RIVALS OR COLLABORATORS? RELATIONAL AMBIDEXTERITY AND ABSORPTION SPEED

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February 2021
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INTRODUCTION

Absorption speed, referred to as how quickly a firm can recognize, assimilate, and exploit external knowledge from an alliance partner (Leone & Reichstein, 2012), is critical for a firm to achieve sustainable competitive advantage in technology-intensive industries where time-based competition and learning races are paramount. For instance, in the pharmaceutical industry, when virtually identical products are introduced to the market as little as 3—6 months apart, the first-to-market product tends to achieve the largest market share and maintains this advantage indefinitely (Macher & Boerner, 2006).

Given the prevalence of learning races in strategic alliances (Hamel, 1991; Panico, 2017), prior research on absorption speed has primarily focused on two streams. One stream focuses on organizational antecedents affecting firms’ capabilities of absorbing external knowledge, ranging from learning experience (Zahra & George, 2002) to internal informal networks (Volberda, Foss & Lyles, 2010). The other stream focuses on governance mechanisms that can facilitate interfirm knowledge flows, such as equity joint ventures (Oxley & Wada, 2009) and licensing-in (Leone & Reichstein, 2012). In this study, we move beyond prior focus on individual firms or dyad-level alliances by examining how the configuration of a firm’s alliance portfolio affects its speed of absorbing its partners’ knowledge. An alliance portfolio is referred to as all strategic alliances a firm is engaged in at a certain point in time (Cui, 2013). This shift is important since a firm often simultaneously engages in multiple alliances (Cui, Yang & Vertinsky, 2018) and its learning process is heavily influenced by the configuration of its alliance portfolio (Gulati, Nohria &
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Zaheer, 2000). Two important issues remain to be addressed from prior studies.

First, although the temporal dimension of alliance learning has been discussed (Hamel, 1991), it still has not received significant attention (Bridoux, Smith & Grimm, 2013; Luoma, Ruutu, King & Tikkanen, 2017). Prior studies have predominantly focused on overall interfirm knowledge flows while ignoring the issue of time or speed (Schildt, Keil & Maula, 2012). While scholars have a great understanding of the critical role of alliance portfolio configuration in overall interfirm knowledge flows (Cui et al., 2018; Stuart, 2000), the impact of portfolio configuration on absorption speed remains a puzzle (Leone & Reichstein, 2012).

Second, while previous studies have provided many important insights into the tension between competition and cooperation for value creation and appropriation at the dyadic alliance level (Arslan, 2018; Das & Teng, 2000), they pay little attention to the interplay of competition and cooperation within alliance portfolios (Gnyawali & Ryan Charleton, 2018; Hoffmann, Lavie, Reuer & Shipilov, 2018). Specifically, given that alliances will eventually be dominated by competition or cooperation (Hannah & Eisenhardt, 2018; Sytch & Tatarynowicz, 2014), it is not reasonable to treat all alliance partners as general collaborators. In practice, firms often build a mixture of rival partners (denoted as rivals) and non-rival partners (denoted as collaborators) within their alliance portfolios (Gimeno, 2004). Therefore, we intend to clearly distinguish rivals from collaborators and investigate how the interplay of rivals and collaborators within alliance portfolios may affect a firm’s learning process. We thus ask open questions: How does the relationship configuration of a firm’s alliance portfolio, that is, the distribution of a firm’s rivals and collaborators within its alliance portfolio, affect the firm’s speed of absorbing its partner’s knowledge? What are the boundary conditions?

We address these questions by providing a fine-grained approach toward alliance
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relationships. Instead of treating all alliance partners as general collaborators, we classify a
firm’s alliance partners into two categories: rivals and collaborators (Leask & Parker, 2007;
Short, Ketchen Jr, Palmer & Hult, 2007). We capture the relationship configuration of a firm’s
alliance portfolio using the concept of relational ambidexterity, defined as the simultaneous and
balanced presence of a firm’s rivals and collaborators within its alliance portfolio. Building on
interorganizational learning theory, we argue that relational ambidexterity accelerates a firm’s
speed of absorbing external knowledge by churning up information flows within its alliance
portfolio, providing access to diverse approaches to knowledge (re)combination, and increasing
its partner’s willingness of knowledge sharing. We also examine the contingent roles of both
inward-looking (i.e., internal knowledge variety) and outward-looking (i.e., common third parties)
dimensions related to interfirm knowledge flows. We contend that the positive effect of
relational ambidexterity on absorption speed is amplified by firm internal knowledge variety but
attenuated by common third parties.

Our study makes three major contributions to the literature on interorganizational learning,
and more generally, interfirm knowledge flows. First, we advance research on
interorganizational learning by highlighting the importance of absorption speed rather than
overall knowledge flows. Most previous studies have ignored the issue of time (Bridoux et al.,
2013; Luoma et al., 2017) and only examined overall knowledge flows over relatively long
periods (Schildt et al., 2012). In examining the influence of relational ambidexterity on
absorption speed, this study responds to the call for studies explicitly addressing the issue of time
(Bridoux et al., 2013; George & Jones, 2000; Moreira, Markus & Laursen, 2018).

Second, our study provides an alternative way of accelerating external knowledge
absorption by analyzing the relationship configuration of a firm’s alliance portfolio. Departing
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from prior studies that focus on factors uncontrollable by a single part such as trust (Panico, 2017; Selnes & Sallis, 2003) and governance mechanisms (Yang, Zheng & Zaheer, 2015), our study offers an alternative approach that is largely controllable by the focal firm. That is, balancing rivals and collaborators within its alliance portfolio. Furthermore, this study also responds to a call for studies addressing the interplay of cooperation and competition within alliance portfolios (Gnyawali & Ryan Charleton, 2018; Hoffmann et al., 2018), which is important yet remains under-developed (Asgari, Tandon, Singh & Mitchell, 2018).

Finally, this study extends the broader literature on interfirm knowledge flows by simultaneously examining the contingent effects of inward-looking and outward-looking dimensions related to interfirm knowledge flows (Cohen & Levinthal, 1990; Todorova & Durisin, 2007; Zahra & George, 2002). Although the results of their contingent effects are mixed, prior studies seldom examine both dimensions simultaneously (Caner, Cohen & Pil, 2017; Guler & Nerkar, 2012). By investigating the contrasting contingent effects of firm internal knowledge variety and common third parties, we show the different roles of inward-looking and outward-looking dimensions in a firm’s speed of absorbing external knowledge.

THEORY AND HYPOTHESES

Interorganizational Learning Theory and Absorption Speed

Accelerating the innovation process is crucial for pharmaceutical firms to survive and achieve competitive advantage (Macher & Boerner, 2006). In the pharmaceutical industry, rapid innovation is even more important than overall innovation outcomes (Schildt et al., 2012). The learning races literature has long recognized the importance of faster learners (Khanna, Gulati & Nohria, 1998; Larsson, Bengtsson, Henriksson & Sparks, 1998). Allying firms that lag behind their alliance partners are more likely to be misappropriated by their superior partners (Hamel,
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Therefore, absorption speed plays a vital role in winning learning races and achieving sustainable competitive advantage (Tzabbar, Aharonson & Amburgey, 2013).

Interorganizational learning theory suggests that effective knowledge flows between firms require both a firm’s receptivity and its partner’s transparency (Hamel, 1991; Larsson et al., 1998). Receptivity represents a firm’s assertiveness of absorbing external knowledge, and transparency refers to the partner firm’s willingness of knowledge sharing (Holmqvist, 2003; Larsson et al., 1998). On the one hand, firms without the required receptive abilities are less likely to absorb external knowledge. Prior research has indicated that firms are better able to absorb external knowledge when they have a relevant knowledge base (Dussauge, Garrette & Mitchell, 2000) and the required absorptive capacity (Yang et al., 2015), especially the capacity built on internal knowledge bases (Cohen & Levinthal, 1990) and learning experience (Argote & Miron-Spektor, 2011; Chandler & Hwang, 2015). Absorptive capacity refers to a firm’s ability to recognize and assimilate external knowledge (Cohen & Levinthal, 1990). On the other hand, a firm’s absorption of external knowledge in an alliance also hinges on its partner’s willingness of knowledge sharing (i.e., transparency). For instance, if a firm’s partners establish isolating mechanisms to constrain interfirm knowledge flows, the firm’s speed of absorbing external knowledge will be seriously undermined. This is because knowledge and skills within a firm are generally complex and not reducible to specific task resources (Soda & Furlotti, 2017).

Accordingly, from the lens of interorganizational learning, both a firm’s receptivity and its partner’s transparency are required to quickly absorb external knowledge.

Effect of Relational Ambidexterity on Absorption Speed

It is common for firms to form alliances with their rivals (Luo, Rindfleisch & Tse, 2007; Ryu, Reuer & Brush, 2020) and build a mixture of rivals and collaborators within their alliance
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portfolios (Gimeno, 2004). For instance, more than 50 percent of strategic alliances are formed
between rivals (Gnyawali, He & Madhavan, 2006; Harbison & Pekar Jr, 1998). By classifying a
firm’s alliance partners into rivals and collaborators, we contend that maintaining a balance
between rivals and collaborators in a firm’s alliance portfolio (i.e., relational ambidexterity)
increases the firm’s speed of absorbing external knowledge. Specifically, building on
interorganizational learning theory, we contend that relational ambidexterity increases a firm’s
absorption speed by simultaneously increasing the firm’s receptivity and its partner’s willingness
of knowledge sharing (i.e., transparency).

