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When does knowledge acquisition in R&D alliances increase new product development?

The moderating roles of technological relatedness and product-market competition*

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Abstract

In studying the performance consequences of research and development (R&D) alliances, one stream of research has concentrated on the acquisition of partners' technological knowledge whereas another has focused on firms' new product development outcomes. Bridging these two research streams, this study directly connects knowledge acquisition through R&D alliances to new product development and examines when R&D alliances enable firms to apply acquired technological knowledge in the product domain. Using unique longitudinal data on a sample of firms engaged in R&D alliances in the information technology industry, I find that knowledge acquisition is on average positively associated with firms' numbers of new products. However, I also find that knowledge acquisition is substantially more beneficial for new product development both when firms and their partners are active in similar technology domains and when they operate in distinct product markets.

1. Introduction

Research and development (R&D) alliances are formal agreements through which firms conduct joint research and development relating to new technologies, products, or processes, eventually with the objective to enable firms to bring new products to market (Hagedoorn, 1993). One stream of research has concentrated on the potential for technological learning through R&D alliances, showing that such alliances can enable firms to acquire technological knowledge developed by their alliance partners (Frankort, 2013; Frankort, Hagedoorn, and Letterie, 2012; Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Mowery, Oxley, and Silverman, 1996; Oxley and Wada, 2009; Rosenkopf and Almeida, 2003). Another stream of research has focused instead on the role of R&D alliances in new product development, showing that such alliances may have consequences in the product domain as well (Chen and Li, 1999; Deeds, Decarolis, and Coombs, 1999; Deeds and Hill, 1996; Kotabe and Swan, 1995; Rothaermel and Deeds, 2004).

Nevertheless, in focusing virtually exclusively on either knowledge acquisition or new product development, both research streams have tended to underemphasize the relationship between these two distinct outcomes.[1] Furthering the understanding of the relationship between knowledge acquisition through R&D alliances and new product development is critical, however, because the competitiveness of manufacturing firms engaged in research and development may not derive from knowledge acquisition per se; it is ultimately some function of whether they are able to apply acquired technological knowledge in the product domain (e.g., Blundell, Griffith, and Van Reenen, 1999; Sorescu and Spanjol, 2008). Motivated by these observations, in this study I propose and test a conceptual framework that directly connects knowledge acquisition through R&D alliances to firms' new product development.

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[1] While some studies have examined the role of alliances in shaping both upstream and downstream outcomes (e.g., Rothaermel and Deeds, 2004), even that research has not systematically considered the importance of technological knowledge acquired from alliance partners as a factor influencing new product development.

My starting point is constituted by narrative accounts suggesting that knowledge acquisition may represent a key mechanism linking firms' R&D alliances to new product development (e.g., Rindfleisch and Moorman, 2001; Soh, 2003). Specifically, I begin by arguing that acquired technological knowledge may generate opportunities for new product development both within and beyond the terms of firms' R&D alliances and so one might expect a positive association between knowledge acquisition on the one hand and firms' new product development on the other. In this study, knowledge acquisition is defined as the extent to which firms' novel technological knowledge builds on technological content knowledge acquired from R&D alliance partners, while new product development refers to a firm's propensity to design, manufacture, and market products that are new to the firm (Eisenhardt and Tabrizi, 1995).

However, while the acquisition of technological knowledge may increase the potential for new product development, it will simultaneously increase firms' dependence on partners' tacit process knowledge necessary to apply acquired technological knowledge in the product domain. More specifically, knowledge acquisition intensifies demands both on firms' abilities to understand partners' tacit process knowledge and on partners' incentives to facilitate access to such strategic competencies (Gerwin, 2004). Therefore, drawing from research on interfirm learning (e.g., Lane and Lubatkin, 1998; Nooteboom et al., 2007) and interpartner competition (e.g., Hamel, 1991; Khanna, Gulati, and Nohria, 1998), I argue that the new product development benefits from acquired technological knowledge will be especially pronounced when the technological knowledge bases of a firm and its R&D alliance partners are related and when a firm and its partners operate in distinct product markets.

I test these ideas using unique longitudinal data on a sample of 44 manufacturing firms engaged in R&D alliances in the information technology industry, where profitability depends critically on firms' propensities to bring new products to market (Bayus, Erickson, and Jacobson,

2003). The empirical results suggest that knowledge acquisition through R&D alliances has a positive association with firms' new product development. However, I also find that the new product development benefits from knowledge acquisition are significantly enhanced when firms and their partners are active in similar technology domains, while such benefits are substantially reduced instead when firms and their partners are active in identical product markets.

Integrating the insights from the knowledge acquisition literature with the literature on knowledge application (Fiol, 1996; Lane, Koka, and Pathak, 2006; Meier, 2011), this study fills a gap in the alliance literature by directly examining the role of R&D alliances in connecting firms' technology and product domains. Specifically, one contribution lies in offering a systematic assessment of whether knowledge acquisition through R&D alliances influences firms' new product development. The second contribution lies in showing that the knowledge acquisition association with new product development is subject to important scope conditions—specifically, those rooted in partners' levels of technological relatedness and product-market competition.

2. Theory and hypotheses

2.1 Knowledge acquisition through R&D alliances and new product development

Firms may use their R&D alliances to acquire technological knowledge otherwise unavailable internally (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996) and such knowledge acquisition can enrich firms' pools of commercialization options (Chen and Li, 1999; Fey and Birkinshaw, 2005; Grant and Baden-Fuller, 2004; Kotabe and Swan, 1995; Moorman and Slotegraaf, 1999). Therefore, firms acquiring more technological knowledge through R&D alliances may be more productive in developing new products than otherwise identical firms that acquire less technological knowledge from their alliance partners (e.g., Yli-Renko, Autio, and Sapienza, 2001). Prior research suggests at least two distinct paths through which the acquisition of partners' technological knowledge may enhance firms' new product development (Sampson,

2007: 366). On the one hand, knowledge acquisition directly enriches firms' pools of technological knowledge relevant to the development activities within the terms of their R&D alliances. On the other hand, acquired technological knowledge may also have broader relevance for new product development activities beyond firms' individual alliance projects. Indeed, once acquired, technological knowledge can in principal be applied to new products even beyond the terms of firms' R&D alliances (Hamel, 1991). Consequently, while technological knowledge may be acquired within specific R&D alliances, knowledge acquisition is likely to increase firms' rates of new product development more generally. I therefore predict the following baseline association between knowledge acquisition and new product development:

> **Hypothesis 1.** *Knowledge acquisition through R&D alliances is positively associated with a firm's new product development.*

Prevailing alliance research provides no direct empirical evidence on this first hypothesis, even though it has alluded to the downstream importance of knowledge acquisition in R&D alliances (e.g., Rindfleisch and Moorman, 2001; Soh, 2003). However, prior studies would also suggest that straightforward application of knowledge in the product domain may not always be an inevitable consequence of acquiring partners' technological knowledge (e.g., Meier, 2011). Therefore, it is reasonable to imagine that important scope conditions underlie H1 and so I next identify two moderating factors that previous research suggests are important in shaping coordination and cooperation between alliance partners engaged in new product development (Gerwin, 2004). First, research on interfirm learning suggests that firms may vary systematically in their *abilities* to understand how partners' technological knowledge can be applied in the product domain (e.g., Lane and Lubatkin 1998; Nooteboom et al., 2007). Second, research on interpartner competition would suggest that partners may also vary systematically in their *incentives* to facilitate firms' new product development (e.g., Hamel, 1991; Khanna et al., 1998).

2.2 The moderating role of technological relatedness

The first moderating factor concerns the extent to which firms are able to understand how partners' technological knowledge can be applied in the product domain. Research on interfirm learning suggests that the relatedness of a firm's technological knowledge base to that of its partners is an important determinant of such ability (Cohen and Levinthal, 1990; Mowery et al., 1996; Nooteboom et al., 2007; Lane and Lubatkin, 1998). *Technological relatedness*, defined here as the extent to which the knowledge bases of a firm and its alliance partners cover similar technology domains, reflects the degree to which firms have experience solving comparable types of problems. Therefore, at a basic level technological relatedness reflects common content knowledge and so it increases a firm's understanding of the technological knowledge held by its partners (Lane and Lubatkin, 1998). More importantly, firms familiar with each other's knowledge domains have a common reference frame and so they are more likely to be deeply exposed to the tacit process knowledge embedded in each other's skills and routines (Zander and Kogut, 1995), which in turn facilitates richer communication and deeper mutual understanding. Consequently, at higher levels of technological relatedness, firms are better able to understand and share the more tacit process knowledge necessary both to identify commercial applications for acquired knowledge (Lane and Lubatkin, 1998) and to actually transform such knowledge into new products (Rindfleisch and Moorman, 2001).

