm can rely on these alters as a relevant source of information about corporate behavior (Kilduff, Elfenbein, & Staw, 2010). Hence, technological proximity is expected to facilitate the firm's monitoring and learning of the exploration levels of partners and competitors. In fact, technologically proximate firms explore in similar knowledge domains (Phene et al., 2006; Rosenkopf & Almeida, 2003) and thus are likely to develop similar perceptions about opportunities and adopt common behaviors (Giachetti & Lanzolla, 2016). Technological proximity to partners and competitors can even foster identification and common perceptions of opportunities in the industry, which create a shared vision about exploration prospects (Dobrev, 2007; Kraatz, 1998; O'Neill et al., 1998). This leads to consensus about competencies for entering new knowledge domains, which further promote imitation in the reference group. The greater the technological proximity, the more relevant the expertise of partners and competitors and the better the firm can comprehend their exploration, which prompts it to more closely follow their exploration levels. Hence, technological proximity reinforces imitation and convergence of exploration tendencies.

Finally, the firm's search for legitimacy may gain from technological proximity because convergence with the behavior of technologically proximate alters can legitimize the firm's decisions to enter new knowledge domains (Deephouse, 1996). Convergence with the exploration tendencies of technologically proximate partners and competitors is especially important given the inherent riskiness of exploration. The firm's managers may become more confident about pursuing risky exploration when the firm's closest partners and competitors engage in exploration, assuming that conformity will reduce these managers' liability in case of failure (Schimmer & Brauer, 2012).

In sum, technological proximity to partners and competitors increases the attention that the firm pays to their exploration, facilitates comprehension of exploration opportunities that those alters have identified, and legitimizes exploration. Accordingly, technological proximity reinforces vicarious learning and convergence with the exploration levels of partners and competitors.

Hypothesis 4a. Technological proximity of a firm's alliance partners strengthens the positive association between the firm's tendency to explore and the exploration level of its partners.

Hypothesis 4b. Technological proximity of a firm's primary competitors strengthens the positive association between the firm's tendency to explore and the exploration level of its competitors.

RESEARCH METHODS

Sample and Data

We tested our hypotheses with panel data on firms that were publicly traded in the United States and operated in sectors of the electronics industry during the period 1990–2006. These sectors encompassed manufacturers of electronic devices, semiconductor components, and computer hardware, including industrial and commercial machinery and computer equipment (Standard Industrial Classification, or SIC, code 35); electronic and electrical equipment and components (SIC code 36); and measurement, analysis, and control instruments (SIC code 38). The intensive competition and alliance formation in these sectors (Stuart, 2000) ensured variance in firms' patents, competitors, and partners. These sectors were chosen because at least 40% of all firms in these sectors apply for patents, which is essential for calculating patent-based measures (Cockburn & Griliches, 1987). To develop meaningful measures of exploration, we limited our sample to firms with financial data that applied for patents for at least five consecutive years and that had a median patent application count of at least four patents per year. We corrected potential sampling bias with our first-stage model. The resulting sample included 184 firms.

We relied on National Bureau of Economic Research (NBER) patent data to consistently assess firms' exploration tendencies (Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001), and we corrected or supplemented incomplete data from Comets Patent database (Griliches, 1998).[3] We studied patent applications rather than granted patents because the year in which a patent is applied for is closer to the time of invention (Hall & Ziedonis, 2001; Jaffe, Trajtenberg, & Henderson, 1993).[4] Because patents are often assigned to subsidiaries rather than to the headquarters, we identified each firm's subsidiaries using the NBER and the Corporate Affiliations

[3] The focus on U.S. patents is justified by firms' incentives to secure legal protection in the United States and the reputation of the U.S. judicial system in providing effective protection of intellectual property (Gallini, 2002). We limit our data to utility patents, while excluding design, reissue, and plant patents (Hall, Jaffe, & Trajtenberg, 2001).

[4] The delay between the time of invention and the patent application does not generally exceed three months, but the time lag between a patent application and the granting of the patent by the U.S. Patent Office may be three to four years. The patent application date thus better reflects the time of knowledge creation (Griliches, 1998).

databases, and cross-validated acquisitions in the Securities Data Company (SDC) database. Thus, we accounted for patents of the firm's subsidiaries, but discarded patents of acquired firms that were applied for prior to the acquisition (Puranam & Srikanth, 2007). This enabled us to study exploration relative to a firm's existing knowledge domains in a given year. We gathered data on firms' patents since 1985, to measure exploration experience starting the five years preceding the study's timeframe. In total, the 184 sampled firms and their subsidiaries applied for 280,080 patents during the period 1985–2006. We aggregated patent counts to the firm-year level. The same procedure served for measuring the exploration tendencies of partners and primary competitors.

To identify the firm's alliance partners, we compiled alliance records from the SDC database, considering active alliances as those formed in the past five years (e.g., Stuart, 2000). In total, 162 of the 184 sampled firms formed 6,735 alliances with 1,351 partners during 1985–2006.[5] On average, a firm formed 3.90 alliances per year and had a portfolio of 20.93 alliances during 1990–2006, with 74.50% of alliances formed with partners outside its two-digit SIC. To construct our measures, we pooled records across all alliances in a firm-year.[6]

Next, we identified the firm's competitors based on resource similarity (Chen, 1996), acknowledging that firms tend to rely on supply-based (e.g., technologies developed) rather than demand-based (e.g., customers served) definitions of competitors (Clark & Montgomery, 1999) when observing exploration in knowledge domains. In the electronics industry, resource similarity is more important than market communality as a result of the prolonged R&D process that precedes product introduction to a common market. Because knowledge is the most relevant resource in this industry (Dothan & Lavie, 2016), we relied on technological similarity captured by the overlap in firms' patent classes (e.g., Grimpe & Hussinger 2014; Polidoro, Ahuja, & Mitchell, 2011). For each of the 184 firms, we identified competitors by tracking publicly traded firms that had at least one patent class overlapping with those of the focal firm in the past five years. In line with research on competitors' reference groups and competitor identification (Clark & Montgomery, 1999; Porac & Thomas, 1990), we selected the five primary competitors with the largest overlap. The overlap was computed using the Jaffe (1986: 986) measure:

$$\mathrm{P_{ij}} = \frac{F_i F_j'}{\left[\left(F_i F_i'\right)\left(F_j F_j'\right)\right]^{\frac{1}{2}}}$$

where P_{ij} captures the annual technological similarity of firm i to competitor j based on the angular separation between their knowledge domain vectors, F_i and F_j. These knowledge domains represent the cumulative number of patent applications across patent classes in a five-year window. For every firm-year, we selected the firm's five primary competitors with the highest Jaffe scores and pooled records across them.[7]

Finally, we gathered financial data from the Compustat and Center for Research in Security Prices (CRSP) databases. For each firm-year, we pooled the data across all partners and primary competitors. After listwise deletion of 275 records with missing data (10.53% of 2,612 records), the remaining data for testing the effect of competitor exploration had 2,337 firm-year observations for 180 firms during 1990–2006. Following the listwise deletion of 255 records with missing data (14.75% of 1,729 records), the data for testing the effect of

[5] Following prior research, we excluded 633 alliances with 236 privately held partners for which data were unavailable in the NBER database (e.g., Conti, 2014; Schilling, 2015; Sears & Hoetker 2014). Excluding the 8.59% alliances with private partners is consistent with our theory because, unlike private partners, publicly traded partners are required to disclose information about their exploration endeavors, while the exploration of private partners is less visible. Furthermore, firms are likely to benchmark against alters with similar or higher status as role models for imitation and legitimation (Haunschild & Miner, 1997; Haveman, 1993; Henisz & Delios, 2001). Therefore, public firms are more likely to follow public partners than private partners. We applied a similar logic when focusing on public competitors. Because we consider only the exploration levels of the primary competitors, a private competitor is unlikely to serve as a benchmark. Comparisons of the 6,735 selected alliances to the 7,368 alliances including private partners reveal no significant differences, so excluding private partners has limited implications. Finally, we account for potential selection bias due to the exclusion of observations on private partners with our two-stage Heckman model.

[6] We identified 718 patents (0.38%) that were jointly assigned to 28 firms (18.30%) and their 46 partners (3.65%). Our findings remain unchanged when we exclude these jointly assigned patents from our data.

[7] Increasing the reference group to seven top competitors did not materially affect our reported findings.

partner exploration had 1,474 firm-year observations for 153 firms.[8]

Measures

Dependent variable. We measured *firm exploration* as a continuous variable (e.g., Greve, 2007; Lavie & Rosenkopf, 2006; Sidhu, Commandeur, & Volberda, 2007; Uotila et al., 2009),[9] using the inverse of a normalized Herfindahl index that captures the diversity of unique patent classes at year *t* based on patents applied for in the past five years. The measure took the form:

$$1 - HI_{it} = \frac{N}{(N-1)}\left(1 - \sum_{r=1}^{N} S_r^2\right)$$

where S_r is the share of patent class r in firm i's patent classes, and N is the number of distinct patent classes. This measure captures a firm's breadth of knowledge in a given year, on a range between 0 and 1 (e.g., Argyres & Silverman, 2004; Trajtenberg, Henderson, & Jaffe, 2002). Increase in the breadth of knowledge across various knowledge domains indicates the firm's tendency to explore (Ganzaroli, De Noni, Orsi, & Belussi, 2016; Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Guan & Liu, 2016). Thus, by tracking patent applications in new patent classes (e.g., Ahuja & Lampert, 2001) while controlling for the firm's exploration in the previous year, we captured the firm's tendency to explore by expanding into new knowledge domains. To ensure that the knowledge domains to which the firm expands are indeed new to the firm, we relied on patent classes rather than on patent subclasses, which can be potentially related to each other.[10]

To avoid an inherent bias in calculating exploration (Lavie & Rosenkopf, 2006), we assumed that observations with fewer than two patents were balanced and assigned them a value of 0.5 (Stettner & Lavie, 2014).[11] Our measure was preferred to more complex measures based on patent citations (e.g., Eggers & Kaul, 2018; Katila & Ahuja, 2002) that capture exploration as knowledge that is new to the world rather than new to the firm (e.g., Eggers & Kaul, 2018; Fleming, 2001), and hence not fully in line with our theory on exploration and vicarious learning. Explanatory variables were lagged by one year relative to our dependent variable.