First, the interplay of rivals and collaborators within a firm’s alliance portfolio accelerates
the firm’s learning process by churning up information flows within its alliance portfolio. The
learning literature suggests that introducing a different type of species into a pool previously
consisting of only one type of species could churn up information flows and nurture some
productive interactions (Chuang, Tsai & Yang, 2011). The portfolio perspective on interfirm
alliances also suggests that firms can derive additional value from the interaction between
different components within their alliance portfolios (Hoehn-Weiss, Karim & Lee, 2017;
Wassmer, 2010). Specifically, we contend that the interplay of rivals and collaborators within
alliance portfolios churns up information flows in the following ways.

On the one hand, the presence of rivals within a firm’s alliance portfolio forces the firm to
accelerate its learning process (Derfus, Maggitti, Grimm & Smith, 2008; Giachetti, Lampel &
Pira, 2017). The learning literature suggests that competition and learning trigger each other in a
continuous and self-reinforcing process (Colm, Ordanini & Bornemann, 2020; Derfus et al.,
2008). Following this logic, we contend that the existence of rivals within a firm’s alliance
portfolio compels the firm to continuously improve its learning capabilities faster than the rivals
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to avoid being selected out, which in turn allows the firm to quickly identify and assimilate external knowledge (Cohen & Levinthal, 1990; Moreira et al., 2018). In other words, facing rivals motivates firms to increase their speed of absorbing external knowledge. On the other hand, the simultaneous presence of collaborators enables the focal firm to counterbalance the competitive pressure imposed by its rivals (Gimeno, 2004) and maintain strategic flexibility (Lado, Boyd & Hanlon, 1997). This is because simultaneously forming alliances with different types of partners allows a firm to offset the constraints across these partners (Connolly, 2005). The focal firm is thus able to maneuver among different partners. The leveraged role played by collaborators is critically important since a firm needs to dedicate substantial resources to safeguard the alliances with its rivals (Dussauge et al., 2000), which inhibits the firm’s ability to utilize external knowledge (Luo et al., 2007). Therefore, we contend that the interplay of rivals and collaborators within a firm’s alliances portfolio churns up information flows between firms, accelerating the firm’s speed of absorbing external knowledge.

In contrast, facing only one type of partner is less likely to accelerate a firm’s learning process. In the case of an alliance portfolio consisting merely of collaborators, the focal firm is less motivated to accelerate its learning process because the lack of rivals will make the firm less aggressive (Derfus et al., 2008). Similarly, since collaborators can be used to leverage and offset the competitive pressure coming from rivals (Gimeno, 2004; Jiang, Xia, Cannella & Xiao, 2018), in the case of an alliance portfolio consisting merely of rivals, the lack of collaborators generates strategic inflexibility (Park, Kim & Kang, 2015). That is, without the leveraged role played by collaborators, the costs of managing a portfolio consisting merely of rivals may outweigh the benefits as firms need to dedicate substantial resources to monitor their rivals (Dussauge et al., 2000; Ryu, McCann & Reuer, 2018).
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Second, relational ambidexterity provides access to different types of approaches to knowledge (re)combination, reducing the time needed to absorb external knowledge (Moreira et al., 2018; Rodan & Galunic, 2004). A simultaneous development and evaluation of multiple alternatives accelerates cognition processing and hence, processing speed (Judge & Miller, 1991). This is because exposure to different types of approaches to knowledge (re)combination deepens the understanding of the relationships among knowledge elements (Rodan & Galunic, 2004), which in turn enables a firm to accumulate experience in combining diverse sources of knowledge and enhances the firm’s capabilities of quickly recognizing and assimilating external knowledge, i.e., faster absorption speed (Moreira et al., 2018). Different types of firms offer different pools of cognitive frames (Colombo, 2003) and routines (Cui, 2013; Harrison, Hitt, Hoskisson & Ireland, 2001). For instance, since firms from different fields have different operating routines and strategic resources (Jiang, Tao & Santoro, 2010), a firm’s rivals and collaborators tend to provide distinctive approaches to knowledge (re)combination (Short et al., 2007). Therefore, we contend that a blend of rivals and collaborators within alliance portfolios provides firms with access to different types of approaches to knowledge (re)combination and cognitive frames¹, increasing their speed of absorbing external knowledge. In addition, facing competitive and cooperative ties simultaneously stimulates divergent thinking because of their contradictory competitive nature (Lado et al., 1997), further increasing firms’ capabilities of absorbing external knowledge.

In contrast, a portfolio consisting merely of rivals or collaborators provides access to only one type of approach to knowledge (re)combination. This, in turn, hampers firms’ capabilities of absorbing external knowledge because overemphasizing one type of approach engenders core rigidities and constrains the development of organizational learning capabilities (Benner &
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Tushman, 2003; Levinthal & March, 1993; March, 1991). Prior research also indicates that participants in a pool consisting merely of one type of species tend to be trapped in their local optimum (Chuang et al., 2011; Cui & He, 2018). For instance, an overemphasis on rivals leads to the problem of propinquity traps because a firm and its rivals have shared operating routines (Jiang et al., 2010), and overemphasizing this type of approach results in propinquity traps (Zahra & George, 2002). Similarly, an overemphasis on collaborators impedes a firm’s development of core competence. This is because a firm and its collaborators come from different fields (Short et al., 2007), and the knowledge communication between them is difficult (Jiang et al., 2010). The excessive searching costs of overemphasizing this type of approach hamper the development of core competence (March, 1991; Wuyts & Dutta, 2014). Therefore, we contend that firms with a portfolio consisting merely of rivals or collaborators tend to exhibit a lower speed of external knowledge absorption.

Finally, relational ambidexterity further increases a firm’s absorption speed by encouraging its partner’s willingness of knowledge sharing. Compared to a portfolio consisting merely of rivals or collaborators, we argue that relational ambidexterity increases the partner’s willingness of knowledge sharing by improving a focal firm’s control over valuable resources (i.e., a portfolio of different types of approaches to knowledge (re)combination as mentioned above). This is because firms always prefer partners with valuable resources (Lin, Yang & Arya, 2009; Stuart, 2000) and are more likely to disclose their knowledge to those attractive partners (Ahuja, Polidoro Jr & Mitchell, 2009; Shah & Swaminathan, 2008), even under unfavorable conditions (Ahuja et al., 2009). As both direct and indirect ties serve as conduits for knowledge flows within networks (Aggarwal, 2020; Bell & Zaheer, 2007), a firm can access the resources of its partner’s partners without forming direct ties with those partners. Therefore, a firm’s control
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over a portfolio of valuable resources provides its partner with access, at least potential access, to those valuable resources, increasing its attractiveness to that partner. Following this logic, we argue that a firm’s control over a portfolio of valuable resources accruing to relational ambidexterity increases its partner’s willingness of knowledge sharing, accelerating its absorption speed (Larsson et al., 1998). In summary, we argue that relational ambidexterity increases a firm’s receptivity and its partner’s willingness of knowledge sharing, accelerating its absorption speed. Therefore:

Hypothesis 1: Relational ambidexterity (i.e. a balance between rivals and collaborators within a focal firm’s alliance portfolio) has a positive effect on a firm’s speed of absorbing external knowledge.

The Moderating Role of Internal Knowledge Variety

To ensure speedy and effective interfirm knowledge flows, organizations require competitive internal knowledge structures that facilitate knowledge flows (Rodan & Galunic, 2004). That is, relational ambidexterity provides a firm with resource advantage, especially the different types of approaches to knowledge (re)combination. The agitated information flows and increased partner’s willingness of knowledge sharing created by relational ambidexterity mentioned above further enhance this advantage. However, exposure to the resource benefits created by relational ambidexterity per se does not guarantee a high level of ability to absorb external knowledge as a firm’s utilization of external knowledge sourcing depends on its internal knowledge structures (Grigoriou & Rothaermel, 2017; Matusik, 2000; Zahra & George, 2002). Consequently, we propose that a focal firm’s internal knowledge variety, defined as the dispersion of research activities across technological domains (Caner et al., 2017), enables the firm to effectively capture the resource benefits accruing to relational ambidexterity, augmenting
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the positive effect of relational ambidexterity on absorption speed. That is, firms characterized
by high internal knowledge variety tend to benefit more from relational ambidexterity.

Under the condition of high internal knowledge variety, we argue that firms are more likely
to take advantage of the resource benefits accruing to relational ambidexterity, amplifying the
positive effect of relational ambidexterity on absorption speed. In particular, firms characterized
by high internal knowledge variety tend to have broad knowledge bases and rich experience in
combining diverse knowledge (Caner et al., 2017; Fleming, 2001; Kaplan & Vakili, 2015),
which in turn help them to effectively utilize the diverse sources of resources created by
relational ambidexterity (Katila & Ahuja, 2002; Nerkar & Roberts, 2004). Therefore, while
forming alliances with rivals and collaborators simultaneously (i.e., relational ambidexterity)
provides firms with opportunities to access diverse sources of knowledge and routines, a high
level of internal knowledge variety enables firms to effectively capture these opportunities. In
contrast, firms with a portfolio consisting merely of rivals or collaborators may not benefit much
from high internal knowledge variety as access to only one type of approach to knowledge
(re)combination constrains the application of research experience derived from high internal
knowledge variety. Following this logic, we argue that under the condition of high internal
knowledge variety, firms tend to benefit much more from relational ambidexterity than merely
emphasizing rivals or collaborators.