Technological relatedness is likely to be especially relevant in exploitation activities, such as the application of acquired technological knowledge in the product domain studied here. Indeed, once technological knowledge has been acquired and attention shifts to *applying* such knowledge in new product development, firms require a small 'cognitive distance' to their partners in order to achieve effective understanding and coordination (Nooteboom, 2000; Nooteboom et al., 2007). Yet, even though a small cognitive distance and so a high level of

technological relatedness enhances understanding between partners, one might argue that it simultaneously reduces the novelty value of R&D alliances (Nooteboom, 2000). However, an important counterargument is that in knowledge application, which is an exploitation activity focused on implementing acquired knowledge, the value of novelty is much lower than in exploratory activities, while the value of absorptive capacity is likely much greater instead (March 1991; Nooteboom et al., 2007; Rindfleisch and Moorman, 2001). Therefore, the exploitation of acquired technological knowledge through the application of such knowledge in the product domain should increase in effectiveness as technological relatedness increases.[2]

Because it provides the absorptive capacity necessary in knowledge application, technological relatedness is likely to shape the knowledge acquisition association with new product development. Specifically, technological relatedness should be most effective in situations where a deep understanding of tacit process knowledge is required, while requisite deep understanding should in turn increase with the extent to which a firm acquires more of its partners' technological knowledge. Indeed, at higher levels of knowledge acquisition, a firm must be able to understand the more tacit aspects associated with its partners' technological knowledge in progressively greater detail in order to be able to apply that knowledge within the product domain. Therefore, the knowledge acquisition association with new product development should be stronger when firms are more technologically related to their alliance partners.

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[2] Nooteboom et al. (2007) tested the effects of cognitive distance, measured as technological distance (i.e., the inverse of technological relatedness as defined here), across exploration and exploitation outcomes. Their results showed that *exploration* outcomes peaked at intermediate cognitive distance (Nooteboom et al., 2007: 1026), suggesting that neither novelty nor absorptive capacity alone would optimize exploratory innovation. In stark contrast, cognitive distance did not show an inverted U-shaped effect on *exploitation* outcomes. Moreover, though the authors did not show regression estimates of the linear association between cognitive distance and exploitation, reported correlations (Nooteboom et al., 2007: 1024) suggest that the correlation between cognitive distance and exploitation (i.e., '# of exploitation patents') is negative and marginally significant ($p < 0.1$) and this negative correlation becomes stronger ($p < 0.05$) once one holds constant firm size, age, and R&D intensity. These findings converge with the idea that in exploitation, performance reduces monotonically with cognitive distance, fully consistent with Rindfleisch and Moorman's (2001: 11) finding that knowledge relatedness between partners in new product alliances monotonically enhanced knowledge application. Consequently, I expect that the downstream application of acquired technological knowledge will increase in effectiveness as technological relatedness increases.

Hypothesis 2. *Knowledge acquisition through R&D alliances is more beneficial for a firm's new product development when technological relatedness between the firm and its alliance partners is high rather than low.*

One might argue that instead of reflecting absorptive capacity, technological relatedness perhaps also reflects competition between firms. However, in their study of R&D alliances in the electronics and telecommunications equipment industries, Oxley and Sampson (2004) found evidence consistent with the idea that firms viewed technological relatedness more as a source of absorptive capacity rather than competitive rivalry. In the information technology industry more broadly, which is my empirical setting, the absorptive capacity effect of technological relatedness is similarly likely to dominate due to a comparatively loose connection between firms' knowledge and product domains (Grant and Baden-Fuller, 2004). Indeed, information technologies have a myriad of distinct applications (Hall, Jaffe, and Trajtenberg, 2002) Therefore, technological relatedness need not have implications for downstream competition between R&D alliance partners (Harrigan, 2003). I next focus on a second moderating factor that, unlike technological relatedness, is more directly related to interpartner competition.

2.3 The moderating role of product-market competition

The second moderating factor concerns the extent to which alliance partners have incentives to facilitate a firm's new product development. Prior research suggests that the degree of interpartner competition is a key correlate of partners' incentives to cooperate. An important source of interpartner competition is *product-market competition*, defined here as the extent to which a firm and its partners are (potential) competitors in products markets (Khanna et al., 1998). Product-market competition signifies that partners' commercial goals are likely to be in direct conflict. As such, it makes partners more suspicious of one another because competitive partners are more likely to be on the lookout for proprietary, organizationally embedded skills (Bamford, Gomes-Casseres, and Robinson, 2003: 81). Protection of core strategic competencies

is therefore critical (Laursen and Salter, 2014; Oxley and Sampson, 2004) and so competitive partners should be less motivated to facilitate each other's new product development, for fear of creating stronger marketplace competitors (Harrigan, 2003). Indeed, firms failing to protect embedded process knowledge from leakage to competitors may run the risk of handing such partners market share (Fosfuri and Giarratana, 2009). Consequently, interpartner competition can destabilize interfirm alliances and turn such alliances from collaborative vehicles into competitive ones, where conflict ensues and firms try to maximize their private interests at the expense of their partners (Hamel, 1991; Park and Russo, 1996). Overall, because competing partners are likely to be more protective of their own strategic competencies, product-market competition may substantially reduce the benefits each partner can draw from an R&D alliance.

For product-market competition to have negative effects in R&D alliances, it is not necessary that alliance partners are concerned with, or even aware of, any such effects from the outset (e.g., Faems, Janssens, and Van Looy, 2007). Indeed, R&D alliances among competitors are regularly formed to collaborate on technologies that may have a number of different product applications. In such alliances, partners' limited farsightedness means that the downstream implications for product-market competition can be unclear *ex ante* (Rothaermel and Deeds, 2004). Nevertheless, once technologies crystallize and "*product development proceeds…, the competitive element may begin to color the relationship, with each firm's trying to gain insight into the core competencies of the other*" (Yoshino and Rangan, 1995: 21).

Whether from the outset or—due to partners' perhaps limited farsightedness—later on in an R&D alliance, product-market competition is likely to shape the knowledge acquisition association with new product development. Specifically, product-market competition should be especially problematic for firms that are more dependent on partners' tacit process knowledge necessary to apply acquired technological knowledge in the product domain. Such dependence

will in turn be greater to the extent firms draw more extensively on partners' technological knowledge as a building block for the creation of novel technological knowledge (and so, by implication, knowledge acquisition is substantial). In contrast, firms will be less dependent on partners' more tacit process knowledge to the extent knowledge acquisition is limited.[3] Therefore, the positive association between knowledge acquisition and new product development should be weaker when firms and their partners operate in identical product markets, while it should be stronger when they operate in distinct product markets instead.

> **Hypothesis 3.** *Knowledge acquisition through R&D alliances is more beneficial for a firm's new product development when product-market competition between the firm and its alliance partners is weak rather than strong.*

3. Method

I tested the three hypotheses using a unique dataset on a sample of manufacturing firms engaged in R&D alliances in information technology (IT) during 1994-1999. This industry provided a setting particularly well suited to examining my hypotheses. In the IT industry, R&D alliances have long constituted important new product development vehicles (Hagedoorn, 2002). Moreover, patenting has been prevalent in IT (Hall et al., 2002) and so I was able to follow previous studies in using patent data to measure two of the key constructs. Finally, new product development represents an important concern for IT firms because their profitability depends critically on the ability to bring new products to market (Bayus et al., 2003).

R&D alliance data were drawn from the Cooperative Agreements and Technology Indicators database (CATI; see Hagedoorn, 2002); new product announcement data for 1997-2000 from Dialog's online New Product Announcements/Plus database (NPA/Plus); U.S. patent

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[3] A different argument might be that firms' dependence on partners also varies with technological relatedness. Specifically, greater technological relatedness facilitates learning and so it should reduce dependence, perhaps rendering product-market competition less problematic. A counterargument is that the potential for comparatively easy spillovers at high levels of technological relatedness is likely to intensify the efforts of competing partners to protect embedded process knowledge from leaking out (e.g., Harrigan, 2003; Yoshino and Rangan, 1995). The net effect of such countervailing forces is unclear *a priori*. Either way, H3 assumes constant *Technological relatedness*.

data for 1992-1999 from the NBER patent data file (see Hall et al., 2002); and data for the

product-market competition and control variables from COMPUSTAT, Datastream, and a variety

of other sources. Importantly, to evade a common-source bias, data for the hypothesis-testing

variables were drawn from several independent data sources. R&D alliances were identified

using a distinct data source; the two moderators measuring different aspects of such alliance

relationships each came from separate sources; and data for the dependent variable also came

from a unique data source.