Independent variables. We applied a similar procedure for measuring the two independent variables. *Partner exploration* was measured with an inverse Herfindahl index capturing the annual diversity of patent classes of the firm's alliance partners, considering all the patents applied for by each partner in the past five years ending at year $t-1$. We measured partner exploration by averaging this index across the firm's partners that formed an alliance with the firm during this five-year window. *Competitor exploration* was measured with an inverse Herfindahl index relating to the average annual diversity of patent classes of the firm's five primary competitors with the highest Jaffe score for patent class overlap in year $t-1$.

Moderating variables. We measured *firm-specific uncertainty* based on the volatility in the firm's stock price in year $t-1$ (Beckman et al., 2004). We calculated this measure as the difference between the standardized monthly volatility of the firm's stock price and the average standardized monthly volatility in the stock prices of all sampled firms that year. By subtracting this market-specific uncertainty component, we capture only the uncertainty that is idiosyncratic to the firm. We divided the standard deviation in monthly closing stock price by its mean value (Gulati et al., 2009). Hence, the measure took the form:

$$\sqrt{\frac{\sum_{T=1}^{12}\left(p_{iT} - p_i\right)^2}{11 \times p_i^2}} - \sqrt{\frac{\sum_{T=1}^{12}\left(p_{mT} - p_m\right)^2}{11 \times p_m^2}}$$

where p_{iT} is firm i's stock closing price at the end of month T, which ranges from January to December. Similarly, p_{mT} is the average closing price of the sampled firms' stocks at the end of month T.

[8] Missing data in Table 3a correspond to lack of patents for partners (7.40%) and incomplete data in Compustat (13.30%), CRSP (11.80%), and Corporate Affiliations (11.39%) databases; missing data in Table 3b correspond to lack of patents for competitors (0.15%), and incomplete data in Compustat (9.72%), CRSP (8.12%), and Corporate Affiliations (7.47%) databases.

[9] The transition from exploration to exploitation is gradual, and the distinction between them is a matter of degree rather than kind. Such transitivity and relativity call for their conceptualizing along a continuum (Lavie et al., 2010).

[10] In auxiliary analysis, we replaced variables that were measured at the patent class level with measures at the patent section, subclass, group, and subgroup levels. Classification at a higher level, e.g., section, yielded weaker support for our hypotheses because of loss of discriminating power. Classification at a lower level, e.g., subclass (Rosenkopf & Nerkar, 2001; Uotila et al., 2009), furnished consistent findings with the exception of Hypothesis 2a.

[11] We obtained consistent findings when we dropped observations in which firms applied for fewer than two patents per year. Consistent findings were also obtained when we allowed the value for balance to range between 0.25 and 0.75.

We measured the *variation in exploration* levels of partners and competitors in year $t-1$ by correspondingly calculating the variance in the independent variables. These measures captured the variance in the exploration tendencies of alliance partners and the five primary competitors. We measured the *technological proximity* of the firm to its partners and competitors using the Jaffe (1986) proximity measure. Specifically, the technological proximity to a partner was measured with the formula:

$$\mathrm{P_{ij}} = \frac{F_i F_j'}{\left[\left(F_i F_i'\right)\left(F_j F_j'\right)\right]^{\frac{1}{2}}}$$

where F_i and F_j are vectors representing the knowledge domains of firm *i* and partner *j* based on classes of patents applied for during a five-year window. To compute the technological proximity to partners, we averaged this measure across the firm's partners in each year. Technological proximity to competitors was calculated using the average Jaffe (1986) proximity measure corresponding to the firm's five primary competitors.

Control variables. We included control variables characterizing the firm, its alliance portfolio, and competitors. In particular, we controlled for the firm's exploration level in year $t-1$, so that our model estimated the firm's exploration tendency—that is, its inclination to change its exploration level relative to its level of exploration in the preceding year. We also controlled for the firm's age, size, R&D intensity, corporate strategy function, financial solvency, and performance gap. A *firm's size* can affect its innovation output by decreasing exploration (Beckman et al., 2004). Firm size was measured using the firm's total revenues (Tallman & Li, 1996).[12] We measured a *firm's age* as elapsed years since the firm's incorporation. As a firm matures, it tends to decrease its exploration level (Kang & Uhlenbruck, 2006). A *firm's R&D intensity* reflects the extent to which the firm invests in new technologies and builds its absorptive capacity (Cohen & Levinthal, 1990), which can facilitate exploration by enabling the firm to incorporate external knowledge (Lavie & Rosenkopf, 2006). R&D intensity was measured by dividing the firm's R&D expenses by its total revenue. We measured a firm's *corporate strategy function* by counting its upper-echelon positions related to strategy making, as documented in the Corporate Affiliations database. This function may proactively engage in developing and executing plans for exploration and exploitation (Menz & Scheef, 2014). A *firm's solvency* captures the financial resources available to support exploration (Nohria & Gulati, 1996). We measured firm solvency with the ratio of cash to long-term debt (Stettner & Lavie, 2014). Finally, a firm's *performance gap*—that is, the difference between the firm's actual performance and its performance aspiration—can affect its propensity to explore (Dothan & Lavie, 2016; Greve, 2007). Performance aspiration was measured as a weighted linear combination of the firm's historical aspiration (return on assets in the preceding year) and its social aspiration (median return on assets of publicly traded firms in the United States that operate in its four-digit SIC that year),[13] with weights determined using grid search. We then calculated the firm's performance gap as the difference between its performance and performance aspiration. We used a spline function to model the firm's reaction to performance feedback, splitting the performance gap into positive (performance above aspiration) and negative (performance below aspiration) (Greve, 2003).

With respect to the alliance portfolio, we measured the *alliance portfolio size* by counting the number of partners that formed alliances with the firm in the preceding five years. We also measured the *strategic significance of the alliance portfolio* (Lavie, 2007), by calculating the proportion of alliances that were classified as strategic in the SDC database out of the total number of alliances that were formed during the past five years. Because a firm may intensify its exploration efforts when competition becomes intensive (Jansen et al., 2005), we controlled for the intensity of competition by counting the *number of competitors* that the firm encountered in the past five years that attained a technological proximity score (Jaffe, 1986) higher than 0.25. Setting this threshold at 0.25 generated a reasonable median competitor count of 524, with a range of 24 to 1,807.[14] All controls were lagged by one

[12] Using alternative measures based on assets and number of employees did not affect our findings.

[13] We considered alternative measures such as those based on return on sales, revenue growth, and average patent counts, which produced consistent results, albeit less significant. This is in line with prior research that identifies ROA as the most relevant and commonly used proxy in performance feedback studies (Greve, 2003).

[14] Defining competitors using 0.15, 0.5, and 0.75 Jaffe scores or four-digit SIC overlap yielded consistent findings.

year relative to the dependent variable. We accounted for remaining interfirm heterogeneity by including firm fixed effects. Inter-temporal trends were controlled for with the exploration level in the previous year and the first-order autoregression AR(1) parameter.

Analysis

We tested our hypotheses with a two-stage model specification to account for potential selection bias in our sampling procedure and because not all firms form alliances. We used two panel probit models to correspondingly estimate the selection to our sample and whether a firm had formed alliances in the past five years (Heckman, 1979). In line with prior research, we predicted the probability of being sampled based on lagged measures of the firm's patenting experience,[15] age, size, R&D intensity, financial solvency, corporate strategy function, number of industry peers in the same four-digit SIC, and market size proxied by the sum of industry revenues in the firm's primary four-digit SIC. We then estimated the probability of partnering based on lagged measures of the firm's partnering experience, age, size, R&D intensity, financial solvency, corporate strategy function, number of competitors, and market size. Market size and the firm's experience in patenting or partnering served as the exclusion restriction variables. We calculated the inverse Mills ratios (λ) based on the predicted values from the first-stage models and controlled for them in the second-stage models. The lambda parameter for partnering was included only in the second-stage model estimating the effect of partners' exploration.

The second-stage models served for testing our hypotheses. Given the high proportion of observations with no partners (36.93%), and since we sought to include these observations in the analysis of competitor exploration, we split our sample:[16] the analysis of competitor exploration relied on the full sample of 180 firms with 2,337 observations, whereas the analysis of partner exploration relied on a subsample of 153 firms with alliances and their 1,474 observations. We conducted panel data analysis with firm fixed effects, since our theory focuses on within-firm change in the level of exploration over time. Incorporating firm fixed effects also alleviates the need to control for industry conditions such as dynamism and resource munificence. Additionally, we accounted for autocorrelation of errors within cross-sections with the AR(1) parameter (Baltagi & Wu, 1999). We estimated the models using maximum likelihood and evaluated model fit with log likelihood ratio tests comparing each model to the baseline model. Maximum variance inflation factor values exceeded the threshold level (Hair, Black, Babin, & Anderson, 2010) but can be attributed to the multiple instances of the main effect, with no symptoms of multicollinearity observed.