Conversely, a low level of internal knowledge variety prevents firms from fully taking
advantage of the resource benefits accruing to relational ambidexterity. The main reason is that
they lack the relevant capabilities to capture these benefits as firms with low internal knowledge
variety have narrow knowledge bases and poor experience in combining diverse knowledge
(Caner et al., 2017). Specifically, prior research has indicated that firms always search locally
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and focus on knowledge related to their existing knowledge bases because of limited attention
span (Grigoriou & Rothaermel, 2017) and path dependency (Katila & Chen, 2008; Nerkar &
Paruchuri, 2005). Given that opportunity per se is not enough (Reinholt, Pedersen & Foss, 2011),
we argue that firms with low internal knowledge variety are more likely to focus on their existing
limited knowledge domains while overlooking the different types of resources provided by
relational ambidexterity\(^3\) (Audia & Goncalo, 2007; Caner et al., 2017; Dane, 2010). Therefore,
under the condition of low internal knowledge variety, it might be better for firms to emphasize
either rivals or collaborators to match their existing knowledge bases. In summary, we contend
that firms with high internal knowledge variety are more likely to capture the resource benefits
created by relational ambidexterity. Therefore:

_Hypothesis 2: Internal knowledge variety amplifies the positive effect of relational
ambidexterity on absorption speed. The higher the internal knowledge variety, the
stronger the relationship between relational ambidexterity and absorption speed._

The Moderating Role of Common Third Parties

The value a firm can derive from an alliance is influenced by its partner’s partners
(Aggarwal, 2020). That is, firms are always embedded in and constrained by their alliance
networks, which are commonly captured by common third parties (Cui et al., 2018). Therefore,
we contend that the number of common third parties between a firm and its partner, referred to as
the extent to which the partner is directly connected to other firms in the focal firm’s alliance
portfolio (Asgari et al., 2018), will attenuate the positive effect of relational ambidexterity on the
firm’s speed of absorbing external knowledge.

Common third parties between a firm and its partner reduce the salience of the focal firm as
a conduit between that partner and other firms in its alliance portfolio (Asgari et al., 2018;
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Podolny, 2001). The direct paths between a firm’s partner and other firms in the firm’s alliance portfolio allow that partner to directly access the resources of the focal firm’s other partners (Aggarwal, 2020; Asgari et al., 2018). When the level of common third parties between a firm and its partner is high, they become increasingly similar in the resources to which they have access and their partnership becomes more symbiotic (Cui et al., 2018), mitigating the benefits of resource advantage and strategic flexibility arising from relational ambidexterity as mentioned above. That is, although firms that balance rivals and collaborators within their alliance portfolios have more opportunities to access different types of knowledge (re)combination approaches than do firms with a portfolio consisting merely of rivals (or collaborators), a high level of common third parties mitigates such benefits by enabling their partners to access those valuable resources. In addition, common third parties increase the costs of deriving private benefits at the expense of others (Zhong, Su, Peng & Yang, 2017), further reducing a firm’s likelihood of taking advantage of relational ambidexterity. We thus contend that firms tend to benefit much less from relational ambidexterity under the condition of high levels of common third parties.

In contrast, when the level of common third parties between a firm and its partner is low, the focal firm tends to maintain exclusive control over network resources. This is because the lack of common third parties (i.e., a firm’s partner has few direct ties with the firm’s other partners) prevents that partner from accessing the firm’s other partners without the involvement of the focal firm (Moran, 2005; Verspagen & Duysters, 2004), increasing the focal firm’s control over network resources. Therefore, under low levels of common third parties, we argue that firms are able to sustain the resource advantage provided by relational ambidexterity. However, firms with a portfolio consisting merely of rivals (or collaborators) will still suffer the problems
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doing accessing only one type of approach to knowledge (re)combination as mentioned above.

Following this logic, we argue that a low level of common third parties enables a firm to maintain exclusive control over its partners’ resources, leading the firm to benefit more from relational ambidexterity. In summary, we argue that common third parties attenuate the positive effect of relational ambidexterity on absorption speed. Therefore:

Hypothesis 3: The number of common third parties between a firm and its partner attenuates the positive effect of relational ambidexterity on the firm’s speed of absorbing external knowledge. The greater the number of common third parties, the weaker the relationship between relational ambidexterity and absorption speed.

METHODS

Sample and Data

We used the strategic alliances formed by U.S. pharmaceutical firms as our sample. We selected the pharmaceutical industry for the following reasons. First, technology and innovation are critical for pharmaceutical firms to develop and sustain competitive advantage as this industry is characterized as research and development (R&D) intensive and technology-driven (Moreira et al., 2018). Second, pharmaceutical firms are especially eager to accelerate the innovation process (Cardinal, 2001; Macher & Boerner, 2006; Todorova & Durisin, 2007) as learning races are prevalent among them (Cardinal, 2001; DiMasi & Faden, 2011). Thus, the pharmaceutical industry represents a salient context to examine absorption speed. Third, strategic alliances have become a critical source of innovation (Stuart, 2000) and the U.S. pharmaceutical industry has been characterized by high alliance frequency (Cui et al., 2018; Ryu et al., 2020). For instance, the recent investments of pharmaceutical firms in R&D arrangements have been in a range of 15—40 billion U.S. dollars per annum (Devarakonda & Reuer, 2018). Fourth, the
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patenting behavior of pharmaceutical firms can be well tracked as these firms proactively patent their innovations (Alcácer, Gittelman & Sampat, 2009; Reuer & Devarakonda, 2016).

Additionally, since the patents of pharmaceutical firms are referred to as discrete technologies (Alcácer et al., 2009; Cohen, Nelson & Walsh, 2000), a pharmaceutical firm’s knowledge absorption is primarily manifested by its patents, providing the theoretical basis for measuring knowledge absorption by patents. Finally, U.S. pharmaceutical firms dominate the global pharmaceutical industry. They play a dominant role in the global innovation network and account for more than 40 percent of the global new molecular entities (Keyhani, Wang, Hebert, Carpenter & Anderson, 2010). In addition, focusing on U.S. firms enables us to control for differences across countries (Bierly & Chakrabarti, 1996).

We obtained data from several different databases. First, we used the Securities Data Corporation (SDC) and Recombinant Capital (Recap) databases, which are two of the comprehensive information sources that support large-scale empirical research on strategic alliances (Jiang et al., 2018; Sampson, 2007), to obtain firms’ alliance activities for the period 1990-2010. We ended the sample in 2010 to minimize right censoring concerns because the SDC and Recap rarely provide alliance termination information, and the life span of a strategic alliance is generally no more than five years (Yang, Lin & Peng, 2011). Stopping the sample in 2010 allows us to track the subsequent patent information up to 2015, minimizing right censoring concerns. Second, we obtained patent data from the United States Patent and Trademark Office (USPTO). The detailed patent information provided by the USPTO allows us to match the patents linked to our alliance activities. Third, we used the COMPUSTAT database to construct our financial variables.

Since our theory is based on interfirm knowledge flows, we dropped alliances that do not
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focus on knowledge flows by analyzing the detailed activity description provided by the SDC
and Recap databases. As this study investigates how the configuration of a firm’s alliance
portfolio affects the firm’s speed of absorbing its alliance partners’ knowledge, we estimated our
models from the focal firm’s perspective. Our analysis unit is the individual dyadic alliance. If an
alliance involves more than two firms, we separated it into every possible dyadic linkage (Rosenkopf, Metiu & George, 2001). Therefore, we further dropped dyadic alliances involving
firms that we cannot obtain their patent information. After the above process, we finally obtained
2,089 dyadic alliances formed by 467 firms from 1990 to 2010.

Dependent Variable

Absorption speed. Previous studies have always employed patent citations as evidence of
interfirm knowledge flows and learning rates (Almeida, Dokko & Rosenkopf, 2003; Schildt et al.,
2012). Following previous research (Leone & Reichstein, 2012; Moreira et al., 2018), we
measured absorption speed as the number of months between the alliance formation date and the
first time a focal firm incorporated its partner’s knowledge as a backward citation in a new patent.
For the cited patents shared by the two firms, we treated them as the focal firm’s knowledge and
excluded them from the measure of absorption speed. For cases that a focal firm has cited the
partner’s same patents prior to the alliance, we conducted two robustness tests. First, we
estimated our models without those alliances. Second, we excluded the partner’s patents that
have been previously cited by the focal firm from the measure of absorption speed. All the
results are consistent.

To eliminate the influence of different patent application processes, we used the patent
application date rather than the patent grant date (Leone & Reichstein, 2012). In order to model
the absorption speed, we constructed a dummy variable taking the value 1 if the focal firm has
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successfully cited its partner’s knowledge and 0 otherwise (this is an assistant indicator required in the analysis process, see Moreira et al. (2018) for more details).

Explanatory Variables

Relational ambidexterity. While many studies roughly define a firm’s rivals as firms operating in the same industry (Cui, Calantone & Griffith, 2011; Wang & Zajac, 2007), one major concern for this measure is that interfirm competitive relations may be asymmetric (Gur & Greckhamer, 2018). To address this issue, we adopted the competitive group (or strategic group) approach to define each partner’s role (Leask & Parker, 2007; Short et al., 2007). A competitive group is a group of firms whose managers perceive each other as rivals. Firms in the same competitive group not only compete in the same market segments, but also have similar product scope, resources, and capacities (Leask & Parker, 2007).

We measured the balance between rivals and collaborators within a firm’s alliance portfolio (i.e., relational ambidexterity) in three steps. To illustrate the measure process, we used the Infinity Pharmaceuticals Inc.’s alliances in 2006 as an example. First, we constructed a firm’s ego alliance network (i.e., alliance portfolio) using a five-year moving window based on its alliance activities (Jiang et al., 2018; Stuart, 2000). For instance, in the focal year 2006, Infinity Pharmaceuticals Inc. had formed alliances with four different partners during the previous five years, including Amgen Inc., Integral Press SA, MedImmune Inc., and Novartis AG.