To address concerns of left censoring, all alliance- and partner-related measures (except

alliance experience) were based on a three-year alliance horizon: in the initial observation year

(1996) the alliance and partner variables reflected all R&D alliances a firm had formed during

1994-1996, in 1997 all those formed during 1995-1997, and so on. The three-year horizon

reflected that those sampled R&D alliances for which I was able to trace their duration lasted

about three years on average. After discarding firms without patents during 1992-1999, those

without new product introductions during 1997-2000, and firm-years with missing data, the final

panel consisted of 120 firm-years for 44 firms (40 U.S. firms and 4 others) during 1996-1999.

3.1 Dependent variable

New product development$_{it+1}$ was measured as the annual count of new products that each

of the sample firms announced across computers, networks, office, semiconductors, and telecom

during 1997-2000. New product announcements proxy for firms' productivity in new product

development (Brown and Eisenhardt, 1995) and have been used to measure new product

development in studies focusing on the product-development correlates of innovative search

(Katila and Ahuja, 2002), knowledge combination and exchange (Smith, Collins, and Clark,

2005), biotechnology alliances (Deeds and Hill, 1996; Rothaermel and Deeds, 2004), and

mergers and acquisitions (Hitt et al., 1996; Puranam, Singh, and Zollo, 2006). I was able to match

5,852 unique press releases listed in NPA/Plus, and announcing new IT products during 1997-

2000, to the sampled firms. I subsequently transformed these 5,852 press releases into yearly

firm-level counts of new product announcements to obtain the dependent variable. I took special

care to ensure that none of the press releases concerned new projects, which might otherwise

confound the alliance and new product development measures.

3.2 Independent variable and moderators

3.2.1   Knowledge acquisition

Following a large number of studies examining knowledge transfer in alliances (e.g.,

Frankort et al., 2012; Gomes-Casseres et al., 2006; Mowery et al., 1996; Oxley and Wada, 2009;

Rosenkopf and Almeida, 2003), I used patent citation data to measure knowledge acquisition. For

each firm in each year, I counted a firm's number of patent citations to the patents of its R&D

alliance partners that it did *not* cite prior to engaging in one or more R&D alliances with each of

its partners. Subsequently, for each firm-year I obtained *Knowledge acquisition*$_{it}$ by dividing this

citation count by the firm's total number of patent citations during that year (e.g., Mowery et al.,

1996). The empirical focus on citations to partners' patents not cited by the focal firm prior to

engaging in one or more R&D alliances with each of its partners ensured a close link with my

conceptual focus on knowledge acquisition through R&D alliances.[4]

While an aggregated citation measure may represent a valid indicator of knowledge

acquisition (e.g., Jaffe ,Trajtenberg, and Fogarty, 2000), two concerns merit consideration. First,

patent data are perhaps crude indicators of interfirm knowledge transfer and so noise in patent

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[4] Citations to partners' patents that the firm *did* cite prior to engaging in R&D alliances with each of its partners
might have effects on new product development as well, even though such citations are unlikely to reflect knowledge
acquisition through R&D alliances per se. To assess the potential confounding effects of such re-use of pre-alliance
knowledge, I also constructed an additional citation-based measure in the same way I constructed *Knowledge
acquisition*, yet used as the numerator a firm's number of patent citations to the patents of its R&D alliance partners
that it also cited prior to engaging in one or more R&D alliances with each of its partners. Unreported robustness
checks adding this measure to the specifications as shown in the Results section did not reveal changes in the main
results, while the coefficients on this additional measure were mostly insignificant.

citation measures appears unavoidable. However, because the effect of noise is to inflate standard errors, it should produce conservative parameter estimates. Second, Alcácer and Gittelman (2006) suggest that examiner-inserted citations can systematically bias citation-based proxies and so patent citations might both underestimate as well as overestimate knowledge acquisition. It is unlikely that patent examiners pattern their interventions on a firm's R&D alliance activities (e.g., Frankort et al., 2012: 518) and so biases in alliance-related counts of patent citations should roughly parallel those in a firm's patent citations more generally. Dividing a firm's citations to partners' patents by all of the firm's patent citations therefore assuaged concerns of bias.

3.2.2 *Technological relatedness*

I used Jaffe's (1986) vector correlation measure as the basis for constructing a measure of technological relatedness (Oxley and Sampson, 2004; Oxley and Wada, 2009). I began by calculating patent class distribution vectors for a firm and each of its partners. Specifically, $\mathbf{F}_{it} = (F_{i1t}, \ldots, F_{ikt}, \ldots, F_{iKt})$ was the patent class distribution vector for firm i in year t (Jaffe, 1986), based on the firm's successful patent applications within each of the USPTO's K primary patent classes during years t-4 to t (Hall et al., 2002: 452-453). F_{ikt} represented firm i's successful patent applications in patent class k during years t-4 to t. Next, I calculated the technological relatedness of a focal firm i and its partner j as $\mathbf{F}_{it}\mathbf{F}_{jt}'/[(\mathbf{F}_{it}\mathbf{F}_{it}')(\mathbf{F}_{jt}\mathbf{F}_{jt}')]^{1/2}$. I averaged this dyadic measure across the relationships in a firm's R&D alliance portfolio to obtain *Technological relatedness*$_{it}$. This measure was bounded by 0 and 1, and values closer to 1 indicated a greater relatedness of the technological knowledge bases of a firm and its R&D alliance partners.

3.2.3 *Product-market competition*

Product-market competition$_{it}$ gauged the proportion of a firm's partners operating in the same primary three-digit SIC code as that firm in year t. If firms viewed their competitor landscape at a more granular (e.g., four-digit SIC) level, then this should push the parameter

estimates toward insignificance, especially in cases where a firm and its partners were active in the same three-digit SIC code but not in the same four-digit SIC code. Thus, the product-market competition variable based on three-digit SIC codes should produce conservative estimates.

3.3 Control variables

I controlled for various potential alternative explanations at the firm, R&D alliance portfolio, and partner levels of analysis. At the firm level, I controlled for *Firm size*$_{it}$, measured as the logarithm of a firm's total asset value in a given year, while *Firm age*$_{it}$ was measured as the logarithm of a firm's age in years since incorporation. *Firm patent applications*$_{it}$ was measured as the logarithm of a firm's number of successful patent applications in a given year. To capture the effects of a firm's experience in managing R&D alliances, *Firm alliance experience*$_{it}$ represented the logarithm of the aggregated number of R&D alliances that a firm had formed in IT by year t (Sampson, 2005). *Firm technological diversity*$_{it}$ was measured using a modified diversity index (Phelps, 2010: 903), based on a firm's successful patent applications across all the USPTO's primary patent classes during years t-4 to t:

$$\textit{Firm technological diversity}_{\text{it}} = \left[1 - \sum_{k=1}^{K} \left(\frac{F_{ikt}}{N_{it}} \right)^2 \right] \times \frac{N_{it}}{N_{it} - 1},$$

where N_{it} represented firm i's total number of successful patent applications during years t-4 to t.[5] This measure was bounded by 0 and 1, and values closer to 1 indicated a greater distribution of a firm's technologies across distinct technology domains.

At the R&D alliance portfolio level, I captured the potential effects of alliance governance (e.g., Oxley and Wada, 2009) through *Joint venture relationships*$_{it}$, measured as the proportion of a firm's R&D alliance partners that the firm was connected to through one or more equity-based

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[5] In Herfindahl-type measures based on patent counts, patent classes in which a firm has no patents are discarded from the calculations, which will bias diversity scores downward. Because none of the sampled firms had patents in all the USPTO's primary patent classes, it was important to correct for such a bias. Hall (2005) showed that multiplication of the diversity measure by $N_{it} / (N_{it} - 1)$ effectively achieves such a correction.

joint ventures in year *t*. To control for differences in geographic location between a firm and its partners (e.g., Lavie and Miller, 2008), *Same country relationships*$_{it}$ captured the proportion of a firm's partners that were located in the firm's home country. Finally, I controlled for a firm's focus on research versus development across its R&D alliance portfolio (e.g., Frankort et al., 2012). I began at the alliance level and, following Frankort et al. (2012: 519), coded joint research pacts, research corporations, and all joint ventures with the stated aim to perform basic and/or applied research as 'research focused'. Next, I calculated *Research-focused relationships*$_{it}$ as the proportion of a firm's R&D alliance partners that the firm was connected to through one or more research-focused R&D alliances in year *t*.