RESULTS

Tables 1a, 1b, and 1c report descriptive statistics.[17] Table 2 reports the results of the first-stage models, which indicate that the probability of selection increases with prior patenting experience and firm age, but declines with firm size, firm solvency, and market size. This suggests that the propensity to patent increases with absorptive capacity (Cohen & Levinthal, 1990), but declines as a firm accumulates assets (Hill & Rothaermel, 2003) or when the market is sufficiently large to accommodate established technologies (Katila & Shane, 2005). Similarly, the propensity to partner increases with firm size, R&D intensity (Veugelers, 1997), and prior partnering experience (Gulati, 1999), suggesting that resource-rich firms are attractive partners (Stuart, 2000). In turn, a firm's propensity to partner declines with the number of its competitors, and its market size, as alliance formation decreases as markets grow (Eisenhardt & Schoonhoven, 1996).

[15] Patenting experience was modeled with a memory decay function that preserves 90% of the value from the preceding year over a 10-year period. A similar function served for modeling partnering experience based on alliances formed.

[16] In auxiliary analysis, we relied on a combined dataset to test the associations with partner exploration and competitor exploration simultaneously, obtaining consistent results despite the severe loss of degrees of freedom.

[17] Correlations between variables in the first-stage model (Tables 1a and 1b) were low, with the exception of the correlation of firm size with partnering experience ($r = .72$) and patenting experience ($r = .60$) (Stuart, 2000). Still, no symptoms of multicollinearity were observed (Table 2), with the maximum variance inflation factor values reaching 1.92 and 2.32 in the selection and partnering models, below the threshold level (Hair et al., 2010). Correlations between variables in the second-stage model (Table 1c) were low, with the exception of the size of the alliance portfolio and the firm's size ($r = .64$) (Lavie, 2007; Stuart, 2000). Besides the lambda parameter for selection, which was correlated with firm age ($r = -.90$), other high correlations relate to variables that were not included in the same model.

TABLE 1a
First-Stage Descriptive Statistics and Correlations for Sample Selection, 1990–2006

	Variables for Sample Selection	Mean	*SD*	Min.	Max.	1	2	3	4	5	6	7
1	Patenting Experience$_{t-1}$	13.32	72.32	0	1877.52							
2	Firm Age$_{t-1}$	15.35	19.22	0	169	.19***						
3	Firm Size$_{t-1}$	1.68	7.97	0	192.32	.60***	.22***					
4	Firm R&D Intensity$_{t-1}$	2.28	22.65	0	889.50	−.02**	−.05***	−.02***				
5	Firm Solvency$_{t-1}$	1.06	6.16	0	659.03	−.02***	−.07***	−.03***	.04***			
6	Corporate Strategy Function$_{t-1}$	0.01	0.09	0	4	.09***	.15***	.09***	−.01	−.01		
7	Number of Industry Peers$_{t-1}$	125.84	153.37	1	673	−.04***	−.23***	−.07***	.04***	.05***	−.03***	
8	Market Size$_{t-1}$	65.84	119.17	0	1482.92	.10***	−.02***	.38***	.03***	.00	.01	.29***

Note: $n = 30{,}976$.

TABLE 1b
First-Stage Descriptive Statistics and Correlations for Partnering, 1990–2006

	Variables for Partnering	Mean	*SD*	Min.	Max.	1	2	3	4	5	6	7	8
1	Partnering Experience$_{t-1}$	5.92	17.48	0	209.88								
2	Firm Age$_{t-1}$	51.09	36.76	1	168	.01							
3	Firm Size$_{t-1}$	3.96	10.78	0	151.80	.72***	.21***						
4	Firm R&D Intensity$_{t-1}$	0.10	0.26	0	7.94	.00	−.21***	−.06**					
5	Firm Solvency$_{t-1}$	0.38	1.24	0	28.16	−.02	−.16***	−.06**	.08***				
6	Corporate Strategy Function$_{t-1}$	0.06	0.29	0	4	.14***	.09***	.19***	−.04*	−.04*			
7	Number of Competitors$_{t-1}$	556.47	344.92	0	1821	.32***	−.14***	.24***	.10†	−.01	.13***		
8	Market Size$_{t-1}$	45.06	60.72	0.01	434.84	.34***	−.07***	.32***	.23***	.14***	.10***	.35***	
9	Lambda Selection$_{t-1}$	4.38	3.48	0	12.96	−.04*	−.91***	−.21***	.28***	.23***	−.10***	.11***	.35***

Note: $n = 2{,}612$.

TABLE 2
First-Stage Probit Panel Model for Probabilities of Selection and Partnering

Dependent Variables (DV):	Probability of Selection$_t$		Probability of Partnering$_t$	
Partnering Experience$_{t-1}$			24.37**	(0.04)
Patenting Experience$_{t-1}$	1.84***	(0.00)		
Firm Age$_{t-1}$	9.03***	(0.01)	0.43	(0.00)
Firm Size$_{t-1}$	−1.03*	(0.01)	2.06***	(0.03)
Firm R&D Intensity$_{t-1}$	−11.90	(0.14)	0.69*	(0.59)
Firm Solvency$_{t-1}$	−2.48***	(0.03)	−0. 31	(0.08)
Corporate Strategy Function$_{t-1}$	0.07	(0.36)	0.16	(0.22)
Number of Industry Peers$_{t-1}$	0.26	(0.00)		
Number of Competitors$_{t-1}$			−0.25†	(0.00)
Market Size$_{t-1}$	−6.11***	(0.00)	−1.03***	(0.00)
Probability of Selection			0.97†	(0.07)
n firms	3,624		184	
n firm-years	30,976		2,612	
n firms (Selected)	184		162	
n firm-years (Selected)	2,612 (8.43%)		1,729 (66.20%)	
Pseudo R^2	0.86		0.14	
−2 log likelihood	1,620.50		1794.74	
Wald χ^2	810.25***		262.61***	

Note: Standardized beta coefficients; standard errors in parentheses.

$^{\dagger}p < .10$

$^{*}p < .05$

$^{**}p < .01$

$^{***}p < .001$

TABLE 1c
Second-Stage Descriptive Statistics and Correlations for Sample, 1990–2006

	Variables	Mean	*SD*	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11
1	Firm Exploration$_{t}$	0.73	0.17	0.09	0.99											
2	Firm Exploration$_{t-1}$	0.76	0.17	0.09	1	.82***										
3	Firm Age$_{t-1}$	50.65	37.58	2	168	.20***	.28***									
4	Firm Size$_{t-1}$	5.65	13.10	0	151.80	.16***	.16***	.24***								
5	Firm R&D Intensity$_{t-1}$	0.11	0.22	0	5.40	−.040	−.07**	−.23***	−.09***							
6	Firm Solvency$_{t-1}$	0.33	0.48	0	6.32	−.16***	−.18***	−.32***	−.13***	.14***						
7	Firm Uncertainty$_{t-1}$	0.06	0.19	−0.14	2.36	−.01	−.04	−.22***	−.08**	.06*	.05†					
8	Performance Gap (Below Aspiration)	−0.04	0.09	−1.18	0	.03	.04	.13***	.08**	−.14***	−.02	−.20***				
9	Performance Gap (Above Aspiration)	0.04	0.08	0	1.39	−.07**	−.06*	−.12***	−.08**	.07**	.12***	.19***	.17***			
10	Alliance Portfolio Size$_{t-1}$	20.05	45.60	1	470	.05†	.01	.00	.64***	−.03	−.05†	−.01***	.02	−.04		
11	Strategic Alliance Portfolio$_{t-1}$	0.80	0.29	0	1	−.05†	−.10	−.25	−.08†	.11***	.11***	.11***	−.08**	.02	.01	
12	Number of Competitors$_{t-1}$	621.53	358.10	24	1807	.20***	.18***	−.14***	.23***	.12***	.06*	.14***	−.03	−.01	.24	.15†
13	Corporate Strategy Function$_{t-1}$	0.07	0.33	0	4	.10***	.12***	.11***	.17***	−.05*	−.10***	−.02	.04†	−.05†	.16***	.16†
14	Lambda Selection$_{t-1}$	4.50	3.51	0	12.96	−.21***	−.26***	−.90***	−.25***	.33***	.38***	.22***	−.14***	.14***	.09***	−.14***
15	Lambda Partnering$_{t-1}$	0.25	0.34	0	3.05	−.01	.05†	.28***	−.22***	−.09***	.12***	−.07**	.06*	.00	−.29***	−.06**
16	Partner Exploration$_{t-1}$	0.75	0.16	0.17	1	−.02	−.03	.05†	.08†	−.06†	−.05†	−.03	.04	−.09**	.10***	−.05*
17	Competitor Exploration$_{t-1}$	0.77	0.14	0.13	1	.32***	.41***	.14***	−.07**	−.05*	−.05*	−.08***	.06†	−.00	−.17***	−.04
18	Variation in Partner Exploration$_{t-1}$	0.02	0.03	0	0.16	−.07*	−.11***	−.13***	.24***	.10***	.03	.02	.02	−.05*	.33***	.05**
19	Variation in Competitor Exploration$_{t-1}$	0.03	0.04	0	0.26	−.27***	−.27***	−.01	−.05*	−.04	−.00	.00	−.01	−.02	−.04*	.06†
20	Technological Proximity to Partners$_{t-1}$	0.22	0.11	0.02	0.53	−.06*	−.09***	−.43***	.15***	.17***	.17***	.14***	−.07**	−.09***	.35***	.18***
21	Technological Proximity to Competitors$_{t-1}$	0.19	0.08	0.03	0.55	−.12***	−.10***	−.32***	−.02	.30***	.19***	.08**	.001	.01	.08***	.18***