Second, by adopting the competitive group approach, we classified a firm’s partners into two categories—rivals and collaborators. Specifically, we classified partners as rivals if they belong to the same competitive group as the focal firm, and collaborators otherwise (Leask & Parker, 2007). We used the two-stage clustering procedure to group firms (Leask & Parker, 2007; Short et al., 2007), and the hierarchical clustering (i.e., Ward’s method) to determine both the
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number of groups and their cluster centroids. Following previous research (Short et al., 2007), we defined the competitive group based on two competitive traits—scope of operations and resource deployment methods. We captured scope of operations with two variables—geographic scope and number of product types, and resource deployment methods with three variables—physical resources, financial resources, and firm size (Short et al., 2007).

To capture geographic scope, we used the percentage of domestic sales divided by total sales. A high percentage means that the firm is more likely to focus on the domestic market than the global market. We measured number of product types by the number of patents granted to a firm in the focal year since a patent represents a firm’s ability to achieve competitive advantage through product scope. Physical resources indicate a firm’s physical technology, equipment, and access to raw materials. We measured it as the capital expenditures divided by sales. Financial resources provide the means for achieving strategic flexibility and competitive advantage. We used current ratio, dividing current assets by current liabilities, to measure financial resources. A higher level of current ratio indicates more slack resources. Finally, we measured firm size as the natural log of total sales. Firm size reflects a firm’s general capacities and resources, indicating the firm’s scope of operations and competitive advantage. To ensure the stability and consistency of firms’ competitive traits, we measured all the variables as the average value during the previous five years (Short et al., 2007). Accordingly, we categorized Novartis AG as a rival since it belongs to the same competitive group to which Infinity Pharmaceuticals Inc. belongs. The other three firms were then classified as collaborators.

Third, after the above steps, we measured relational ambidexterity by the Blau Index (Wassmer, Li & Madhok, 2017). The Blau Index is calculated as: \( 1 - \sum_{i=1}^{N} p_i^2 \). Where \( N \) refers to the number of different categories, and \( p_i \) refers to the proportion of a firm’s partners in each
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category. In our study, we have two categories—rivals and collaborators. Therefore, the value of
relational ambidexterity ranges from 0 (perfect unbalanced partners) to 0.5 (perfect balanced
partners). For the above example, there are three collaborators and one rival in the alliance
portfolio of Infinity Pharmaceuticals Inc. Therefore, the relational ambidexterity is 0.375.

Since the Blau Index does not control for a firm’s total number of partners in its portfolio
(i.e., portfolio size), we measured the Blau Index with a Hall correction for robustness (Hall,
2005). The formula is: \( 1 - \frac{NN \times \sum_{i=1}^{N} p_i^2 - 1}{NN - 1} \), where NN refers to a firm’s portfolio size. All the
results are quite similar. As ego networks are referred to as portfolios (Uzzi, 1999), we also
controlled for portfolio size by degree centrality (see the control variables section).

**Internal knowledge variety.** We measured the internal knowledge variety (IKV) of a focal
firm \( i \) as the distribution of patents across patent classes with the inverse of the nonbiased
Herfindahl Index (Caner et al., 2017). That is: \( \text{Internal knowledge variety} = 1 - \frac{N_i \times HI_i - 1}{N_i - 1} \),
where \( HI_i = \sum \left[ \frac{N_{ik}^2}{N_i} \right] \), \( N_{ik} \) is the number of patents in class \( K \) by the focal firm \( i \), and \( N_i \) is the total
number of patents in all patent classes by the focal firm \( i \). It ranges from 0 to 1, where a higher
value indicates a higher level of internal knowledge variety.

Since the Blau Index is also known as the Herfindahl Index (Harrison & Klein, 2007), the
nonbiased Herfindahl Index is in nature an improved version of the Blau Index by controlling for
the size of a firm’s knowledge pool (Hall, 2005). For robustness, we also measured IKV with the
Blau Index, i.e., \( 1 - HI_i \). All the results remain consistent.

**Common third parties.** We measured the number of common third parties between a focal
firm and its partner as the number of alliance partners shared by the two firms during the
previous five years (Cui et al., 2018; Polidoro Jr, Ahuja & Mitchell, 2011).
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Control Variables

We controlled for a number of factors that may affect our proposed relationships. We first controlled for the focal firm’s attributes—firm size, firm age, current ratio, firm performance, organizational absorptive capacity, and alliance experience, which may affect the firm’s capabilities and resources available for strategic alliances. Firm size was measured as the natural log of total sales and current ratio was measured by dividing current assets by current liabilities (Short et al., 2007). Firm age was measured as the number of years from a firm’s initial public offering date to the year t. Firm performance was measured by return on assets, dividing net income before interest and taxes by total assets (Wassmer et al., 2017).

We controlled for organizational absorptive capacity as R&D intensity, calculated as total R&D expenditure divided by total sales. Alliance experience was measured as the number of strategic alliances formed by a firm during the previous five years divided by its sales (Phelps, 2010). For total sales used in measuring R&D intensity and alliance experience, we used the mean value of a firm’s total sales during the previous five years to ensure consistency. For robustness, we conducted two tests. On the one hand, we estimated our models without R&D intensity and alliance experience, as well as without either one. On the other hand, we used the original values of total sales. All the results remain consistent.

We then controlled for alliance network factors—degree centrality, structural holes, and multilateral competition, which may affect interfirm knowledge flows. Degree centrality was measured as the total number of a firm’s directed connection ties. Structural holes was measured as one minus network constraint (Burt, 1992). Using the UCINET VI package, we constructed each firm’s ego alliance network for each year and obtained the above variables directly from the package. We computed the multilateral competition among a focal firm’s partners based on the
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inversed Berry–Herfindahl diversification index, measured as the sum of the squared proportions of partners’ sales in each industry segment (Lavie, 2007).

Finally, we controlled for several dyad level factors—technological distance, repeated tie, joint venture, cross-border alliance, the focal firm’s prior citation, the partner’s prior citation, alliance propensity, and partner technological class. These factors may affect a firm’s ability and motivation to absorb external knowledge. We measured technological distance in three steps (Phelps, 2010; Sampson, 2007). We first used a five-year moving window to construct a firm’s patent portfolio. Since some patent classes might be closer to each other than others, we measured technological distance based on the eight USPTO biotechnological patent classes widely used in prior studies (Rothaermel & Hess, 2007). We then measured the distribution of a firm’s patents across the primary patent classifications to acquire the multidimensional vector \( F_i = [f_{i1} \ldots f_{ik}] \), where \( f_{ik} \) represents the fraction of firm i’s patents in patent class k. Finally, we measured the technological distance between firm i and firm j as:

\[
\text{Technological distance} = 1 - \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}
\]

where \( i \neq j \). Technological distance varies from 0 (minimum technological distance) to 1 (maximum technological distance). We also conducted three additional robustness tests. (1), we used the Euclidean distance approach to measure the technological distance between two firms (Yang et al., 2015). (2), we employed an alternative approach to measure the technological distance between two firms. Prior studies have used a firm’s primary industry SIC code as a proxy for the firm’s technologies and resources (Cui, 2013; Wang & Zajac, 2007). Referring to previous research (Cui, 2013), we used the distance between two firms’ two-digit SIC codes to measure their technological distance. For robustness, we also measured the distance between the
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Two firms’ SIC codes at the three-digit and four-digit levels. (3), we excluded technological distance from our estimation models. All the above results remain consistent.

We controlled for repeated tie (takes the value 1 if the two firms have previously formed alliance(s) and 0 otherwise) and joint venture (takens the value 1 if the alliance is a joint venture and 0 otherwise). Since knowledge tends to cluster geographically and cultural distance may affect interfirm knowledge communication, we controlled for cross-border alliance (takes the value 1 if the alliance is a cross-border alliance and 0 otherwise) (Schildt et al., 2012). We controlled for firms’ prior citations by two variables: a focal firm’s prior citation, which refers to the extent to which a focal firm has cited its partner’s patents prior to the alliance, and its partner’s prior citation, which refers to the extent to which the partner has cited the focal firm’s patents prior to the alliance. A firm’s prior citation was measured as the number of cited patents belonging to its partner divided by the total number of cited patents during the previous five years. The very similar approach has been widely used in previous research (Yang et al., 2015).

For robustness checks, we also measured a firm’s prior citation during the previous seven years, as well as all years before the focal year. All the results are consistent. As resource relationships between two firms, usually measured by industry SIC codes (Cui, 2013), affect their motivations to form an alliance (Rothaermel & Boeker, 2008), we used a dummy variable that takes the value 1 if a focal firm and its partner share the same four-digit SIC code and 0 otherwise as a proxy for alliance propensity. Finally, since the technological classes of a firm’s partner may affect the learning process, we controlled for partner technological class as the proportion of a partner’s patents that belong to the eight USPTO biotechnological classes.

Model Specification and Estimation

Since our dependent variable (absorption speed) is the time taken to absorb external
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knowledge, we transformed the data into event history data and adopted a survival model to test our hypotheses (Leone & Reichstein, 2012). We employed the event history analysis for two reasons. First, this technique allows us to precisely measure the months a firm takes to absorb external knowledge rather than using dummies. Second, this technique is particularly powerful in handling censoring data. By considering the right-censoring issue as a non-random process, this technique enables us to model observations that do not experience a successful transition (i.e., external knowledge absorption in this study) during the analysis period (Blossfeld, Golsch & Rohwer, 2007). Following previous studies, we employed the log-logistic model specification for our time-dependence data transition (Leone & Reichstein, 2012).