At the partner level, I controlled for the general attractiveness of a firm's R&D alliance partners as sources of technological knowledge. *Partner citations*$_{it}$ measured the logarithm of the number of patent citations received by a firm's partners in year *t*. Moreover, I controlled for partners' new product development activities through *Partner new products*$_{it+1}$, capturing the logarithm of the number of new IT products introduced by a firm's partners in year *t*+1. Both measures absorbed several unobserved, time-varying factors at the partner level and so any such factors should not confound the empirical identification. Finally, by analogy with *Firm technological diversity*, I measured *Partner technological diversity*$_{it}$ as follows:

$$\textit{Partner technological diversity}_{it} = \left[1 - \sum_{k=1}^{K}\left(\frac{F_{Jkt}}{N_{Jt}}\right)^2\right] \times \frac{N_{Jt}}{N_{Jt}-1},$$

where F_{Jkt} represented the total number of successful patent applications by a firm's partners *J* in patent class *k* during years *t*-4 to *t*, and N_{Jt} represented the total number of successful patent applications by a firm's partners *J* during years *t*-4 to *t*. This measure was bounded by 0 and 1, and values closer to 1 indicated that the technologies of a firm's partners showed a greater dispersion across distinct technology domains.

To capture any time-varying factors homogeneously affecting all sampled firms, all models included year fixed effects for 1996-1998, while 1999 was the reference category.

3.4 Estimation

The dependent variable was an overdispersed count variable and so I estimated all models using a Poisson quasi-maximum likelihood (Poisson QML) estimator with conditional firm fixed effects that captured time-invariant unobserved heterogeneity at the firm level (Wooldridge, 1999).[6] While conditional fixed effects estimation drops all firms without temporal variation on the dependent variable, the resulting estimates are nevertheless unbiased and consistent. To avoid simultaneity, *New product development* took a one-year lead to the hypothesis-testing variables. A one-year lag was also consistent with some findings on R&D projects within firms (e.g., Hausman, Hall, and Griliches, 1984: 925; Pakes and Schankerman, 1984: 83), suggesting that traceable inventive activities, such as the creation of novel technological knowledge, may closely follow a project's inception, while the time to commercial application is likely somewhat longer.[7]

4. Results

Table 1 shows summary statistics and Table 2 shows the conditional fixed effects Poisson QML estimates of new product development. In Models 2-4 and 6, the main effects for *Knowledge acquisition*, *Technological relatedness*, and *Product-market competition* were standardized prior to calculating the interaction terms.

--- Insert Table 1 about here ---

--- Insert Table 2 about here ---

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[6] In an unreported supplementary analysis, I found that a considerable part of the variance in *New product development* was due to stable differences across the sampled firms. This finding resonates both with prior research suggesting that firms may differ substantially in their levels of innovation activities (e.g., Chen and Miller, 2007) and with studies showing inter-temporal persistence in innovation productivity within firms in high-tech industries (e.g., Raymond et al., 2010). The Hausman (1978) specification test showed that unobserved and time-invariant firm effects correlated significantly with the covariate matrix, which is why I opted for a fixed effects estimator.

[7] Findings such as those reported in Pakes and Schankerman (1984) are based on R&D projects within firms. In an interfirm setting, the lag structure may of course be different. Therefore, after reporting the main results, I also show results using alternative lags between *Knowledge acquisition* and *New product development*.

4.1 Hypotheses

In support of H1, Model 1 in Table 2 shows that the coefficient on *Knowledge acquisition* is positive and significant. This effect is also substantive in real terms, as a one standard deviation increase in knowledge acquisition is associated with a 29% increase in the multiplier of new product development (i.e., exp[2.817*0.09] = 1.29), holding all else constant.

Model 2 shows that the interaction between *Knowledge acquisition* and *Technological relatedness* is positive and significant. Therefore, knowledge acquisition benefits a firm's new product development more when technological relatedness is greater, which supports H2. As Figure 1a shows, the knowledge acquisition association with new product development is significantly stronger when technological relatedness is high rather than low. Moreover, Figure 1a shows that below the mean level of *Knowledge acquisition*, low technological relatedness tends to be *more* beneficial for new product development than high technological relatedness. This finding implies that low levels of technological learning in R&D alliances allow for greater technological specialization of the partnered firms (e.g., Grant and Baden-Fuller, 2004; Mowery et al., 1996).

--- Insert Figures 1a/b about here ---

Supporting H3, Model 3 shows that the interaction between *Knowledge acquisition* and *Product-market competition* is negative and significant and so knowledge acquisition benefits a firm's new product development progressively less when product-market competition increases. As Figure 1b shows, knowledge acquisition is positively associated with new product development when product-market competition is weak, while the knowledge acquisition association with new product development turns negative when product-market competition is strong instead. However, the estimates of the effects of low levels of knowledge acquisition on new product development in Figure 1b—specifically, those below the mean level of *Knowledge*

acquisition—also suggest that strong product-market competition results in significantly *more*

new products than weak product-market competition. One way to explain this result is that a firm

may not acquire technological knowledge from partners in its own industry if rather than

competitors such partners are in fact the firm's *complementors* in product markets. The purpose

of alliances between complementors is likely not to outlearn one another so much as it is to

coordinate in order to achieve complementarity in the product domain. For that reason, at low

levels of *Knowledge acquisition*, partners active in the same product market as the focal firm may

contribute more to its new product development than partners in other product markets.

Next, I examined the implications of potential multicollinearity for the parameter

estimates. Specifically, because a fixed-effects specification applied to a relative short panel

tends to increase standard errors on time-varying variables that do not vary much over time,

within-firm collinearity may be a concern. Though variance inflation factors for all covariates

were below the standard threshold of ten (Belsey, Kuh, and Welsch, 1980; Kennedy, 2003), to

assess the stability of the key results, I nevertheless re-estimated Models 1 and 4 after excluding

all time-varying control variables. Models 5 and 6 in Table 2 show that the estimates are still

consistent with all three hypotheses, though Models 1 and 4 provide a significantly better overall

fit to the data ($\chi^2_{5 \text{ vs. } 1}$ [11 d.f.] = 68.40, $p < 0.001$; and $\chi^2_{6 \text{ vs. } 4}$ [11 d.f.] = 50.54, $p < 0.001$).

While Models 1-6 show associations among the study variables at the focal firm's alliance

portfolio level of analysis, it is reasonable to imagine that the interaction effects as proposed in

H2 and H3 may come into being at the dyadic, firm-partner level of analysis.[8] To assess this

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[8] The question whether aggregation of the main effects to the portfolio level prior to calculating the interaction terms hides more granular dyadic effects is directly relevant to the hypothesis tests. A more basic question concerns whether using measures of *Technological relatedness* and *Product-market competition* based on a straightforward aggregation across dyads may itself obscure relevant variance in these measures across different firm-partner dyads. In an unreported robustness check, I therefore re-estimated Models 1-6 in Table 2 while including the standard deviations of *Technological relatedness* and *Product-market competition*, both capturing variance in these measures across a firm's dyadic relationships. The coefficient on the standard deviation of *Technological relatedness* was

possibility, I performed an additional analysis in which interactions between *Knowledge acquisition* and, respectively, *Technological relatedness* and *Product-market competition* were constructed at the dyadic, firm-partner level prior to averaging scores on these interactions across a firm's portfolio of R&D alliance partners. Substituting these alternative measures for the portfolio-level interactions, Model 7 in Table 2 shows that the interaction between *Knowledge acquisition* and *Technological relatedness* is positive and significant. This finding suggests that firms that develop more new products are the ones that are more technologically related to especially those partners they acquire more technological knowledge from. However, the interaction between *Knowledge acquisition* and *Product-market competition* constructed using dyad-level scores is insignificant. I will return to this finding in the discussion section.

4.2 Further analysis

In various additional analyses, I further assessed the validity of the empirical findings in Table 2. Specifically, I examined the potential endogeneity of *Knowledge acquisition*; I allowed for different time lags between *Knowledge acquisition* and *New product development*; and I explored potential nonlinearity in the moderating effect of *Technological relatedness*.