	Variables	Mean	*SD*	Min.	Max.	12	13	14	15	16	17	18	19	20
13	Corporate Strategy Function$_{t-1}$	0.07	0.33	0	4	.10***								
14	Lambda Selection$_{t-1}$	4.50	3.51	0	12.96	.09***	−.14***							
15	Lambda Partnering$_{t-1}$	0.25	0.34	0	3.05	−.15***	−.11***	−.18***						
16	Partner Exploration$_{t-1}$	0.75	0.16	0.17	1	−.08**	.05*	−.09***	−.28					
17	Competitor Exploration$_{t-1}$	0.77	0.14	0.13	1	−.10***	−.00	−.14***	.14***	.03				
18	Variation in Partner Exploration$_{t-1}$	0.02	0.03	0	0.16	.27**	.02	.13***	−.40***	−.10***	−.17***			
19	Variation in Competitor Exploration$_{t-1}$	0.03	0.04	0	0.26	.02*	−.03*	.00	.00	−.06*	−.39***	.04		
20	Technological Proximity to Partners$_{t-1}$	0.22	0.11	0.02	0.53	.69***	.05†	.42***	−.30***	−.01	−.20***	.38***	.69***	
21	Technological Proximity to Competitors$_{t-1}$	0.19	0.08	0.03	0.55	.66***	.02	.34***	−.05*	−.07**	−.13***	.22***	.15***	.82***

Note: $n = 2{,}337$.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 3a
Second-Stage Panel Models for Partners with Fixed Effects and AR(1) Process

DV: Firm exploration$_t$	Model 1		Model 2a		Model 2b		Model 3		Model 4		Model 5	
Firm Fixed Effects	Included		Included		Included		Included		Included		Included	
Firm Exploration$_{t-1}$	0.56***	(0.04)	0.55***	(0.04)	0.54***	(0.04)	0.55***	(0.04)	0.54***	(0.04)	0.54***	(0.04)
Firm Age$_{t-1}$	−1.41***	(0.00)	−1.38***	(0.00)	−1.55***	(0.00)	−1.64***	(0.00)	−1.69***	(0.00)	−1.73***	(0.00)
Firm Size$_{t-1}$	0.06	(0.00)	0.07	(0.00)	0.07	(0.00)	0.06	(0.00)	0.08	(0.00)	0.07	(0.00)
Firm R&D Intensity$_{t-1}$	−0.01	(0.02)	−0.01	(0.02)	−0.00	(0.02)	−0.00	(0.02)	0.00	(0.02)	−0.00	(0.02)
Firm Solvency$_{t-1}$	0.00	(0.01)	0.00	(0.01)	−0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Performance Gap (Below Aspiration)$_{t-1}$	0.01	(0.03)	0.01	(0.03)	0.01	(0.03)	0.02	(0.03)	0.02	(0.03)	0.02	(0.03)
Performance Gap (Above Aspiration)$_{t-1}$	−0.07*	(0.04)	−0.06*	(0.04)	−0.06*	(0.04)	−0.06*	(0.04)	−0.06*	(0.04)	−0.06*	(0.04)
Corporate Strategy Function$_{t-1}$	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)
Alliance Portfolio Size$_{t-1}$	−0.02	(0.00)	−0.03	(0.00)	−0.03	(0.00)	−0.04	(0.00)	−0.03	(0.00)	−0.03	(0.00)
Strategic Alliance Portfolio$_{t-1}$	−0.04†	(0.01)	−0.04†	(0.01)	−0.04†	(0.01)	−0.04	(0.01)	−0.04†	(0.01)	−0.04†	(0.01)
Lambda Sample Selection$_{t-1}$	0.02	(0.01)	0.01	(0.01)	−0.05	(0.01)	−0.11	(0.01)	−0.11	(0.01)	−0.13	(0.01)
Lambda Partnering$_{t-1}$	−0.03	(0.02)	−0.02	(0.02)	0.01	(0.02)	0.01	(0.02)	0.02	(0.02)	0.01	(0.02)
Partner Exploration$_{t-1}$			0.04*	(0.02)	0.54***	(0.14)	0.49***	(0.14)	0.62***	(0.16)	0.62***	(0.16)
Partner Exploration$_{t-1}{}^2$					−0.51***	(0.10)	−0.46**	(0.10)	−0.59***	(0.11)	−0.59***	(0.11)
Firm Uncertainty$_{t-1}$							−0.14†	(0.07)	−0.13	(0.07)	−0.13†	(0.07)
Firm Uncertainty$_{t-1}$ × Partner Exploration$_{t-1}$							0.22**	(0.09)	0.21**	(0.08)	0.22**	(0.09)
Variation in Partner Exploration$_{t-1}$									0.32**	(0.60)	0.31**	(0.61)
Variation in Partner Exploration$_{t-1}$ × Partner Exploration$_{t-1}$									−0.35***	(0.89)	−0.34***	(0.91)
Technological Proximity to Partners$_{t-1}$											0.05	(0.15)
Technological Proximity to Partners$_{t-1}$ × Partner Exploration$_{t-1}$											−0.01	(0.18)
AR(1)	0.18		0.18		0.18		0.17		0.16		0.16	
n firm-years	1474		1474		1474		1474		1474		1474	
n firms	153		153		153		153		153		153	
F	36.3		33.9		32.7		31.4		29.1		26.3	
Degrees of freedom	1309		1308		1307		1305		1303		1301	
Log likelihood	1746.03		1748.47		1755.69		1770.00		1777.43		1778.10	
χ^2 (Δ2LL)			4.88*		19.32***		47.96***		62.81***		64.14***	

Note: Standardized beta coefficients; standard errors in parentheses.
$^{\dagger}p < .10$
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

TABLE 3b
Second-Stage Panel Models for Competitors with Fixed Effects and AR(1) Process

DV: Firm exploration$_t$	Model 1		Model 2a		Model 2b		Model 3		Model 4		Model 5	
Firm Fixed Effects	Included		Included		Included		Included		Included		Included	
Firm Exploration$_{t-1}$	0.41***	(0.03)	0.40***	(0.03)	0.40***	(0.03)	0.40***	(0.03)	0.40***	(0.03)	0.42***	(0.03)
Firm Age$_{t-1}$	−2.14***	(0.00)	−2.15***	(0.00)	−2.19***	(0.00)	−2.22***	(0.00)	−2.25***	(0.00)	−2.28***	(0.00)
Firm Size$_{t-1}$	0.03	(0.00)	0.04	(0.00)	0.04	(0.00)	0.04	(0.00)	0.04	(0.00)	0.04	(0.00)
Firm R&D Intensity$_{t-1}$	−0.01	(0.01)	−0.01	(0.02)	−0.01	(0.02)	−0.01	(0.02)	−0.01	(0.02)	−0.01	(0.02)
Firm Solvency$_{t-1}$	−0.00	(0.00)	−0.00	(0.00)	−0.00	(0.00)	−0.00	(0.00)	−0.00	(0.00)	−0.01	(0.00)
Performance Gap (Below Aspiration)$_{t-1}$	−0.00	(0.02)	−0.00	(0.02)	−0.00	(0.02)	0.00	(0.03)	0.01	(0.03)	0.01	(0.03)
Performance Gap (Above Aspiration)$_{t-1}$	−0.01	(0.03)	−0.01	(0.03)	−0.01	(0.03)	−0.02	(0.03)	−0.02	(0.03)	−0.02	(0.03)
Corporate Strategy Function$_{t-1}$	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)
Number of Competitors$_{t-1}$	0.21***	(0.00)	0.22***	(0.00)	0.22***	(0.00)	0.20***	(0.00)	0.2***	(0.00)	0.26***	(0.00)
Lambda Sample Selection$_{t-1}$	−0.03	(0.01)	−0.05	(0.01)	−0.07	(0.01)	−0.09	(0.01)	−0.12	(0.01)	−0.08	(0.01)
Competitor Exploration$_{t-1}$			0.03*	(0.02)	0.24**	(0.11)	0.23**	(0.11)	0.36***	(0.13)	0.49***	(0.14)
Competitor Exploration$_{t-1}{}^2$					−0.21*	(0.08)	−0.21*	(0.08)	−0.33***	(0.09)	−0.34***	(0.09)
Firm Uncertainty$_{t-1}$							−0.08	(0.07)	−0.09	(0.07)	−0.12	(0.07)
Firm Uncertainty$_{t-1}$ × Competitor Exploration$_{t-1}$							0.14†	(0.09)	0.15*	(0.09)	0.17*	(0.09)
Variation in Competitor Exploration$_{t-1}$									0.19**	(0.31)	0.17*	(0.31)
Variation in Competitor Exploration$_{t-1}$ × Competitor Exploration$_{t-1}$									−0.21**	(0.46)	−0.19**	(0.47)
Technological Proximity to Competitors$_{t-1}$											0.09	(0.19)
Technological Proximity to Competitors$_{t-1}$ × Competitor Exploration$_{t-1}$											−0.26**	(0.23)
AR(1)	0.26		0.26		0.26		0.26		0.25		0.24	
n firm-years	2337		2337		2337		2337		2337		2337	
n firms	180		180		180		180		180		180	
F	59.5		54.4		50.5		45.3		40.6		39.4	
Degrees of freedom	2147		2146		2145		2143		2141		2139	
Log likelihood	2420.09		2422.69		2425.93		2435.09		2441.42		2456.99	
χ^2 (Δ2LL)			5.21*		11.69**		30.01***		42.670**		73.81***	

Note: Standardized beta coefficients; standard errors in parentheses.