Unobserved heterogeneity (substantial frailty) effects may influence our estimations because of some omitted variables (Leone & Reichstein, 2012). This unobserved heterogeneity is firm-specific as a firm may form several alliances during our analysis period. Following previous research, we addressed this issue by using a shared frailty model approach and applying a likelihood ratio test to compare the restricted and unrestricted model specifications (Gutierrez, 2002; Leone & Reichstein, 2012). In shared frailty models, the frailties are shared across groups of observations and the observations within the same group are assumed to be correlated (Cleves, Gould, Gutierrez & Marchenko, 2010). That is, shared frailty models are the survival data analogue to random-effects models where the frailties are shared among groups of individuals and randomly distributed across groups (Gutierrez, 2002) (see Gutierrez (2002) and Cleves et al. (2010) for more details on the frailty model). We also used robust standard errors to control for the potential lack of independence of observations.

Endogeneity

Since we focus on strategic alliances that emphasize knowledge exchange, there might be
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sample selection bias. In line with prior studies, we employed the Heckman two-stage selection model to control for this potential bias (Nerkar & Shane, 2007; Wetzel, Hammerschmidt & Zablah, 2014). An effective selection model requires at least one variable that should influence the likelihood of forming alliances that emphasize knowledge exchange, but not the absorption speed (Nerkar & Shane, 2007). Therefore, we included a firm’s stock ownership type (e.g. publicly traded company and subsidiary of a company not publicly traded) in the first stage model. Stock ownership should affect a firm’s motivation to form strategic alliances that focus on knowledge exchange, but not the absorption speed. For instance, compared to firms that are subsidiaries of not publicly traded firms, publicly traded firms may focus on alliances that can generate benefits in the short term rather than knowledge generation in the long term. Specifically, in the first stage, we ran a probit model to predict the likelihood that an alliance was included in our final sample. We then used the probit estimates to generate the Heckman correction variable (i.e., inverse Mills Ratio) by dividing the probability density function by the cumulative distribution function of the standard normal distribution. Finally, we added the inverse Mills Ratio to our models to control for our sample selection bias.

Furthermore, to eliminate the potential endogeneity caused by relying on a single modeling technique, we estimated our models by the Cox Proportional Hazard Model specification (Cox model), which is also a widely used technique in analyzing survival data (Benner & Tripsas, 2012). The Cox model is powerful in analyzing survival data as it does not make particular assumptions about the shape of the underlying hazard function (Benner & Tripsas, 2012) and allows data with a temporal bias (Yu, Gilbert & Oviatt, 2011). It also incorporates both time-invariant and time-varying covariates (Nerkar & Shane, 2007). We clustered the standard errors on individual firms and used robust standard errors to correct the non-independence of
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observations (Benner & Tripsas, 2012).

RESULTS

Table 1 reports the descriptive statistics of our variables. All correlations are within the accepted standard ranges. The variation inflation factor (VIF) test indicates that multicollinearity is not an issue in our study (maximum and mean VIF values are 2.06 and 1.01 respectively). We tracked firms’ patent information up to December 2015. That is, firms are subject to December 2015 censoring. Therefore, the longest time to absorb external knowledge is 312 months.

[Insert Table 1 about Here]

Table 2 and Table 3 report the log-logistic model and Cox model respectively. In both models, Model 1 only includes the control variables. We then added relational ambidexterity and the moderators in Model 2. Models 3-4 include our interaction terms. We centered relational ambidexterity and the moderators to generate their interaction items. In both estimation techniques, compared to Model 1, Model 2 is significantly improved, providing statistical support for our analysis. In the log-logistic model, the log likelihood is significantly increased from $-1441.15$ to $-1436.52$, and the chi squared is significantly increased from 270.29 to 279.56. Similarly, in the Cox model, the log likelihood is significantly increased from $-2680.46$ to $-2674.86$, and the chi squared is significantly improved from 610.25 to 621.01.

Hypothesis 1 predicts a positive relationship between relational ambidexterity and absorption speed. We found strong support for Hypothesis 1 in both models. As shown in Model 2 of Table 2, relational ambidexterity is negatively related to the time a firm takes to absorb its partner’s knowledge ($b = -2.16$, $p=0.003$), indicating that relational ambidexterity reduces the time a firm takes to absorb external knowledge, i.e., it speeds up the absorption of external knowledge. We also conducted the analysis of effect size, defined as the percentage change in
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the hazard rate of absorption speed as a function of increases or decreases in explanatory variables for a given covariate on the basis of Beta coefficient (Bakker, 2016). Analysis of the effect size indicates that 0.1 units increase in relational ambidexterity can result in 24.1 percent increase in relative hazard in responding to the speed of external knowledge absorption (0.241=exp (-(-2.16)*0.1)-1). That is, the higher the relative hazard, the faster the firm will absorb external knowledge. We used 0.1 units rather than one unit because relational ambidexterity ranges from 0 to 0.5. This result is consistent with the Cox model. Model 2 of Table 3 reveals that relational ambidexterity is positively related to the hazard rate of external knowledge absorption (b =1.03, p= 0.008). Here, we should be aware that in the Cox model, a higher hazard rate means a shorter “survivor” time. In this study, a patent is considered as a “survivor” if it is not absorbed by another firm. Therefore, 0.1 units increase in relational ambidexterity can result in 10.8 percent increase in relative hazard (0.108=exp (1.03*0.1)-1) in responding to the speed of external knowledge absorption.

We also visualized the hazard function based on estimates in Model 2 of Table 2. A one standard deviation increase in the relational ambidexterity can result in 41.3 percent increase in the relative hazard in responding to the speed of external knowledge absorption. As shown in Figure 1, compared to low relational ambidexterity (one standard deviation below the mean value), the higher peak of the hazard function for high relational ambidexterity (one standard deviation above the mean value) indicates a higher likelihood of earlier transition, i.e., a higher absorption speed. These results provide strong support for Hypothesis 1.

[Insert Table 2, Table 3, and Figure 1 about Here]

Hypothesis 2 indicates that internal knowledge variety strengthens the positive relationship between relational ambidexterity and absorption speed. As shown in Model 3 of Table 2, the
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coefficient of the interaction between relational ambidexterity and internal knowledge variety is negative and significant ($b = -4.82, p=0.047$). Following previous research (Bakker, 2016; Dai, Eden & Beamish, 2017), we conducted the marginal effects analysis to explain the effect size.

Our results indicate that when a firm’s internal knowledge variety is high (one standard deviation above the mean value), 0.1 units increase in the relational ambidexterity results in 39.8 percent increase in relative hazard in responding to the absorption speed. Whereas, when the internal knowledge variety is low (one standard deviation below the mean value), the changed value is 0.8 percent. Model 3 of Table 3 also reveals a similar result ($b =2.90, p=0.015$). Similarly, the changed values for high and low internal knowledge variety are 18.8 percent and −2.5 percent respectively. Therefore, Hypothesis 2 is strongly supported.

Hypothesis 3 predicts that the number of common third parties between a focal firm and its partner weakens the positive relationship between relational ambidexterity and absorption speed. As shown in Model 4 of Table 3, the coefficient of the interaction between relational ambidexterity and common third parties is negative and significant ($b = -1.09, p=0.028$). The marginal effects analysis indicates that when a focal firm and its partner have a low number of common third parties (one standard deviation below the mean value), 0.1 units increase in relational ambidexterity results in 19.0 percent increase in relative hazard in responding to the absorption speed. The changed value is 3.5 percent when they have a high number of common third parties (one standard deviation above the mean value). However, as shown in Model 4 of Table 3, the coefficient of the interaction term is not significant in the log-logistic model ($p > 0.1$). Therefore, Hypothesis 3 is weakly supported.

Robustness Checks

We conducted the following robustness tests to make our analysis stronger. First, as
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presented above, we employed two different analysis techniques: the log-logistic model and the Cox model. All our hypotheses are fully supported by both techniques except that the moderating effect of common third parties is weakly supported.

Second, to eliminate the influence of a partner’s newly applied (or old) patents, we excluded the partner’s patents applied earlier beyond five years (and seven years for robustness) from the alliance date from the measure of absorption speed. All the results are quite similar.

Third, to eliminate the concern that a firm’s knowledge absorption might be driven by its partners in a joint project, we conducted the following two tests. In the first test, we dropped alliances whose outcomes might be joint achievements by analyzing the alliance contents. We dropped an alliance if it was described such as “AVI Biopharma Inc and Exelixis Inc also agreed to jointly own (the antisense drug)” and “Sepracor and Creative BioMolecules agreed to jointly develop optically pure compounds.” In the second test, we excluded patents that may involve the partner’s efforts from the measure of absorption speed, including (1), a focal firm’s patents that are jointly owned by its partner. (2), a focal firm’s patents that have been cited by its partner, either before or after their alliance. (3), the partner’s patents that have been cited by the focal firm prior to an alliance or jointly owned by the focal firm. All the results are consistent.

Fourth, to eliminate the concern that the partner’s knowledge absorbed by the focal firm may also be frequently cited by other firms, especially firms that have no alliance with that partner, we excluded those patents (i.e., widely cited patents) from the measure of absorption speed. Specifically, we first listed out all the U.S. pharmaceutical firms from the COMPUSTAT database and their patent citation information from the USPTO. We then counted the number of forward citations a patent receives within five years from the patent’s application date as the patent’s citation-weight (Hess & Rothaermel, 2011). Finally, we classified a patent as a widely
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cited patent if its citation-weight is equal to or higher than the industry-high level (i.e., one
standard deviation above the mean value of all patents applied in that patent’s application year).
All the results remain consistent.