4.2.1   Potential endogeneity of knowledge acquisition

The finding that technological relatedness and product-market competition are significant and substantive moderators of the knowledge acquisition association with new product development does not rule out the possibility that these two moderators are also antecedents of knowledge acquisition in the first place (e.g., Preacher, Rucker, and Hayes, 2007). Indeed, it is reasonable to imagine that technological relatedness and product-market competition may first

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insignificant, while that of *Product-market competition* was negative and significant. The latter finding suggests that firms with similar numbers of partners in their own primary industry and in other industries introduced fewer new products than firms with partners mainly either inside or outside their primary industry. One way to explain this result is that requisite collaborative routines may be distinct between intra- and inter-industry alliances, such that firms focusing on one of the two reap greater efficiency benefits across their portfolios of R&D alliances. The results on the hypothesis-testing variables were unaffected by inclusion of these two measures of variation.

determine knowledge acquisition (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996; Oxley and Wada, 2009), to then condition its association with new product development in the ways I theorized and tested. Fixed effects OLS estimates of *Knowledge acquisition* as a function of all other variables included in Table 2, Model 1, indeed revealed a positive association between *Technological relatedness* and *Knowledge acquisition* ($\beta = 0.195$, $p = 0.031$), while *Product-market competition* was not significantly associated with *Knowledge acquisition* ($\beta = -0.056$, $p = 0.222$).[9]

A key assumption underlying the models in Table 2 is that these and other factors that potentially determine a firm's level of knowledge acquisition are held constant, such that *Knowledge acquisition* can be treated as an exogenous variable in the new product development models. An independent variable is exogenous if it is uncorrelated with the error term of the model in which it is entered, in which case the variable estimate will be consistent (Wooldridge, 2002: 62). Using the average level of knowledge acquisition across all observations within a firm's primary industry in year *t* as an instrument, generalized Durbin-Wu-Hausman tests (Davidson and MacKinnon, 1993: 237-240) failed to reject the null hypothesis of consistent estimates for *Knowledge acquisition* across all models in Table 2 ($0.157 < p < 0.968$). Therefore, the evidence suggests no reason to suspect that *Knowledge acquisition* suffered from an endogeneity bias in the new product development models.

4.2.2 Alternative time lags for knowledge acquisition

The models presented in Table 2 allow R&D alliances formed between years *t*-2 and *t*, and *Knowledge acquisition* in year *t*, to have an effect on *New product development* in year *t*+1. However, it is possible that technological knowledge acquired earlier in time might have effects

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[9] *Knowledge acquisition* is truncated at zero and so strictly speaking, its distribution is a mixture of both discrete and continuous distributions, potentially rendering fixed effects OLS estimates biased. Nevertheless, Honoré's (1992) implementation of a fixed effects Tobit estimator generated a qualitatively similar conclusion.

on *New product development* as well. To assess this possibility, I also tested the hypotheses using alternative lag specifications.

--- Insert Table 3 about here ---

Table 3 shows the estimates. Model 1 includes *Knowledge acquisition* in years *t* (i.e., the knowledge acquisition measure in Table 2), *t*-1, and *t*-2, showing that the main effect for *Knowledge acquisition (t)* remains positive and significant, while the coefficients on the two alternative lags are insignificant. Models 2-4 show tests of H2 based on alternative lags for knowledge acquisition. Interactions between *Technological relatedness* and, respectively, *Knowledge acquisition (t-1)* (Model 2) and *Knowledge acquisition (t-2)* (Model 3) are insignificant. Model 4 shows that the technological relatedness interaction with knowledge acquisition aggregated across years *t*-2 to *t* is positive and marginally significant, in line with H2.[10] However, the model fit of Table 2, Model 2, is significantly better than that of Table 3, Model 4, suggesting that the aggregated effect is driven largely by *Knowledge acquisition* in year *t*. Finally, Models 5-7 in Table 3 show that tests of H3 using alternative lags all generate insignificant results. Therefore, the most appropriate lag specification is one year between *Knowledge acquisition* and *New product development*, which is the lag used in Table 2.

4.2.3 Potential nonlinearity in the moderating effect of technological relatedness

The theory motivating H2 suggested that in exploitation activities, such as the application of acquired technological knowledge in the product domain, technological relatedness is required "*in order to coordinate rapidly and without errors*", while technological distance instead "*creates uncertainty and complexity, which is undesirable in such a setting*" (Nooteboom et al., 2007: 1019). Accordingly, H2 predicted that technological relatedness would have a linear and

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[10] To construct *Knowledge acquisition (t-2 to t)*, I counted a firm's number of patent citations to the patents of its R&D alliance partners during years *t*-2 to *t* that it did *not* cite prior to engaging in one or more R&D alliances with each of its partners. Subsequently, I divided this citation count by the firm's total number of patent citations during years *t*-2 to *t*.

positive moderating effect on the association between knowledge acquisition and new product development. However, though large differences between a firm's knowledge base and that of its partners may indeed be detrimental for exploiting acquired technological knowledge in the product domain, it is nevertheless possible that a firm derives value from small differences between its knowledge base and that of its partners, in which case technological relatedness might show some decreasing marginal returns (e.g., Nooteboom et al., 2007).

The possibility of such decreasing marginal returns may have implications for the empirical evidence in Table 2 supporting H2. Specifically, if the effect of technological relatedness is curvilinear rather than linear, then the marginal new product development benefits from acquired technological knowledge will reduce at higher levels of technological relatedness. In such case, though we might still observe an average increase in the correlation between knowledge acquisition and new product development as technological relatedness increases (consistent with H2), this increase should occur at a progressively decreasing rate.

--- Insert Figure 2 about here ---

Figure 2 shows how the correlation between *Knowledge acquisition* and the logarithm of *New product development* varied across levels of *Technological relatedness*. I ordered all 120 firm-years by ascending technological relatedness and then divided them into 20 groups containing 6 firm-years each. The 20 black dots in Figure 2 represent these groups. Each group's position on the horizontal axis is determined by the average technological relatedness in the group, while its position on the vertical axis is determined instead by the correlation between *Knowledge acquisition* and the logarithm of *New product development* within that group. The figure shows that the knowledge acquisition correlation with the logarithm of new product development on average increases with technological relatedness, consistent with H2.

--- Insert Table 4 about here ---

To assess whether the observed increase in the correlation between knowledge acquisition and new product development was linear or curvilinear, I regressed the correlations shown in Figure 2 on linear and squared *Technological relatedness*. Table 4, Models 1 and 2, show that the main effect of *Technological relatedness* is positive and significant, while its squared term is insignificant (Model 2). Moreover, the adjusted R-squared for Model 1 is higher than that for Model 2 (i.e., 0.167 versus 0.144). Based on the estimates of Model 1 in Table 2, the solid black line in Figure 2 shows the regression line fitted to the 20 data points. It predicts that a one standard deviation increase in technological relatedness is on average associated with an increase in the correlation between knowledge acquisition and new product development of 0.207. The linear and positive moderating effect of *Technological relatedness* as predicted in H2 and tested in Table 2 is thus clearly borne out by this descriptive correlation analysis.[11]

--- Insert Table 5 about here ---

Beyond this correlation analysis, I also directly introduced a squared term for *Technological relatedness* into the models testing H2. Table 5 shows the estimates. Model 1 shows no evidence of nonlinearity in the effect of *Technological relatedness*, while the interaction between *Knowledge acquisition* and *Technological relatedness* is positive and significant. Model 2 introduces all control variables and again shows no evidence of nonlinearity in the effect of technological relatedness. Though the interaction term in Model 2 in Table 5 is insignificant, the log-likelihood for this model is identical to that for Model 2 in Table 2 and so the latter represents the more parsimonious model. Therefore, both descriptive and inferential analyses fully support H2, by generating consistent evidence for a positive and linear moderating effect of *Technological relatedness*, while providing no evidence of nonlinearity.

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[11] To assess robustness, I also generated five alternative versions of the estimates in Table 4, one using raw counts of new products to construct the correlations, and others using 12, 15, 24, and 30 groups of firm-years, respectively. Across these five alternatives, the average marginal effect of *Technological relatedness* (z-score) on the correlation between *Knowledge acquisition* and *New product development* was 0.209, while I found no evidence of nonlinearity.