† $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TABLE 3c
Second-Stage Panel Models for Partners and Competitors with Fixed Effects and AR(1) Process

DV: Firm exploration$_t$	Model 1		Model 2a		Model 2b		Model 3		Model 4		Model 5	
Firm Fixed Effects	Included		Included		Included		Included		Included		Included	
Firm Exploration$_{t-1}$	0.54***	(0.04)	0.53***	(0.04)	0.52***	(0.04)	0.53***	(0.04)	0.53***	(0.04)	0.54***	(0.04)
Firm Age$_{t-1}$	−1.78***	(0.00)	−1.76***	(0.00)	−1.91***	(0.00)	−1.95***	(0.00)	−2.01***	(0.00)	−2.04***	(0.00)
Firm Size$_{t-1}$	0.07	(0.00)	0.07	(0.00)	0.07	(0.00)	0.06	(0.00)	0.08†	(0.00)	0.11*	(0.00)
Firm R&D Intensity$_{t-1}$	−0.02	(0.02)	−0.02	(0.02)	−0.01	(0.02)	−0.01	(0.02)	−0.01	(0.02)	−0.01	(0.02)
Firm Solvency$_{t-1}$	0.00	(0.01)	0.00	(0.01)	−0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Performance Gap (Below Aspiration)$_{t-1}$	0.02†	(0.03)	0.02	(0.03)	0.02	(0.03)	0.03†	(0.03)	0.03†	(0.03)	0.03†	(0.03)
Performance Gap (Above Aspiration)$_{t-1}$	−0.05**	(0.04)	−0.05**	(0.04)	−0.05**	(0.04)	−0.05*	(0.04)	−0.05*	(0.04)	−0.05*	(0.04)
Corporate Strategy Function$_{t-1}$	0.01	(0.01)	0.01	(0.01)	0.01	(0.01)	0.02	(0.01)	0.02	(0.01)	0.01	(0.01)
Alliance Portfolio Size$_{t-1}$	−0.04	(0.00)	−0.05	(0.00)	−0.06†	(0.00)	−0.06*	(0.00)	−0.04	(0.00)	−0.03	(0.00)
Strategic Alliance Portfolio$_{t-1}$	−0.03	(0.01)	−0.03	(0.01)	−0.03	(0.01)	−0.03	(0.01)	−0.04†	(0.01)	−0.04*	(0.01)
Number of Competitors$_{t-1}$	0.18***	(0.00)	0.19***	(0.00)	0.19***	(0.00)	0.18***	(0.00)	0.17***	(0.00)	0.24***	(0.00)
Lambda Sample Selection$_{t-1}$	0.02	(0.01)	−0.01	(0.01)	−0.06	(0.01)	−0.11	(0.01)	−0.14	(0.01)	−0.12	(0.01)
Lambda Partnering$_{t-1}$	−0.04	(0.02)	−0.03	(0.02)	−0.01	(0.02)	−0.01	(0.02)	−0.01	(0.02)	−0.00	(0.02)
Partner Exploration$_{t-1}$			0.04*	(0.02)	0.41**	(0.14)	0.37**	(0.14)	0.48**	(0.16)	0.38*	(0.16)
Competitor Exploration$_{t-1}$			0.00	(0.02)	0.16†	(0.12)	0.15	(0.12)	0.28*	(0.14)	0.35**	(0.15)
Partner Exploration$_{t-1}{}^2$					−0.38**	(0.10)	−0.35*	(0.10)	−0.44**	(0.11)	−0.38*	(0.11)
Competitor Exploration$_{t-1}{}^2$					−0.17†	(0.09)	−0.16†	(0.08)	−0.27*	(0.10)	−0.27*	(0.10)
Firm Uncertainty$_{t-1}$							−0.26*	(0.09)	−0.26*	(0.09)	−0.23*	(0.09)
Firm Uncertainty$_{t-1}$ × Partner Exploration$_{t-1}$							0.22**	(0.08)	0.20*	(0.08)	0.17*	(0.08)
Firm Uncertainty$_{t-1}$ × Competitor Exploration$_{t-1}$							0.13	(0.09)	0.14†	(0.09)	0.13	(0.09)
Variation in Partner Exploration$_{t-1}$									0.24*	(0.59)	0.24*	(0.60)
Variation in Partner Exploration$_{t-1}$ × Partner Exploration$_{t-1}$									−0.26**	(0.87)	−0.25*	(0.88)
Variation in Competitor Exploration$_{t-1}$									0.25***	(0.34)	0.22**	(0.35)
Variation in Competitor Exploration$_{t-1}$ × Competitor Exploration$_{t-1}$									−0.26***	(0.51)	−0.23**	(0.52)
Technological Proximity to Partners$_{t-1}$											−0.26*	(0.19)
Technological Proximity to Partners$_{t-1}$ × Partner Exploration$_{t-1}$											0.09	(0.18)
Technological Proximity to Competitors$_{t-1}$											0.18†	(0.23)
Technological Proximity to Competitors$_{t-1}$ × Competitor Exploration$_{t-1}$											−0.19*	(0.24)
AR(1)	0.16		0.15		0.15		0.14		0.14		0.13	
N firm-years	1474		1474		1474		1474		1474		1474	
N firms	153		153		153		153		153		153	
F	40.7		35.9		32.7		29.8		26.4		23.9	
Degrees of freedom	1308		1306		1304		1301		1297		1293	
Log likelihood	1775.34		1778.65		1785.30		1798.20		1811.19		1821.14	
χ^2 (Δ2LL)			6.62*		19.92**		45.73***		71.70***		91.60***	

Note: Standardized beta coefficients; standard errors in parentheses.

$^{\dagger}p < .10$
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Tables 3a and 3b report the results of our second-stage models for testing the effects of the exploration levels of partners and primary competitors. The baseline model (Model 1) reveals path dependence in a firm's tendency to explore, indicated by the effect of the firm's exploration in the preceding year ($\beta = 0.56$, $p < .001$; $\beta = 0.41$, $p < .001$) (Lavie & Rosenkopf, 2006). Exploration declines as the firm matures ($\beta = -1.41$, $p < .001$; $\beta = -2.14$, $p < .001$) (Greve, 2007) and when its performance exceeds aspiration ($\beta = -0.07$, $p < .05$) (Dothan & Lavie, 2016; Greve, 2003),[18] but increases with the number of competitors ($\beta = 0.21$, $p < .001$) (Deeds & Hill, 1996). All effects hold in the combined model (Table 3c).

Model 2b (Table 3a) served for testing Hypothesis 1, revealing an inverted U-shaped association between the firm's exploration and the exploration level of alliance partners, as evidenced by the positive main effect ($\beta = 0.54$, $p < .001$) and the negative effect of the squared term of partner exploration ($\beta = -0.51$, $p < .001$). This model offers better fit to the data than Model 2a, which tests a linear function ($\Delta 2LL = 19.32$, $p < .001$). The curvilinear pattern persists in the full model (Table 3a, Model 5) and the combined model (Table 3c, Model 5). Figure 2a depicts this curvilinear function, demonstrating that the inflection point falls within range (min. = 0.17, max. = 1.000) at a partner exploration level of 0.75, where the firm's exploration level reaches a maximum of 0.73, with the 95% confidence interval ranging between 0.71 and 0.76. The slopes around the inflection point are different from zero (positive slope = 0.42, $p < .001$; negative slope = −0.19, $p < .01$), in support of Hypothesis 1a. Using the utest procedure in Stata, we confirm the presence of an inverted U-shaped association ($p = .003$), with a Fieller confidence interval ranging between 0.70 and 0.82 (Haans, Pieters, & He, 2016; Lind & Mehlum, 2010).

Similarly, our findings grant support to Hypothesis 1b (Model 2b, Table 3b), revealing an inverted U-shaped association between the firm's exploration and the exploration level of its primary competitors, as evidenced by the positive main effect ($\beta = 0.24$, $p < .01$) and the negative effect of the squared term of competitor exploration ($\beta = -0.21$, $p < .05$). This model offers better fit than Model 2a ($\Delta 2LL = 11.69$, $p < .01$). This curvilinear association persists in the full model (Table 3b, Model 5) and the combined model (Table 3c, Model 5). Figure 2b depicts this function, showing that the inflection point falls within range (min. = 0.13, max. = 1.00) at a competitor exploration level of 0.82, where the firm's exploration level reaches a maximum of 0.72, with the 95% confidence interval ranging between 0.70 and 0.78. The slopes around the inflection point are different from zero (positive slope = 0.26, $p < .01$; negative slope = −0.07, $p < .10$). The Stata utest procedure confirmed the inverted U-shaped association ($p = .088$), with a Fieller confidence interval ranging between 0.73 and 1.11 (Haans et al., 2016; Lind & Mehlum, 2010), thus offering marginal support for Hypothesis 1b. To ensure that the effects of partner and competitor exploration are inverted U-shaped, we added their cubic terms in auxiliary analysis, which revealed no additional inflection point within range, thus ruling out an S-shaped association.

As predicted by Hypothesis 2a, Model 3 (Table 3a, Figure 3a) reveals that the positive association between a firm's exploration and the exploration level of its partners becomes stronger when firm-specific uncertainty increases ($\beta = 0.22$, $p < .01$). This effect persists in the full model ($\beta = 0.22$, $p < .01$) (Table 3a, Model 5) and the combined model (Table 3c, Model 5). Per Model 3 (Table 3b, Figure 3b), firm-specific uncertainty reinforces the positive association between a firm's exploration and its competitors' exploration ($\beta = 0.14$, $p < .1$). This effect persists in the full model ($\beta = 0.17$, $p < .01$) (Table 3b, Model 5) and the combined model, in line with Hypothesis 2b.

Model 4 (Table 3a, Figure 4a) furnishes support for Hypothesis 3a, revealing that variation in partner exploration levels weakens the positive association between firm exploration and partner exploration ($\beta = -0.35$ $p < .001$). This effect persists in the full model ($\beta = -0.34$, $p < .001$) (Table 3a, Model 5) and the combined model (Table 3c, Model 5). Similarly, Model 4 (Table 3b, Figure 4b) offers support for Hypothesis 3b, indicating that variation in competitors' exploration levels weakens the positive association between a firm's exploration and its competitors' exploration ($\beta = -0.21$, $p < .01$). This effect persists in the full model ($\beta = -0.19$, $p < .01$) (Table 3b, Model 5) and the combined model (Table 3c, Model 5).