Fifth, rivals and collaborators are not mutually exclusive terms since interfirm relationships
are always mixed (Gnyawali & Ryan Charleton, 2018; Panico, 2017). Therefore, we treated the
partnership between two firms as a continuum and constructed relational ambidexterity with a
continuous measure. We measured relational ambidexterity in three steps. In the first step, we
constructed the focal firm’s alliance portfolio with a five-year moving window. In the second
step, we measured the competitive relationship between a focal firm and each of its partners by
the industry SIC codes (Cui et al., 2011; Schildt et al., 2012). The competitive relationship
between two firms takes the value 1 if their four-digit SIC codes are equal, 0.5 if their first three digits SIC codes match, 0.33 if their first two digits SIC codes match, 0.25 if only their first digit SIC codes match, and 0 otherwise (Schildt et al., 2012; Villalonga & McGahan, 2005). The value ranges from 0 (lowest competition) to 1 (highest competition). The value of a focal firm’s competitive relationship is the average of all the dyadic values in its alliance portfolio. In the third step, based on the sample in our study, a firm with a value between the low (one standard deviation below the mean value) and high values (one standard deviation above the mean value) was categorized as maintaining a balance between rivals and collaborators in its alliance portfolio (i.e., relational ambidexterity takes the value 1). Otherwise, relational ambidexterity takes the value 0. The same or very similar approach has been commonly adopted in prior studies (Lin, Yang & Demirkan, 2007). We found strong support for the positive effect of relational ambidexterity on absorption speed (Hypothesis 1). However, the moderating effects of internal knowledge variety (Hypothesis 2) and common third parties (Hypothesis 3) become
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insignificant. Thus, Hypothesis 2 and 3 are weakly supported.

Sixth, the strategic group approach we adopted to classify a firm’s alliance partners allows a partner’s role to remain consistent for a relatively long term (Short et al., 2007). However, it is possible that a partner’s role changes from rivals (collaborators) to collaborators (rivals) as interfirm relationships are always mixed. To address this issue, we have conducted two types of robustness tests. On the one hand, we estimated our models without the cases of role changes during alliances. To keep consistent, we also used the strategic group approach to define the role of a focal firm’s alliance partner. All the results are consistent except that the moderating effect of common third parties (i.e., Hypothesis 3) is weakly supported. Specifically, we found that the cases of role change are not prevalent in our study. Given that the alliance life span is generally no more than five years (Yang et al., 2011), (1), the ratios of such cases from the first year to the fifth year (or the year of experiencing successful transition) after the alliance establishment are 0 percent, 8.64 percent, 5.89 percent, 7.46 percent, and 7.83 percent, respectively. The total ratio of such cases, that is, as long as a partner has encountered role change in any year regardless of whether the partner’s role has changed back in some other years, is 14.37 percent. (2), the likelihoods of changing from rivals to collaborators and from collaborators to rivals during alliances are similar. The ratios of role change cases during alliances are 0 versus 0 percent, 4.05 versus 4.59 percent, 2.92 versus 2.97 percent, 3.40 versus 4.05 percent, and 3.84 versus 4.00 percent, respectively. The total ratios are 6.21 versus 8.16 percent. (3), we conducted robustness tests for each year and each type of role change, and integrated role change cases in three steps. In the first step, we estimated our models by dropping alliances encountering role changes for each year. All the results are consistent except that the moderating effect of common third parties (i.e., Hypothesis 3) is not supported for the second and fifth years. In the second step, we tested
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the roles changed from rivals (collaborators) to collaborators (rivals) for each year, respectively.

All the results remain consistent except that Hypothesis 3 is not supported by dropping cases of roles changed from rivals to collaborators in the fifth year. In the third step, we estimated our models by dropping alliances encountering (a) roles changed from rivals to collaborators, (b) roles changed from collaborators to rivals, and (c) either directional role change, in any year during alliances. All the results remain consistent except that Hypothesis 3 is only supported under condition (b).

On the other hand, although the cases of role changes are not prevalent as indicated above, they may affect the distribution of rivals (collaborators) within alliance portfolios (i.e., relational ambidexterity). To address this issue, we conducted the following three robustness tests. We measured a firm’s relational ambidexterity in a given year as the mean value of its relational ambidexterity (1) during the previous five years, (2) during the five years after the focal alliance year, and (3) during the five years both before and after the focal alliance year (i.e., a ten-year range). All the results remain consistent except that Hypothesis 3 is only supported under condition (1). The above two types of robustness tests indicate that the potential role change during an alliance is not an issue in our study.

Seventh, we measured strategic groups using a deductive approach. There are two distinct approaches in strategic group analysis—inductive approach and deductive approach (Short et al., 2007). While the inductive approach adopted in this study focuses on empirically derived groups, the deductive approach is theory-driven. That is, both the number of strategic groups and group members are decided by a priori theoretical framework. Following Short et al. (2007) research, firms were clustered into four theory-driven groups based on two dimensions—strategic choice and organizational ecology.
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The first dimension indicates a firm’s method of developing competitive advantage, either exploiting existing opportunities or exploring new opportunities. The second dimension focuses on the breadth of operations, either narrow or broad. These two dimensions result in four quadrants. The first quadrant is defenders, who focus on existing opportunities in a narrow domain. The second quadrant is entrepreneurs, who pursue new opportunities in a narrow domain. The third quadrant is analyzers, who efficiently exploit existing opportunities in a broad domain. The last quadrant is prospectors, who pursue new opportunities in a broad domain.

Following previous research (Short et al., 2007), we measured strategic choice by the average R&D intensity during the previous five years. High R&D intensity indicates high capabilities, or at least intention, to explore new opportunities, while low R&D intensity indicates that firms tend to focus on their existing opportunities. We measured organizational ecology by the number of trademarks a firm holds. Since trademarks proxy for the breadth of operations, firms with many trademarks are more likely to provide numerous products while firms with few trademarks tend to focus on a narrow market. The statistical process is similar to the inductive approach. All our hypotheses are supported except the moderating effect of common third parties. Therefore, the above tests indicate the high robustness of our results.

Eighth, to address the concern that the same patent of a focal firm may cite more than one patent belonging to the firm’s different partners at the same time point (i.e., multipoint cases) and this event may be repeated, we conducted the following two tests. (1) We estimated our models with the multivariate point process model. All the results are quite similar. These results are expected as more than 92 percent of the alliances involve only two firms, and we found no multipoint case in our sample. (2) For the cases that a focal firm has absorbed the knowledge of two or more partners in the same alliance but through its different patents, we randomly kept one
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of them. All the results remain consistent.

Ninth, the USPTO provides additional information on a patent’s backward citations added by examiners (examiner citations). Although patents in the pharmaceutical industry have the lowest proportion of examiner citations (25 percent), compared to the highest proportion of 45 percent in the computers and electronics fields (Alcácer et al., 2009), we still excluded examiner citations from our measure of absorption speed for robustness. All the results are consistent.

Post-hoc Analyses

We conducted the following two post-hoc tests to (1) test the learning effect derived from alliances and (2) address the concern that a firm’s patent citations may be influenced by the roles of its cited partners (i.e., rivals or collaborators).

Test for the learning effect derived from alliances. Since patents are available to the public, we conducted the following two tests to examine whether the increased absorption speed we proposed is derived from strategic alliances. First, for a partner firm’s (denoted as firm-A) patent cited by the sample focal firms in our study, we compared the absorption speed between non-alliance firms and alliance-partners in three steps. To keep consistent, we set 2015 as the censoring year. In the first step, we listed out all firms that have cited that patent. We classified firms as alliance-partners if they have formed alliances with firm-A during the period 1990-2015, and non-alliance firms otherwise. In the second step, we measured the mean absorption speed (the starting point is the application date of that patent) of non-alliance firms and alliance-partners respectively. In the third step, we compared their absorption speed by the ANOVA test. The results reveal that alliance-partners absorb the firm-A’s patent much faster than non-alliance firms do (mean absorption speed for alliance-partners and non-alliance firms are 77.26 and 105.61 months respectively, \( p=0.000 \)).
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Second, to address the issue that absorption involves some learning parts that may not be directly measured by patent citations, we treated alliances as events and adopted the difference-in-differences (DiD) approach to test such learning parts (Fisher, Gallino & Xu, 2019). If learning occurs in an alliance, firms engaging in alliances should achieve a higher innovation speed. Since a firm may engage in several alliances in some years while no alliance in the other years, the DiD test allows us to examine not only the differences of a firm’s innovation speed before and after an alliance, but also the differences in innovation speed across firms. Therefore, we compared each firm’s innovation speed (measured as the number of patents a firm applied five years before or after a given year) from 1990 to 2010. We used the same sample firms for our DiD test. The results verify the learning part of absorption not measured by patent citations. Specifically, for the control group, i.e., firms that do not have alliance activities in a given year, the mean patent number a firm applied during the five years before and after an alliance are 19.74 and 19.91 respectively (insignificant, \( p > 0.1 \)). However, for the treatment group, i.e., firms that have alliance activities in a given year, the values are significantly increased from 41.88 to 52.17 (\( p = 0.001 \)). For robustness, we also estimated our models by adding the other U.S. pharmaceutical firms from the COMPUSTAT. The results are consistent. These results indicate that firms engaging in alliances tend to achieve a higher speed of absorbing external knowledge.