5. Discussion and conclusion

This study was motivated by the observation that research on the performance consequences of R&D alliances has focused virtually exclusively on either knowledge acquisition or new product development, while underemphasizing the relationship between these two distinct outcomes. Bridging these two research streams, this study directly connected knowledge acquisition through R&D alliances to new product development and examined when R&D alliances enabled firms to apply acquired technological knowledge in the product domain. My investigation showed that firms acquiring more technological knowledge from their R&D alliance partners were on average more productive in new product development. However, I also found robust evidence showing that knowledge acquisition was significantly more beneficial for firms' new product development both when their technological knowledge bases were more closely related to those of their partners and when they operated in different product markets than their partners.

This study fills a gap in the alliance literature by directly examining the role of R&D alliances in connecting firms' technology and product domains (e.g., Grant and Baden-Fuller, 2004). Different streams of research have shown that R&D alliances may facilitate technological learning (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996), while such alliances may have consequences in the product domain as well (e.g., Deeds and Hill, 1996; Rothaermel and Deeds, 2004). Nevertheless, to date these two research streams have evolved largely independently and so in the context of R&D alliances, little is known about the relationship between knowledge acquisition on the one hand and knowledge application on the other (e.g., Meier, 2011). In the innovation literature more broadly, several studies have called for more research integrating the insights from the knowledge acquisition literature with the literature on knowledge application (Fiol, 1996; Lane et al., 2006). Therefore, the first contribution of this study lies in offering a

direct and systematic assessment of whether knowledge acquisition through R&D alliances influences firms' new product development outcomes.

In connecting technological learning through R&D alliances to new product development, this study also developed and tested a theory of how technological relatedness and product-market competition between R&D alliance partners affects firms' propensity to apply acquired knowledge in the product domain. Accordingly, the study's second contribution lies in showing that the knowledge acquisition association with new product development is subject to important scope conditions. Specifically, though extensive knowledge acquisition requires technological relatedness and low levels of product-market competition between R&D alliance partners, low levels of technological learning from R&D alliance partners may translate into enhanced new product development as well, to the extent that firms have R&D alliances with technologically specialized competitors. These findings empirically support Grant and Baden-Fuller's (2004) prediction that compared to R&D alliances focusing on knowledge acquisition, R&D alliances that instead de-emphasize knowledge acquisition enable greater technological specialization of the partner firms, while they are simultaneously less affected by interpartner competition.

Three of the empirical results directly present opportunities for future research. First, I found that in the application of acquired technological knowledge, partners active in similar technology domains consistently derived the greatest new product development benefits (e.g., Figures 1a and 2). This finding converges with the idea that the value of technological distance and concomitant novelty potential is comparatively low in firms' exploitation activities (e.g., March, 1991; Nooteboom et al., 2007; Rindfleisch and Moorman, 2001). However, it is possible that novelty value varies across different types of new products. For example, it is reasonable to imagine that exposure to somewhat unfamiliar tacit process knowledge is more likely to generate radical rather than incremental new products. If this is the case, then we should observe

nonlinearities in the benefits that firms derive from technological relatedness. Future research can assess such effects using more granular data on the nature of firms' new products.

Second, I found that firms acquiring little technological content knowledge through their R&D alliances benefited disproportionally from partners within their own primary industry (Figure 1b). This finding nicely underscores the conditional benefits of technological learning in R&D alliances, as it suggests that new product development may not always require firms to rely strongly on partners' technological knowledge. I speculated that this effect might reflect potential product-market complementarities between partners active in the same industry, which perhaps reduces the need for extensive acquisition of partners' technological knowledge. While some prior studies have alluded to such complementarity effects (e.g., Grant and Baden-Fuller, 2004; Kapoor and McGrath, 2014), empirical research systematically linking learning in the technology domain to the new product development activities of complementors is needed. Moreover, studies have not directly compared the potentially distinct mechanisms connecting R&D alliances to new product development between competing and complementary partners. There are thus ample opportunities to investigate the effects of competition and complementarity between alliance partners in the process connecting technological learning to new product development.

Third, I found that the interactive effects of knowledge acquisition and technological relatedness came into being at the level of firm-partner dyads rather than at the level of firms' R&D alliance portfolios. Therefore, firms more technologically related to especially those partners they acquired more technological knowledge from achieved the best new product development outcomes. However, I found no such evidence for product-market competition (Table 2, Model 7). This somewhat counterintuitive result perhaps suggests that technological knowledge drawn from a particular partner is not always developed with the cooperation of that same partner. Indeed, one possible mechanism is this: in anticipation of downstream competitive

tensions with particular alliance partners, firms might turn to other partners for the commercialization of knowledge acquired elsewhere, even if such partners are less able to provide the tacit process knowledge this requires. Another possible mechanism is that product-market competition makes firms' knowledge application more dependent on perhaps inadequate internal capabilities (e.g., Hagedoorn and Wang, 2012; Moorman and Slotegraaf, 1999). Future research is needed to identify and distinguish between such more complex mechanisms.

Given my focus on the information technology industry, generalizability to other industries remains a possible concern. Specifically, a key identifying assumption of the theory presented in this study is that technological relatedness represents a suitable indicator of partner-related absorptive capacity. This is conceivable especially in settings where connections between firms' knowledge and product domains are loose rather than strong (Grant and Baden-Fuller, 2004) and the information technology industry represents such a setting. Indeed, technological progress in information technology is cumulative and so the majority of technologies and final products embody numerous pieces of intellectual property that have little value in and of themselves (Cohen, Nelson, and Walsh, 2000). Moreover, information technologies are known to have a myriad of distinct applications (Hall et al., 2002). However, in settings where technologies are more discrete rather than cumulative, and where competition in factor markets maps much more closely onto product-market competition, competitive aspects of technological relatedness may dominate the absorptive capacity effects as predicted and tested here. Future research may explore additional correlates of partner-related absorptive capacity, and how such factors shape the knowledge acquisition association with new product development, in carefully selected settings other than information technology.

In sum, bridging alliance research on knowledge acquisition and that on new product development, this study offers the first systematic empirical examination connecting

technological learning through R&D alliances to firms' new product development outcomes, showing that important scope conditions underlie the application of acquired technological knowledge in the product domain. The study's findings generate several directions for future research that can deepen our understanding of the mechanisms connecting R&D alliances to firm performance.

References

Alcácer J, Gittelman M. 2006. Patent citations as a measure of knowledge flows: the influence of examiner citations. Review of Economics and Statistics 88(4): 774-779.

Bamford JD, Gomes-Casseres B, Robinson MS. 2003. Mastering alliance strategy. John Wiley & Sons, Inc.: San Francisco, CA.

Bayus BL, Erickson G, Jacobson R. 2003. The financial rewards of new product introductions in the personal computer industry. Management Science 49(2): 197-210.

Belsey DA, Kuh E, Welsch RE. 1980. Regression diagnostics. Wiley: New York, NY.

Blundell R, Griffith R, Van Reenen J. 1999. Market share, market value and innovation in a panel of British manufacturing firms. The Review of Economic Studies 66(3): 529-554.

Brown SL, Eisenhardt KM. 1995. Product development: past research, present findings, and future directions. Academy of Management Review 20(2): 343-378.

Chen R, Li M. 1999. Strategic alliances and new product development: an empirical study of the U.S. semiconductor start-up firms. Advances in Competitiveness Research 7(1): 35-61.

Chen W-R, Miller KD. 2007. Situational and institutional determinants of firms' R&D search intensity. Strategic Management Journal 28(4): 369-381.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35(1): 128-152.

Cohen WM, Nelson RR, Walsh JP. 2000. Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not). NBER working paper 7552.

Davidson R, MacKinnon JG. 1993. Estimation and inference in econometrics. New York: Oxford University Press.

Deeds DL, DeCarolis D, Coombs J. 1999. Dynamic capabilities and new product development in high technology ventures: an empirical analysis of new biotechnology firms. Journal of Business Venturing 15(3): 211-229.

Deeds DL, Hill CWL. 1996. Strategic alliances and the rate of new product development: an empirical study of entrepreneurial biotechnology firms. Journal of Business Venturing 11(1): 41-55.

Eisenhardt KM, Tabrizi BN. 1995. Accelerating adaptive processes: product innovation in the global computer industry. Administrative Science Quarterly 40(1): 84-110.

Faems DM, Janssens M, and Van Looy B. 2007. The initiation and evolution of interfirm knowledge transfer in R&D relationships. Organization Studies 28(11): 1699-1728.