Model 5 (Table 3a) offers no support for Hypothesis 4a about the moderating effect of technological proximity to partners. Counter to Hypothesis 4b, Model 5 (Table 3b, Figure 5) reveals that technological proximity to competitors weakens the

[18] Although the difference in coefficients of the performance gap below versus above aspiration was insignificant for competitor exploration, it became significant in the combined model, $F(1, 1293) = 8.48$, $p = .004$, where the firm's exploration increases below aspiration ($\beta = 0.03$, $p < .1$) and declines above aspiration ($\beta = -0.05$, $p < .05$).

FIGURE 2a
The Effect of Partner Exploration on Firm Exploration

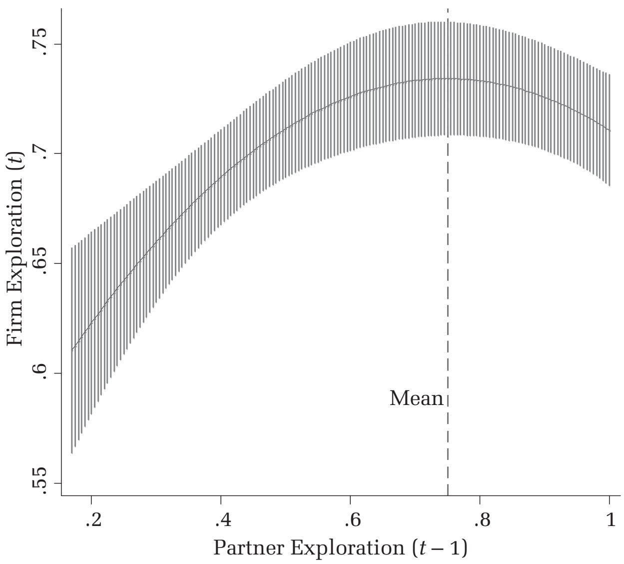
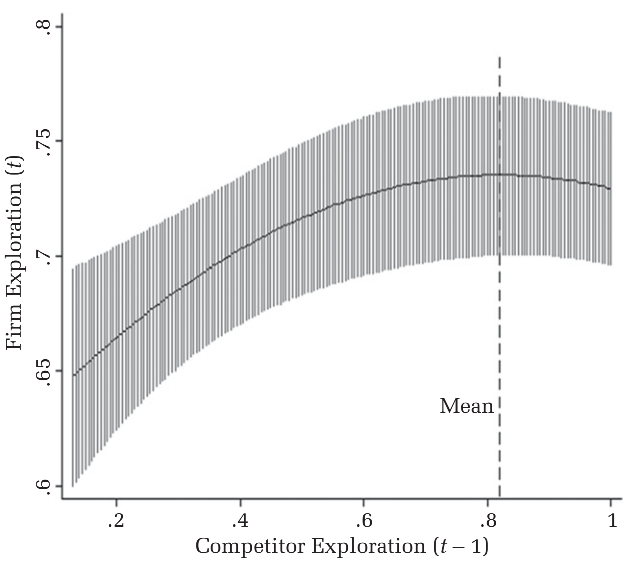


FIGURE 2b
The Effect of Competitor Exploration on Firm Exploration



positive association between a firm's exploration and that of its competitors ($\beta = -0.26$, $p < .01$). These findings indicate that technological proximity does not motivate a firm to more closely follow the exploration levels of its partners and competitors. One explanation for this is that we restricted our sample to the five most proximate competitors, which limits the range of the moderator. Another possibility is that, as the firm operates in knowledge domains similar to those of its competitors, it is already aware of opportunities in these domains, and thus can rely less on its competitors for cues on the desirable exploration level. Although this explanation may apply also for partners, in the case of competitors, the firm's divergence may also be tied to its effort to differentiate itself from proximate competitors and maintain a distinctive industry position vis-à-vis these competitors. Differentiation enables the firm to avoid competitive pressure (Deephouse, 1999) and delineate uncontested markets.

Additional Robustness Tests

We considered alternative model specifications and measures. First, we ran a Tobit model, which produced consistent findings—with the exception of Hypothesis 2b. We retained our reported models because they account for firm fixed effects and correct for autocorrelation. Second, in line with the notion of trait imitation (Haunschild & Miner, 1997), we considered whether a firm follows industry leaders rather than primary competitors and partners (Massini et al., 2005). We replaced our independent variable with the lagged exploration level of the top 10% performers in the firm's four-digit SIC, but found no support for this hypothesis. Third, by controlling for both the linear and quadratic terms of the lagged exploration variable, we ruled out the possibility that our findings are driven by firms' independent efforts to strive toward an intermediate level of exploration. The desirable balance point varies across firms and is difficult to discern, so a firm is more likely to follow the exploration levels of alters. Fourth, we created a matched sample of hypothetical partners using a Mahalanobis distance calculation (e.g., Aguinis, Gottfredson, & Joo, 2013). Results of t tests revealed higher differences in the exploration levels of a firm and its partner relative to the differences with the alternative matched partners, thus ruling out selection of partners with similar exploration levels. When we controlled for the absolute difference in firm or partner exploration levels in the prior year, its effect was insignificant, with our findings remaining intact, suggesting no selection bias.

Fifth, we considered an exploration measure based on knowledge search scope (Dothan & Lavie, 2016; Katila & Ahuja, 2002) that captured the proportion of new patent citations that a firm did not cite in the previous five years. The corresponding findings offer no support for our hypotheses. This suggests that firms follow the exploratory behavior of their partners and

FIGURE 3a
Firm Exploration by Partner Exploration and Firm-Specific Uncertainty

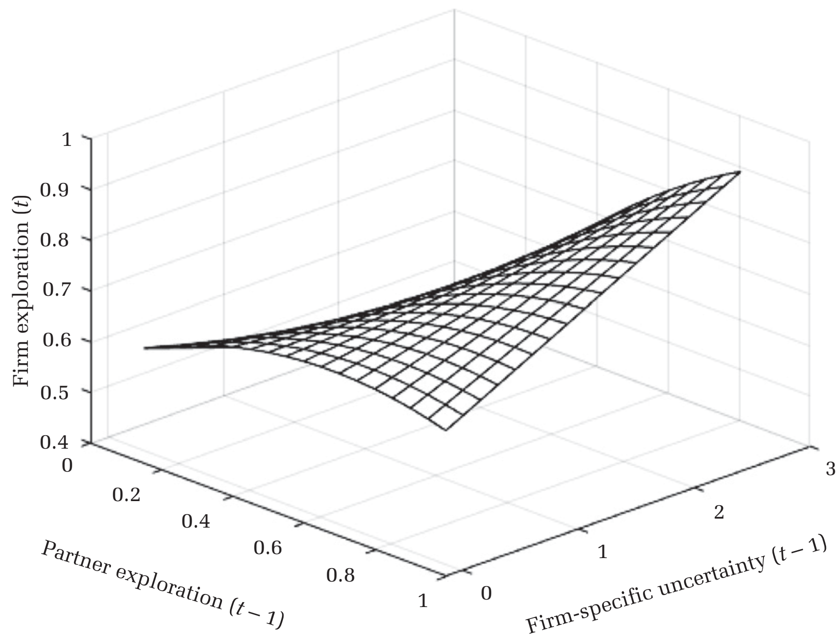
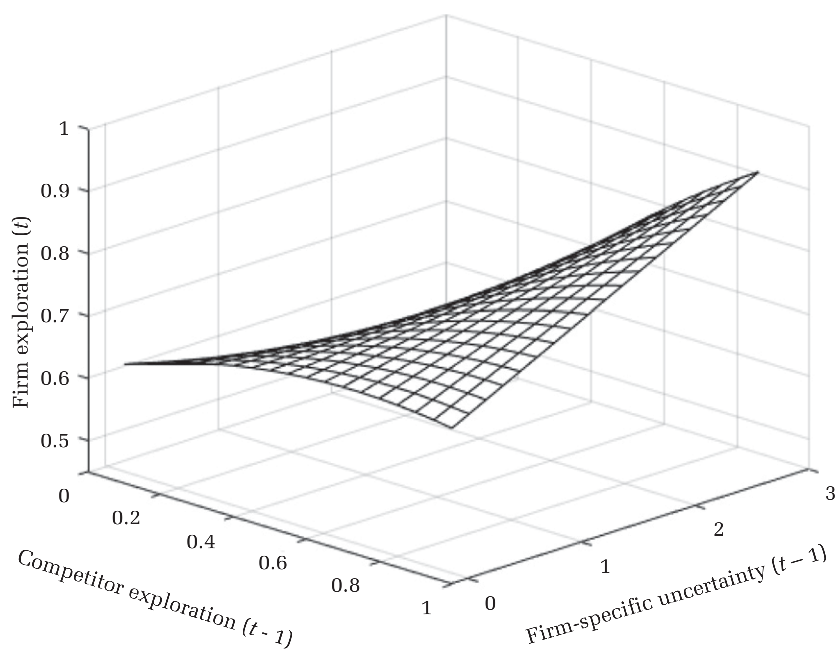


FIGURE 3b
Firm Exploration by Competitor Exploration and Firm-Specific Uncertainty



competitors when entering new knowledge domains rather than when incorporating particular knowledge elements, which in turn are more difficult to observe, and thus do not support vicarious learning. We next considered exploration measures based on the inverse of Fleming's (2001) measures of component, combination, and cumulative familiarity, which capture the extent to which a firm relies on recent and frequently used patent classes. Although we find support for Hypotheses 1 and 2 in the competitor exploration models,

FIGURE 4a
Firm Exploration by Partner Exploration and Variation in Partner Exploration