In summary, the ANOVA test indicates that a firm tends to cite its partner’s knowledge faster than do firms that do not have an alliance with that partner. The DiD test reveals that strategic alliances increase firms’ innovation speed. The above tests indicate that firms not only recognize and assimilate their partners’ knowledge, but also exploit that knowledge in relevant areas. This helps to examine the learning part of absorption not directly measured by patent citations.
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A separate analysis of rivals and collaborators. As we classified a firm’s alliance partners into rivals and collaborators, we further examined whether the citations to a firm’s rivals and collaborators are different. For instance, while the relatively shared routines between a firm and its rivals may facilitate information flows, the rivals always employ defensive mechanisms such as reorganization and resource specificity to prevent knowledge leakage (Dussauge et al., 2000; Ryu et al., 2018). Similarly, the fewer defensive mechanisms caused by the less competitive intensity between a firm and its collaborators might compensate for the relatively difficult technological communication between them. To address this issue, we divided our overall sample into two groups—collaborators and rivals. For the group of collaborators, all our hypotheses are fully supported. For the group of rivals, the positive effect of relational ambidexterity on absorption speed (Hypothesis 1) is still supported. However, none of the moderating effects is significant (Hypothesis 2 and 3). This might be caused by the relatively small observations (221 observations). In summary, our hypotheses are generally consistent for the individual groups of collaborators and rivals.

DISCUSSION

This study investigates the influence of relational ambidexterity on a firm’s speed of absorbing external knowledge. By analyzing the event history data of 2,089 dyadic alliances formed by 467 U.S. pharmaceutical firms, we find that relational ambidexterity exerts a positive effect on absorption speed. Our findings also show the different contingent roles of inward-looking (i.e., internal knowledge variety) and outward-looking (i.e., common third parties) dimensions related to interfirm knowledge flows.

Theoretical Implications

Our study makes several major theoretical contributions. First, a distinct contribution of our
RELATIONAL AMBIDEXTERTY AND ABSORPTION SPEED

study is that we highlight the time dimension of interorganizational learning. This body of work tends to focus on overall interfirm knowledge flows over relatively long periods while ignoring the issue of time (Bridoux et al., 2013; Leone & Reichstein, 2012; Moreira et al., 2018; Schildt et al., 2012). While prior research has acknowledged that there is a significant relationship between time and alliance learning (Oxley & Wada, 2009) and rapid learning largely determines the competitive advantage of firms in technology-intensive industries (Macher & Boerner, 2006), our understanding of the temporal aspect of alliance learning is very limited. By examining the influence of relational ambidexterity on absorption speed, we contribute to this literature by explicitly addressing the time dimension of interorganizational learning.

Second, our study offers a novel perspective to deal with learning races. To answer the question of how to facilitate interfirm knowledge flows, previous literature has predominantly highlighted the roles of trust (Panico, 2017; Selnes & Sallis, 2003) and governance mechanisms (Zollo, Reuer & Singh, 2002). However, both trust and governance mechanisms require the efforts of all alliance participants. That is, a single firm has little or no control over them. Nevertheless, by examining the relationship configuration of alliance portfolios, we find that a focal firm may still be able to speed up interfirm knowledge flows by strategically balancing rivals and collaborators within its alliance portfolio.

Additionally, our study provides an interesting insight into the interplay of rivals and collaborators within alliance portfolios. In addition to the traditional resources perspective (i.e., the different types of knowledge (re)combination approaches and cognitive frames provided by rivals and collaborators), our findings indicate that from the interorganizational learning perspective, the different roles played by rivals and collaborators churn up information flows between firms.
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Finally, we extend research on interorganizational learning by combining the inward-looking and outward-looking dimensions related to interfirm knowledge flows. Most previous studies have predominantly emphasized one-side dimensions, either the inward-looking ones such as inventor network and learning experience (Wang, Rodan, Fruin & Xu, 2014; Zahra & George, 2002) or the outward-looking ones such as conflict management and technological diversity (Arikan & Shenkar, 2013; Sampson, 2007). By investigating the different contingent roles of internal knowledge variety and common third parties, our findings indicate that both inward-looking and outward-looking dimensions matter. Therefore, whether firms benefit from relational ambidexterity depends on the characteristics of both the focal firm and its partners.

Managerial Implications

Our findings have important implications for managerial practice. First, our findings indicate that an appropriate configuration of rivals and collaborators in a firm’s alliance portfolio accelerates the firm’s speed of external knowledge absorption. Therefore, to avoid losing learning races, firms should simultaneously form alliances with their rivals and collaborators.

Second, since firms with high internal knowledge variety tend to benefit more from relational ambidexterity, firms should proactively increase their internal knowledge variety by ways such as attracting experts from other industries and encouraging interfirm communications. In contrast, firms characterized by low internal knowledge variety should carefully manage their levels of relational ambidexterity as the cost of managing a complicated alliance portfolio consisting of different types of partners is high (Jiang et al., 2010; Ozcan, 2018). When a firm’s internal knowledge variety is too low, it might be better for the firm to concentrate on one type of alliance partner to match its knowledge base.

Finally, our findings indicate that common third parties attenuate the positive effect of
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relational ambidexterity on absorption speed. Prior research also suggests that high levels of
common third parties may lock a firm in its existing partnerships (Jiang et al., 2018; Uzzi, 1997),
impeding the firm from accessing new opportunities. Therefore, a firm should form alliances
with partners that share fewer common third parties.

Limitations and Future Research Directions

Our findings should be interpreted in light of limitations. First, since firms and alliance
databases (i.e., SDC and Recap) rarely report alliance termination information (Lavie, 2007;
Schilling, 2009), we are unable to track firms’ behavior after the termination of an alliance.
Therefore, it may be interesting for future studies to analyze a firm’s absorption speed after the
termination of an alliance. Second, we capture a firm’s absorption of external knowledge by
patent citations. However, not all knowledge is transferred to patents. Future research may
measure absorption speed with other approaches such as a combination of quantitative and
qualitative methods. Third, the strategic group approach does not control for the temporally
changed interfirm relationship caused by alliances. Although an alliance partner’s role defined
by the strategic group approach remains consistent for a relatively long period (Short et al.,
2007), an alliance partner’s role might change during the alliance process. Moreover, the
strategic group approach does not control for firm-level heterogeneities within a group.
Therefore, further research may define an alliance partner’s role with some other approaches.
Finally, although both innovation outcomes (Jansen, Van Den Bosch & Volberda, 2006) and
absorption speed (Leone & Reichstein, 2012) are crucial for firms in technology-driven
industries, there is no reason to assume that firms can simultaneously achieve both high
absorption speed and great innovation outcomes. Future research can extend this study by
examining the tradeoff between these two objectives.
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CONCLUSION

This study investigates the influence of relational ambidexterity on absorption speed. Building on interorganizational learning theory, we find that relational ambidexterity has a positive effect on absorption speed. We further find that the positive relationship between relational ambidexterity and absorption speed is weakened by the outward-looking dimensions (i.e., common third parties), but strengthened by the inward-looking dimensions (i.e., internal knowledge variety). The important message of this study is that firms in technology-intensive industries where time-based competition is paramount should strategically maintain a balance between rivals and collaborators within their alliance portfolios in order to achieve a high level of absorption speed. Our study makes a distinct contribution to research on interorganizational learning, calling for more studies to advance the time dimension of knowledge absorption.

NOTES

1. We appreciate the anonymous reviewer’s concern on the firm-level heterogeneity within a group. However, according to research on the strategic group approach, the within-group heterogeneity is much smaller than the between-group heterogeneity. Therefore, from the focal firm’s perspective, we contend that alliance partners from one category (either rivals or collaborators) provide one relatively general type of approach to knowledge (re)combination and cognitive frame.

2. Alliance contracts are not sufficient to ensure smooth interfirm knowledge transfer. This is because knowledge exchanged in most learning alliances is ambiguously defined. In alliances, especially the learning alliances, contracts inevitably entail a degree of incompleteness (Lioukas & Reuer, 2020). Given that licensing alliances may announce the licensed technology, for robustness, we estimated our models without those cases (260 observations). All the results remain consistent except that hypothesis 3 is not supported.

3. We appreciate anonymous reviewers’ concern that firms with low internal knowledge variety (IKV) might be forced to seek new knowledge because they realize that their limited knowledge domains may become outdated. However, we argue that this is not an issue in our study. First, the literature on search behavior has indicated that firms always tend to search for knowledge similar to their existing knowledge domains while ignoring unfamiliar knowledge. Second, only motivation is not sufficient because firms also need relevant opportunities and abilities (Reinholt, Pedersen, & Foss, 2011). Accordingly, although firms with low IKV might be forced to seek new knowledge, they may lack the required opportunities or abilities to absorb their partners’ knowledge. Third, we focus on absorption speed rather than the amount of overall knowledge absorbed. Therefore, it is unlikely for such firms to absorb external knowledge in a relatively...
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short time since low IKV constraints their capabilities of recognizing and absorbing external knowledge (Caner et al., 2017; Fleming, 2001).

4. These cases only occupy less than eight percent of the total observations in our study. For robustness checks, we conducted two additional robustness tests. On the one hand, we estimated our models without these cases. On the other hand, for these cases, we randomly kept only one of the observations for each firm. All the results remain consistent.