Fey CF, Birkinshaw J. 2005. External sources of knowledge, governance mode, and R&D performance. Journal of Management 31(4): 597-621.

Fiol CM. 1996. Squeezing harder doesn't always work: continuing the search for consistency in innovation research. Academy of Management Review 21(4): 1012-1021.

Fosfuri A, Giarratana MS. 2009. Masters of war: rivals' product innovation and new advertising in mature product markets. Management Science 55(2): 181-191.

Frankort HTW. 2013. Open innovation norms and knowledge transfer in interfirm technology alliances: evidence from information technology, 1980-1999. Advances in Strategic Management 30: 239-282.

Frankort HTW, Hagedoorn J, Letterie W. 2012. R&D partnership portfolios and the inflow of technological knowledge. Industrial and Corporate Change 21(2): 507-537.

Gerwin D. 2004. Coordinating new product development in strategic alliances. Academy of Management Review 29(2): 241-257.

Gomes-Casseres B, Hagedoorn J, Jaffe AB. 2006. Do alliances promote knowledge flows? Journal of Financial Economics 80(1): 5-33.

Grant RM, Baden-Fuller C. 2004. A knowledge accessing theory of strategic alliances. Journal of Management Studies 41(1): 61-84.

Hagedoorn J. 1993. Understanding the rationale of strategic technology partnering: interorganizational modes of cooperation and sectoral differences. Strategic Management Journal 14(5): 371-385.

Hagedoorn J. 2002. Inter-firm R&D partnerships: an overview of major trends and patterns since 1960. Research Policy 31(4): 477-492.

Hagedoorn J, Wang N. 2012. Is there complementarity or substitutability between internal and external R&D strategies? Research Policy 41(6): 1072-1083.

Hall BH. 2005. A note on the bias in Herfindahl-type measures based on count data. Revue d'Économie Industrielle 110(2): 149-156.

Hall BH, Jaffe AB, Trajtenberg M. 2002. The NBER patent-citations data file: lessons, insights, and methodological tools. In Patents, citations & innovations, Jaffe AB, Trajtenberg M (eds). The MIT Press: Cambridge, MA; 403-459.

Hamel G. 1991. Competition for competence and inter-partner learning within international strategic alliances. Strategic Management Journal, Summer Special Issue 12: 83-103.

Harrigan KR. 2003. Joint Ventures, alliances, and corporate strategy. Beard Books: Washington, DC.

Hausman JH. 1978. Specification tests in econometrics. Econometrica 46(6): 1251-1271.

Hausman J, Hall BH, Griliches Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. Econometrica 52(4): 909-938.

Hitt MA, Hoskisson RE, Johnson RA, Moesel DD. 1996. The market for corporate control and firm innovation. Academy of Management Journal 39(5): 1084-1119.

Honoré BE. 1992. Trimmed LAD and least squares estimation of truncated and censored regression models with fixed effects. Econometrica 60(3): 533-565.

Jaffe AB. 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. American Economic Review 76(5): 984-1001.

Jaffe AB, Trajtenberg M, Fogarty MS. 2000. Knowledge spillovers and patent citations: evidence from a survey of inventors. American Economic Review Papers and Proceedings 90(2): 215-218.

Kapoor R, McGrath PJ. 2014. Unmasking the interplay between technology evolution and R&D collaboration: evidence from the global semiconductor manufacturing industry, 1990-2010. Research Policy 43(3): 555-569.

Katila R, Ahuja G. 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. Academy of Management Journal 45(6): 1183-1194.

Kennedy P. 2003. A guide to econometrics. The MIT Press: Cambridge, MA.

Khanna T, Gulati R, Nohria N. 1998. The dynamics of learning alliances: competition, cooperation, and relative scope. Strategic Management Journal 19(3): 193-210.

Kotabe M, Swan KS. 1995. The role of strategic alliances in high-technology new product development. Strategic Management Journal 16(8): 621-636.

Lane PJ, Koka BR, Pathak S. 2006. The reification of absorptive capacity: a critical review and rejuvenation of the construct. Academy of Management Review 31(4): 833-863.

Lane PJ, Lubatkin M. 1998. Relative absorptive capacity and interorganizational learning. Strategic Management Journal 19(5): 461-477.

Laursen K, Salter AJ. 2014. The paradox of openness: appropriability, external search and collaboration. Research Policy 43(5): 867-878.

Lavie D, Miller SR. 2008. Alliance portfolio internationalization and firm performance. Organization Science 19(4): 623-646.

March JG. 1991. Exploration and exploitation in organizational learning. Organization Science 2(1): 71-87.

Meier M. 2011. Knowledge management in strategic alliances: a review of empirical evidence. International Journal of Management Reviews 13(1): 1-23.

Moorman C, Slotegraaf RJ. 1999. The contingency value of complementary capabilities in product development. Journal of Marketing Research 36(2): 239-257.

Mowery DC, Oxley JE, Silverman BS. 1996. Strategic alliances and interfirm knowledge transfer. Strategic Management Journal, Winter Special Issue 17: 77-91.

Nooteboom B. 2000. Learning and innovation in organizations and economies. Oxford University Press: Oxford, UK.

Nooteboom B, Van Haverbeke W, Duysters G, Gilsing V, van den Oord A. 2007. Optimal cognitive distance and absorptive capacity. Research Policy 36(7): 1016-1034.

Oxley JE, Sampson RC. 2004. The scope and governance of international R&D alliances. Strategic Management Journal 25(8-9): 723-749.

Oxley J, Wada T. 2009. Alliance structure and the scope of knowledge transfer: evidence from U.S.-Japan agreements. Management Science 55(4): 635-649.

Pakes A, Schankerman M. 1984. The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources. In R&D, patents, and productivity, Griliches Z (ed). The University of Chicago Press: Chicago, IL; 73–88.

Park SH, Russo MV. 1996. When competition eclipses cooperation: an event history analysis of joint venture failure. Management Science 42(6): 875-890.

Phelps CC. 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. Academy of Management Journal 53(4): 890-913.

Preacher KJ, Rucker DD, Hayes AF. 2007. Addressing moderated mediation hypotheses: theory, methods, and prescriptions. Multivariate Behavioral Research 42(1): 185-227.

Puranam P, Singh H, Zollo M. 2006. Organizing for innovation: managing the coordination-autonomy dilemma in technology acquisitions. Academy of Management Journal 49(2): 263-280.

Raymond W, Mohnen P, Palm F, van der Loeff SS. 2010. Persistence of innovation in Dutch manufacturing: is it spurious? The Review of Economics and Statistics 92(3): 495-504.

Rindfleisch A, Moorman C. 2001. The acquisition and utilization of information in new product alliances: a strength-of-ties perspective. Journal of Marketing 65(2): 1-18.

Rosenkopf L, Almeida P. 2003. Overcoming local search through alliances and mobility. Management Science 49(6): 751-766.

Rothaermel FT, Deeds DL. 2004. Exploration and exploitation alliances in biotechnology: a system of new product development. Strategic Management Journal 25(3): 201-221.

Sampson RC. 2005. Experience effects and collaborative returns in R&D alliances. Strategic Management Journal 26(11): 1009-1031.

Sampson RC. 2007. R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation. Academy of Management Journal 50(2): 364-386.

Smith KG, Collins CJ, Clark KD. 2005. Existing knowledge, knowledge creation capability, and the rate of new product introduction in high-technology firms. Academy of Management Journal 48(2): 346-357.

Soh P-H. 2003. The role of networking alliances in information acquisition and its implications for new product performance. Journal of Business Venturing 18(6): 727-744.

Sorescu AB, Spanjol J. 2008. Innovation's effect on firm value and risk: insights from consumer packaged goods. Journal of Marketing 72(2): 114-132.

Wooldridge JM. 1999. Distribution-free estimation of some nonlinear panel data models. Journal of Econometrics 90(1): 77-97.

Wooldridge JM. 2002. Econometric analysis of cross section and panel data. The MIT Press: Cambridge, MA.

Yli-Renko H, Autio E, Sapienza HJ. 2001. Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. Strategic Management Journal 22(6-7): 587-613.

Yoshino MY, Rangan US. 1995. Strategic alliances: an entrepreneurial approach to globalization. Harvard University Press: Cambridge, MA.

Zander U, Kogut B. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test. Organization Science 6(1): 76-92.