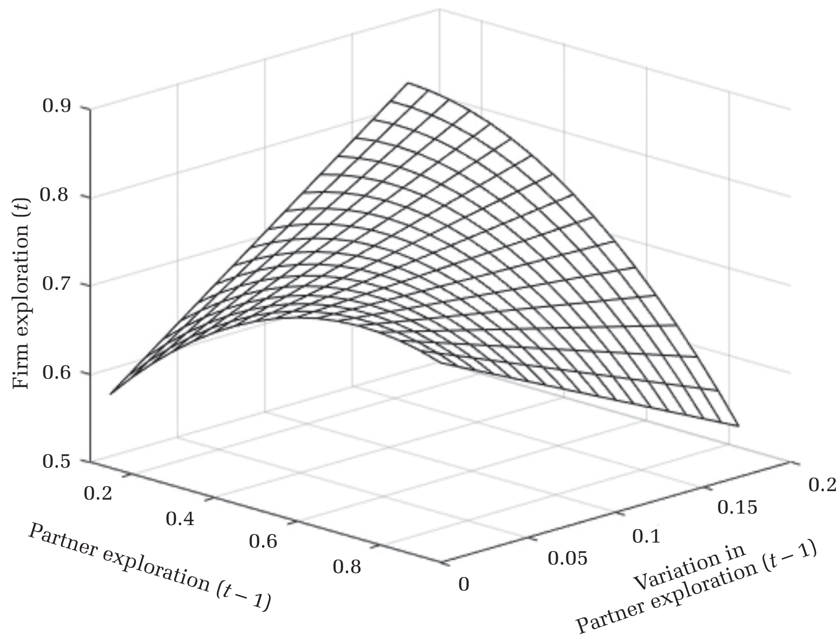
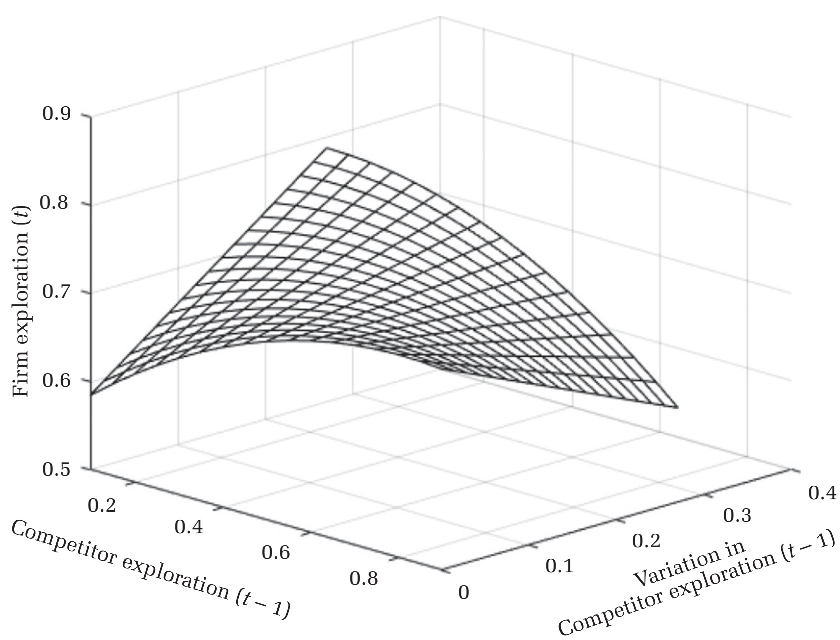


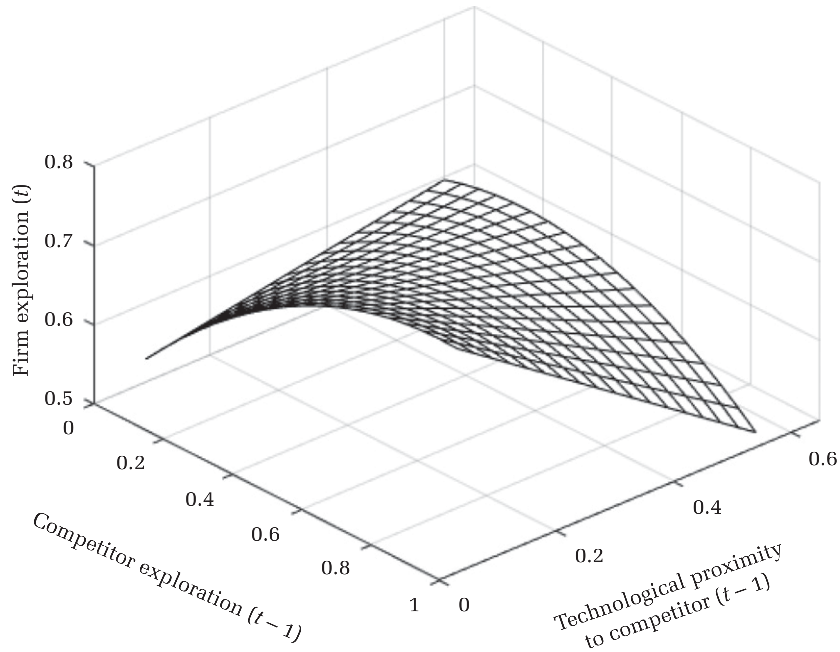
FIGURE 4b
Firm Exploration by Competitor Exploration and Variation in Competitor Exploration



these alternative measures center on knowledge that is new to the world rather than to the firm, and their complexity does not support vicarious learning. For similar reasons, an alternative measure based on Eggers and Kaul (2018) yielded no significant findings. A firm is unlikely to observe class-to-class citation patterns.

Sixth, we tested whether firms adjust their exploration levels based on the number of partners

FIGURE 5
Firm Exploration by Competitor Exploration and Technological Proximity



and competitors with high-level exploration rather than based on these alters' exploration level, but these variables had no significant effect on firm exploration. Seventh, we verified that convergence of exploration levels cannot be ascribed to the pursuit of similar technological opportunities, finding only 2.95% overlap in the new patent classes entered by a firm and its partners. A control for this overlap was insignificant, while our reported findings remained intact. Similar results were obtained for primary competitors (9.36% overlap) and when measuring overlap with a one-year lag. Eighth, we considered an alternative definition of competitors based on firms' competitor lists in annual reports, and found consistent results despite severe loss of degrees of freedom ascribed to 73.34% missing values, which prompted us to retain our original definition of competitors.[19]

[19] The missing values occur because the EDGAR database includes SEC filings only since 1994 and the SEC does not require firms to list competitors, while their voluntary statements can be unsystematic, incomplete, and less reliable (e.g., Botosan & Stanford, 2005; Elshandidy, Fraser, & Hussainey, 2013). Still, the alternative measure of competitor exploration was correlated ($r = .25$, $p < .001$) with our reported measure, which offers a more complete list of competitors, including those that have yet to introduce competing products but operate in relevant knowledge domains.

Ninth, we tested a dynamic panel model using the Arellano–Bond model specification, which produced consistent findings—with the exception of Hypothesis 2a. Nevertheless, our reported findings were insensitive to the exclusion of the lagged dependent variable, thus rendering the Arellano–Bond model estimates redundant. We conclude that our reported model is preferred because of the large number of time points per firm (12.98 observations on average), which restricts potential dynamic panel bias (Roodman, 2009). The number of moment conditions required by the Arellano–Bond generalized method of moments estimator yields weak instruments (Blundell & Bond, 1998), and the estimates generated by this alternative model can be unstable (Greene, 2012: 448).

Tenth, we tested whether our moderators affected the quadratic functions of partner and competitor exploration; however, corresponding models exhibited symptoms of multicollinearity, so we could not interpret their findings. We also tested the effects of our moderators on the positive slope of the spline function relating to the inverted U-shaped effect of partner and competitor exploration. We found consistent results, with the exception of Hypothesis 4b, although, per our theory, the moderators apply at any level of exploration. Eleventh, we tested for the moderating effects of firm size, corporate strategy function, and market size, which turned out insignificant without affecting our findings. For competitor exploration, we also tested the moderating effect of the number of competitors, which weakens the effect of competitor exploration without affecting our reported findings. For partner exploration, we tested the moderating effect of the strategic significance of the alliance portfolio, which turned out negative but left our reported findings virtually intact. Twelfth, we considered a forward-looking measure of uncertainty (Toh & Kim, 2013) capturing the implied volatility of the firm's one-month expiration of a European-style, at-the-money call option on the first trading day of the year. However, we encountered 78.86% missing values in the OptionMetrics database, which provides data only from 1996 and with many publicly traded firms not meeting the requirements for options trading.

Thirteenth, we tested for reversed causality, but the corresponding effects were insignificant and the model fit was significantly lower for both partners and competitors. Indeed, it is unlikely that all of the firm's partners and competitors follow its behavior unless it is the undisputable market leader. Fourteenth, we split our sample into subsamples that include or exclude R&D alliances, strategic alliances, and coopetitors, finding support for our hypotheses in most subsamples for competitor exploration, but weaker support for partner exploration, probably because of the smaller subsample sizes. Fifteenth, we replaced the five-year window with three- and seven-year windows for identifying competitors and partners. The analysis using the seven-year window yielded support for Hypotheses 1a, 1b, and 3a, with consistent findings for Hypothesis 4b. The analysis relying on the three-year window granted support for Hypotheses 1a, 1b, and 3b. These analyses reaffirm our five-year window specification, which is most suitable for the electronics industry. Sixteenth, we considered endogeneity in the choice of exploration alliances versus exploitation alliances by predicting whether a firm had at least one upstream alliance in the first-stage model, but our results remained virtually unchanged. Finally, our findings were insensitive to outliers.[20] Overall, our tests reaffirmed our measures and model specification.