5. We also measured technological distance based on all patent classes for robustness. The results remain consistent. The eight patent classes are 424 (drug, bioaffecting, and body-treating compositions), 435 (molecular biology and microbiology), 436 (analytical and immunological testing), 514 (drug, bioaffecting, and body-treating compositions), 530 (peptides or proteins; natural resins or derivatives; lignins or reaction products thereof), 536 (organic compounds), 800 (multicellular living organisms and unmodified parts thereof, and related processes), and 930 (Peptide or protein sequence).
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*Journal of Marketing Research, 56(5): 732-748.*


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## Table 1

Descriptive Statistics and Correlation Coefficients

<table>
<thead>
<tr>
<th>Mean</th>
<th>S.D</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<th>8</th>
<th>9</th>
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<td>1. Relational ambidexterity</td>
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<tr>
<td>2. Internal knowledge variety</td>
<td>0.50</td>
<td>0.34</td>
<td>0.08</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>3. Common third parties</td>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>4. Technological distance</td>
<td>0.66</td>
<td>0.37</td>
<td>-0.07</td>
<td>-0.34</td>
<td>-0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Firm size</td>
<td>4.05</td>
<td>3.03</td>
<td>0.13</td>
<td>0.07</td>
<td>0.05</td>
<td></td>
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<tr>
<td>6. Current ratio</td>
<td>5.64</td>
<td>6.31</td>
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<td>-0.03</td>
<td>-0.07</td>
<td>0.05</td>
<td></td>
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<tr>
<td>7. Firm performance</td>
<td>-0.26</td>
<td>0.84</td>
<td>-0.00</td>
<td>0.10</td>
<td>0.02</td>
<td>-0.04</td>
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<td>0.04</td>
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<td>8. Firm age</td>
<td>3.72</td>
<td>4.86</td>
<td>0.14</td>
<td>0.09</td>
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<td>-0.06</td>
<td>-0.03</td>
<td>-0.01</td>
<td>-0.04</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>9. Alliance experience</td>
<td>1.93</td>
<td>5.99</td>
<td>-0.08</td>
<td>-0.14</td>
<td>-0.04</td>
<td>0.09</td>
<td>-0.31</td>
<td>0.20</td>
<td>-0.17</td>
<td>-0.07</td>
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<tr>
<td>10. R&amp;D intensity</td>
<td>3.23</td>
<td>7.39</td>
<td>-0.14</td>
<td>-0.08</td>
<td>-0.06</td>
<td>0.05</td>
<td>-0.37</td>
<td>0.14</td>
<td>-0.18</td>
<td>-0.06</td>
<td>0.45</td>
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<td>11. Structural holes</td>
<td>0.63</td>
<td>0.29</td>
<td>0.21</td>
<td>0.11</td>
<td>-0.06</td>
<td>0.17</td>
<td>-0.01</td>
<td>0.06</td>
<td>0.12</td>
<td>-0.03</td>
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<tr>
<td>12. Degree centrality</td>
<td>7.30</td>
<td>7.29</td>
<td>0.16</td>
<td>0.25</td>
<td>-0.04</td>
<td>0.37</td>
<td>-0.16</td>
<td>0.13</td>
<td>0.02</td>
<td>-0.10</td>
<td>-0.17</td>
<td>0.63</td>
</tr>
<tr>
<td>13. Focal firm’s prior citation</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0.01</td>
<td>-0.14</td>
<td>-0.04</td>
<td>0.01</td>
<td>-0.01</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>14. Partner’s prior citation</td>
<td>0.00</td>
<td>0.02</td>
<td>0.06</td>
<td>0.07</td>
<td>-0.01</td>
<td>-0.09</td>
<td>0.09</td>
<td>-0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>-0.04</td>
<td>-0.04</td>
</tr>
<tr>
<td>15. Joint venture</td>
<td>0.04</td>
<td>0.20</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td>16. Repeated tie</td>
<td>0.06</td>
<td>0.24</td>
<td>0.04</td>
<td>0.03</td>
<td>0.10</td>
<td>-0.08</td>
<td>0.05</td>
<td>-0.01</td>
<td>0.03</td>
<td>-0.02</td>
<td>-0.03</td>
<td>-0.05</td>
</tr>
<tr>
<td>17. Cross-border alliance</td>
<td>0.11</td>
<td>0.31</td>
<td>-0.04</td>
<td>-0.05</td>
<td>0.03</td>
<td>-0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.09</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>18. Alliance propensity</td>
<td>0.32</td>
<td>0.47</td>
<td>0.10</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.11</td>
<td>0.08</td>
<td>-0.08</td>
<td>0.03</td>
<td>0.09</td>
<td>-0.05</td>
<td>-0.05</td>
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<tr>
<td>19. Multilateral competition</td>
<td>0.81</td>
<td>0.31</td>
<td>0.15</td>
<td>0.07</td>
<td>0.03</td>
<td>-0.01</td>
<td>0.04</td>
<td>-0.07</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.07</td>
</tr>
<tr>
<td>20. Partner technological class</td>
<td>0.56</td>
<td>0.40</td>
<td>0.10</td>
<td>0.07</td>
<td>-0.00</td>
<td>-0.45</td>
<td>0.08</td>
<td>-0.07</td>
<td>0.03</td>
<td>0.06</td>
<td>-0.05</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

Mean S.D | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19
13. Focal firm’s prior citation | 0.00 | 0.01 | -0.03 |      |      |      |      |      |
14. Partner’s prior citation | 0.00 | 0.02 | 0.10 | 0.01 |      |      |      |      |
15. Joint venture | 0.04 | 0.20 | -0.01 | 0.00 | -0.00 |      |      |      |
16. Repeated tie | 0.06 | 0.24 | 0.09 | 0.03 | -0.02 | 0.05 |      |      |
17. Cross-border alliance | 0.11 | 0.31 | 0.09 | -0.03 | -0.01 | -0.02 | 0.07 |      |
18. Alliance propensity | 0.32 | 0.47 | 0.01 | 0.04 | 0.01 | -0.01 | 0.01 | 0.04 |
19. Multilateral competition | 0.81 | 0.31 | 0.03 | 0.04 | -0.03 | 0.00 | 0.01 | 0.01 |
20. Partner technological class | 0.56 | 0.40 | 0.03 | 0.09 | 0.10 | -0.03 | 0.05 | -0.03 |

Note: N=2,089. Correlation coefficients equal or above |0.05| are significant at a 5% level.
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## Table 2

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td>-26.58&lt;sup&gt;*&lt;/sup&gt;</td>
<td>-26.91&lt;sup&gt;*&lt;/sup&gt;</td>
<td>-26.99&lt;sup&gt;*&lt;/sup&gt;</td>
<td>-26.61&lt;sup&gt;*&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>(13.46)</td>
<td>(13.35)</td>
<td>(13.23)</td>
<td>(13.31)</td>
</tr>
<tr>
<td><strong>Relational ambidexterity</strong></td>
<td>-2.16&lt;sup&gt;**&lt;/sup&gt;</td>
<td>-1.73&lt;sup&gt;*&lt;/sup&gt;</td>
<td>-2.14&lt;sup&gt;**&lt;/sup&gt;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.76)</td>
<td>(0.72)</td>
<td></td>
</tr>
<tr>
<td><strong>Internal knowledge variety</strong></td>
<td>0.09</td>
<td>0.03</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.44)</td>
<td>(0.44)</td>
<td></td>
</tr>
<tr>
<td><strong>Common third parties</strong></td>
<td>-0.03</td>
<td>-0.02</td>
<td>-0.08</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.15)</td>
<td></td>
</tr>
<tr>
<td><strong>Relational ambidexterity X</strong></td>
<td></td>
<td>-4.82&lt;sup&gt;*&lt;/sup&gt;</td>
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<td></td>
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<td><strong>Internal knowledge variety</strong></td>
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<td>(2.43)</td>
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<td><strong>Relational ambidexterity X</strong></td>
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<td>1.06</td>
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<tr>
<td><strong>Common third parties</strong></td>
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<td></td>
<td>(1.08)</td>
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<tr>
<td><strong>Technological distance</strong></td>
<td>2.22&lt;sup&gt;***&lt;/sup&gt;</td>
<td>2.22&lt;sup&gt;***&lt;/sup&gt;</td>
<td>2.24&lt;sup&gt;***&lt;/sup&gt;</td>
<td>2.23&lt;sup&gt;***&lt;/sup&gt;</td>
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<tr>
<td></td>
<td>(0.32)</td>
<td>(0.33)</td>
<td>(0.33)</td>
<td>(0.33)</td>
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<tr>
<td><strong>Firm size</strong></td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
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<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
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<tr>
<td><strong>Current ratio</strong></td>
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<td>0.00</td>
<td>-0.00</td>
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<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
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<td><strong>Firm performance</strong></td>
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<td>(0.39)</td>
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<td><strong>Firm age</strong></td>
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<tr>
<td><strong>Alliance experience</strong></td>
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<tr>
<td><strong>R&amp;D intensity</strong></td>
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<td>(0.02)</td>
<td>(0.02)</td>
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<td><strong>Structural holes</strong></td>
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<td>0.99&lt;sup&gt;*&lt;/sup&gt;</td>
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<td>(0.49)</td>
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<tr>
<td><strong>Degree centrality</strong></td>
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<tr>
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### RELATIONAL AMBIDEXTERITY AND ABSORPTION SPEED

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Note: N=2,089. * p < 0.05 ** p < 0.01 *** P < 0.001. Standard errors in parentheses
## RELATIONAL AMBIDEXTERTY AND ABSORPTION SPEED

### Table 3

Results of Cox Proportional Hazard Model for Absorption Speed

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For Peer Review
# RELATIONAL AMBIDEXTERITY AND ABSORPTION SPEED

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Note: N=2,089. * p < 0.05 ** p < 0.01 *** P < 0.001. Standard errors in parentheses

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**Figure 1**

Estimated Hazard Functions of Low versus High Relational Ambidexterity

![Loglogistic regression graph](http://mc.manuscriptcentral.com/jom)