[20] We tested sensitivity to outliers using various approaches (Aguinis et al., 2013; Billor, Hadi, & Velleman, 2000; Upton & Cook, 1996), and, when we dropped outliers, the results remained virtually unchanged—and even improved.

DISCUSSION

Our study promotes research on the antecedents of exploration by suggesting that firms' tendencies to explore are interdependent and subject to various boundary conditions that restrict convergence with the exploration levels of alliance partners and competitors. Hence, our study goes beyond prior research that showed how firms' exploration tendencies are uniformly shaped by exogenous industry conditions or independently driven by firms' organizational characteristics. Unlike some prior research that relates exploration to the sheer number of competitors (e.g., Skilton & Bernardes, 2015) or alliance partners (e.g., Lavie & Drori, 2012; Rothaermel & Deeds, 2004), we consider these alters as reference groups for firms' exploration efforts. We conjecture that firms seek to learn not only from their partners' and competitors' knowledge (Mowery et al., 1996), but also from these alters' exploratory behaviors. Acknowledging this interdependence vis-à-vis alliance partners and competitors is essential for understanding the antecedents of exploration and for explaining heterogeneity in firms' exploration tendencies.

In this study, we advance a vicarious learning theory and identify boundary conditions that explain how partners and competitors shape a firm's exploration tendency. At low exploration levels, a firm increases its tendency to explore when either its partners or competitors increase their exploration levels. Convergence at that level is ascribed to imitation and legitimation (e.g., Haunschild & Miner, 1997; Lieberman & Asaba, 2006). However, as these alters' exploration tendencies become excessive, the firm diverges from these tendencies and reverts to exploitation. This divergence is ascribed to the perceived risk of excessive exploration and to a firm's efforts to leverage external exploration efforts of partners, while restricting its own exploration tendency (Stettner & Lavie, 2014). In turn, the divergence from competitors' exploration is attributed to the firm's differentiation efforts. We contend that specialization in a relatively narrow set of knowledge domains provides the impetus for both division of labor with partners and differentiation vis-à-vis competitors. Nevertheless, a decline in a firm's exploration is stronger for excessive partner exploration than for excessive competitor exploration. This is in line with research suggesting that recurrent cycles of imitation and innovation reinforce status quo with rivals (Giachetti, Lampel, & Pira, 2017). Still, our findings stand in contrast to optimal distinctiveness theory that implies that firms would strive to reconcile the tension between conformity (convergence) and differentiation (divergence) by reaching an intermediate level of novelty (Zhao, Fisher, Lounsbury, & Miller, 2017) irrespective of the observed level of exploration. Instead, we find that firms either converge or diverge, depending on the level of exploration exhibited by their partners and competitors.

Our study further contributes by showing how convergence with the exploration tendencies of partners and competitors is subject to boundary conditions that influence a firm's motivation and ability to learn and follow the typical exploration levels in its reference groups. In particular, we show that, as firm-specific uncertainty increases, the firm tends to better align its exploration tendency with the exploration levels of its partners and competitors. However, a firm's abilities to learn the typical exploration pattern, imitate it, and gain legitimacy depend on the coherence of that pattern (Rhee et al., 2006). When alters pursue diverse exploration levels, this inconsistent pattern limits the firm's ability to systematically react to increases in their exploration levels. Finally, counter to expectations, we reveal that the motivation and ability to converge with the exploration exhibited by partners and competitors do not increase with their proximity to the firm (e.g., Rosenkopf & Almeida, 2003). The fact that partners and competitors develop expertise in knowledge domains similar to those of a firm suggests that the firm has already learned about opportunities in related domains, so need not rely on these alters' exploratory behavior as a cue for its desirable exploration tendency. Rather, the firm's efforts to differentiate itself from proximate competitors outweigh the ease of convergence, and thus lead to divergence. By revealing several boundary conditions for convergence with the exploration levels of partners and competitors, we complement research that has shown how environmental conditions such as market concentration reinforce interdependence in firms' innovation strategies (Turner, Mitchell, & Bettis, 2010). We claim that firms do not respond merely to uniform industry conditions, but to idiosyncratic exploration tendencies in their particular cooperation and competition networks.

Our main contribution is in enhancing understanding of the antecedents of exploration (Lavie et al., 2010). We reveal how a firm's exploration tendencies converge with the typical exploration level of alters in its main reference groups—namely, alliance partners and competitors—depending on the nature of the firm's relations with them. Convergence is explained by vicarious learning that is driven by imitation and legitimation. However, the perceived risk of excessive exploration restricts convergence. Finally, we claim that specialization reinforces divergence, as the firm divides labor with partners and improves its position vis-à-vis competitors. This enables the firm to leverage its partners' complementary skills while maintaining competitive parity with its rivals.

Our study also contributes to the literature on exploration and exploitation by identifying conditions that shape firms' interdependent exploration efforts. When considering the desirable balance between exploration and exploitation, firms observe alters and consider adopting their behavior. A firm's partners and competitors serve as relevant reference groups, but the extent of convergence with their exploration tendencies depends on firm-specific uncertainty, the coherence of their behavior, and their technological proximity to the firm. Thus, we extend research on environmental antecedents (e.g., Sidhu et al., 2004) by showing that exploration is shaped by conditions that vary across firms with unique portfolios of interfirm relations. We also complement research on learning from performance feedback, which shows how a firm intensifies exploration when its performance falls below aspiration (Chen, 2008; Dothan & Lavie, 2016; Greve, 2007), by revealing that the firm's reference groups play a more profound role, not only in shaping the firm's performance aspiration but also in offering a benchmark for the desirable level of exploration.

Moreover, our study contributes to research on vicarious learning, imitation, and legitimation (e.g., Lieberman & Asaba, 2006; Suddaby et al., 2017; Terlaak & Gong, 2008) by demonstrating that, when a behavior is risky and its outcomes are unforeseen, firms deviate from the paradigm of convergence. Specifically, they follow the population average rather than a small group of leaders (Massini et al., 2005) and engage in frequency imitation rather than in trait imitation or outcome imitation (Haunschild & Miner, 1997). Lastly, as alters' exploration further increases, we expect perceived risk to mitigate imitation and legitimation, while specialization offsets them and fosters divergence of behaviors. Hence, whereas prior research has suggested that perceived risk can lead to convergence of behaviors (e.g., Lieberman & Asaba, 2006), we show that it results in divergence when the risk is inherent to the imitated behavior as opposed to the targeted market or technology (Srinivasan et al., 2007). We further identify boundary conditions that restrict convergence of behaviors—namely, firm-specific uncertainty, variance in alters' behavior, and proximity. We expect these conditions to influence vicarious learning irrespective of the type of observed behavior.

Finally, we offer managerial implications for firms seeking to balance exploration and exploitation. We advise firms to consider departing from industry conventions and adjusting their exploration tendencies in line with the typical exploratory behavior of their specific set of partners and competitors. In particular, under uncertainty, a firm's decision to enter new knowledge domains should take into account the idiosyncratic competitive position and the unique configuration of its alliance portfolio, rather than simply be based on industry trends dictated by environmental conditions. We found that learning from primary competitors can complement learning from partners, irrespective of performance feedback that is limited in the case of exploration. Given uncertainty about the prospects of exploration, managers often opt for mimicking the behavior of the reference group, expecting to gain legitimacy if not enhanced performance. However, managers should not blindly adopt the observed exploration level prevalent in the firm's reference groups, and even depart from it when the firm's close competitors engage in excessive exploration or their exploration pattern is incoherent. In turn, this enables increased specialization in the firm's knowledge domain. Understanding the pathways of convergence and divergence can help managers foresee the exploration tendencies of their partners and competitors, which in turn can influence the firm's own exploration tendencies. Still, given the disparity between observed behavioral patterns and prescriptive advice, future research should study the performance implications of convergence with the exploration levels exhibited by partners and competitors.

Although our study advances research on the antecedents of exploration, it faces several limitations that pave directions for future research. Conceptually, one may study the performance implications of convergence with the exploration tendencies of alliance partners and competitors. Additionally, future research may identify additional reference groups based on various corporate relations such as corporate venture capital investors, customers, and suppliers that may influence a firm's tendency to explore (Sidhu et al., 2007). Furthermore, given the implications of variation in competitors' exploration levels, scholars should study a firm's ability to learn from a reference group that exhibits incoherent tendencies and decide which partner or competitor to follow. It is possible that firms pay more attention to partners with which they engage in more substantial collaborative relations, or to certain types of alliances, such as joint ventures versus non-equity alliances. Thus, more insights can be gained by studying when, why, how, and whom a firm follows or benchmarks against when converging with a typical pattern of exploration. Additionally, as we furnish no direct evidence of our proposed mechanisms, future research may operationalize and test the effects of imitation, legitimacy, perceived risk, balance across modes, and differentiation. Such research can indicate, for instance, whether convergence is driven mostly by imitation or legitimacy (Zajac & Westphal, 2004). Moreover, since we study exploration in the knowledge domain, future research may generalize our findings to other domains, such as business diversification and internationalization (Wilden et al., 2018). Along the same lines, we identified a firm's competitors based on their knowledge similarity, so future research may define competitors based on other types of resource similarity, market communality, or perceived rivalry (Chen, 1996). Furthermore, our measure of exploration captures the increase in the diversity of the firm's patent classes. Future research may consider more complex measures of exploration (e.g., Eggers and Kaul 2018; Fleming, 2001; Katila & Ahuja, 2002) that capture novelty to the world rather than to the firm, and that pose challenges for vicarious learning. Finally, given our focus on the electronics industry, it is worth testing the generalizability of our findings to other industries. Despite its limitations, our study sheds new light on previously overlooked antecedents of exploration and enhances our understanding of this important organizational phenomenon.

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