Figure 1.
New product development multipliers of knowledge acquisition interactions with technological relatedness and product-market competition
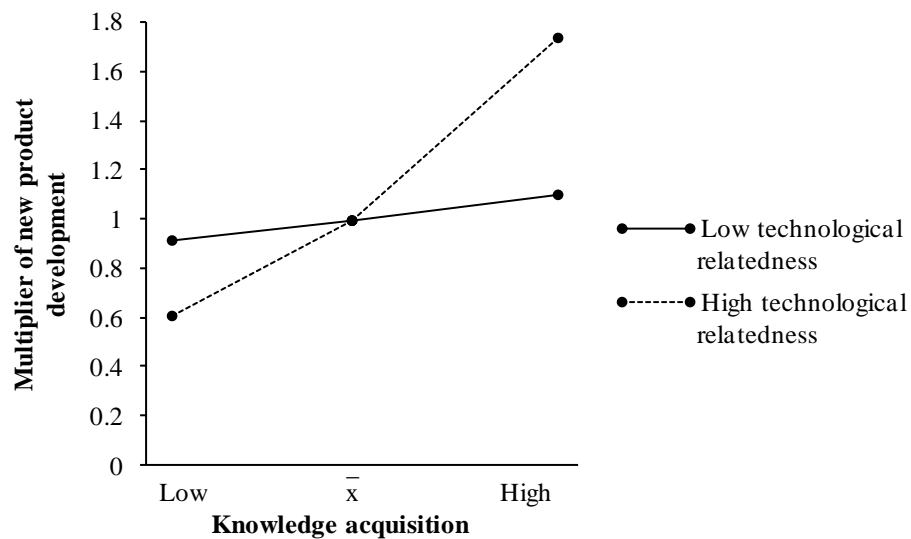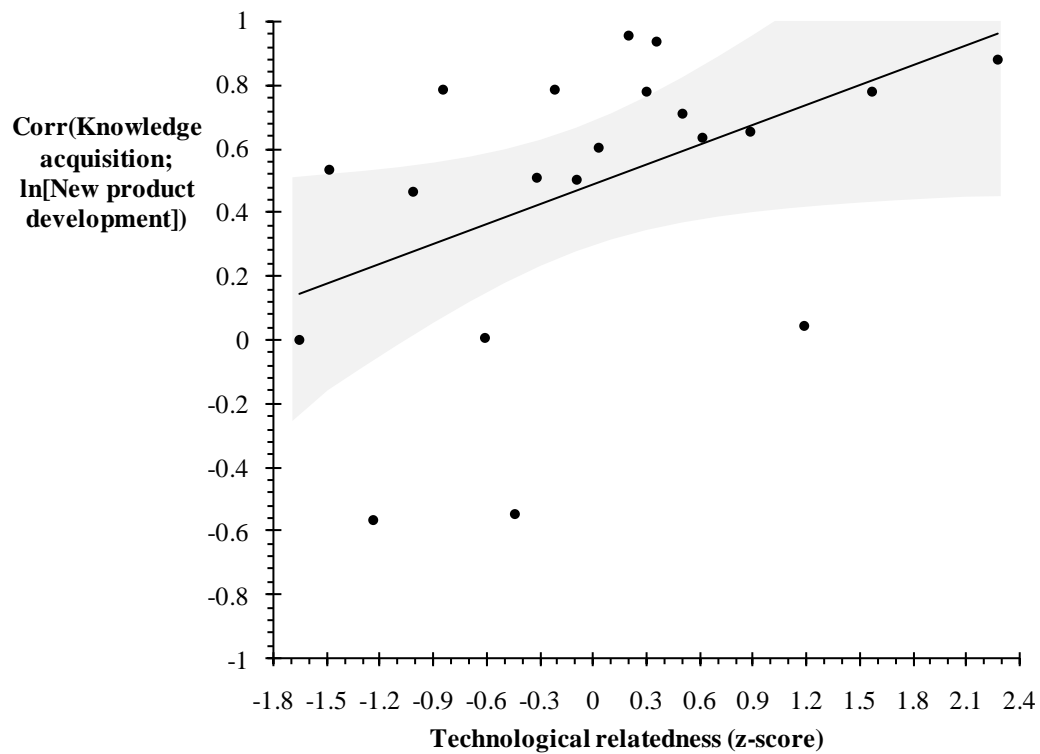

(1a) *Technological relatedness (Table 2, Model 2)*
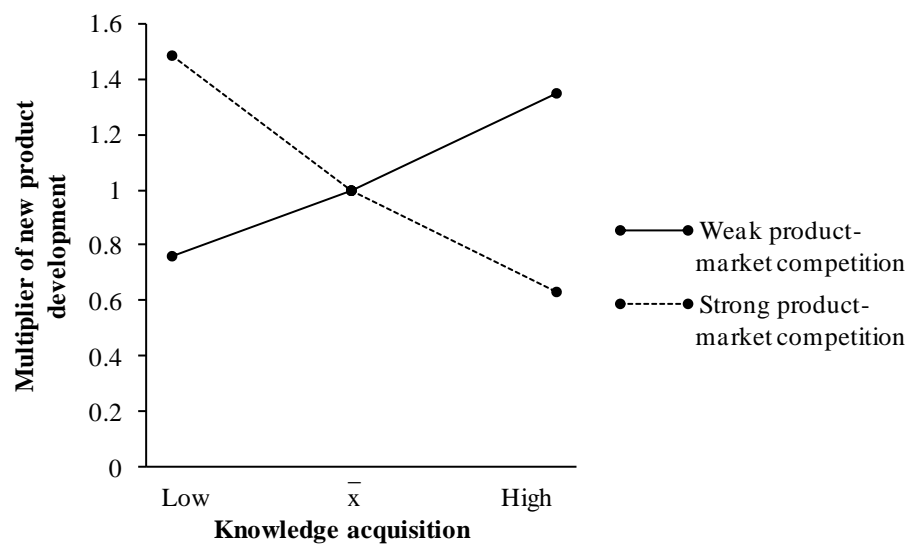
(1b) *Product-market competition (Table 2, Model 3)*

Figure 2.
Correlations between knowledge acquisition and the logarithm of new product development across levels of technological relatedness

—— Predicted correlation (Table 4, Model 1); 95% confidence band in grey

Table 1.
Summary statistics and correlation matrix (N = 120)

Variable name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 New product development (t+1)	1.00														
2 Knowledge acquisition	0.49	1.00													
3 Technological relatedness	0.16	0.37	1.00												
4 Product-market competition	-0.06	0.07	0.57	1.00											
5 Firm size[a]	0.39	0.12	-0.15	-0.37	1.00										
6 Firm age[a]	0.10	-0.16	-0.41	-0.42	0.55	1.00									
7 Firm patent applications[a]	0.58	0.24	0.18	-0.02	0.34	0.14	1.00								
8 Firm alliance experience[a]	0.68	0.55	0.14	-0.12	0.58	0.18	0.48	1.00							
9 Firm technological diversity	0.28	0.16	-0.14	-0.43	0.65	0.45	0.24	0.42	1.00						
10 Joint venture relationships	0.39	0.34	0.23	0.12	0.28	0.22	0.40	0.63	0.27	1.00					
11 Same-country relationships	0.00	0.29	-0.07	0.21	0.03	-0.05	-0.01	0.15	-0.03	0.12	1.00				
12 Research-focused relationships	-0.01	0.10	0.34	0.39	0.03	-0.10	0.17	0.17	-0.01	0.54	0.13	1.00			
13 Partner citations[a]	0.42	0.41	0.08	-0.12	0.17	-0.04	0.60	0.38	0.28	0.12	0.00	0.02	1.00		
14 Partner new products (t+1)[a]	0.49	0.44	0.10	-0.14	0.30	-0.02	0.44	0.52	0.29	0.18	0.00	0.03	0.65	1.00	
15 Partner technological diversity	0.14	0.17	0.16	-0.01	0.22	-0.10	0.10	0.14	0.27	-0.06	-0.09	0.02	0.38	0.34	1.00
Mean	48.77	0.08	0.33	0.20	3.91	3.62	3.78	2.10	0.92	0.21	0.79	0.09	7.26	4.68	0.95
Standard deviation	65.81	0.09	0.20	0.30	0.70	0.78	1.64	1.30	0.05	0.26	0.32	0.19	2.47	2.10	0.09
Minimum	0.00	0.00	0.00	0.00	2.03	2.20	0.69	0.00	0.74	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	305	0.43	0.85	1.00	5.48	4.80	7.47	4.72	1.00	1.00	1.00	1.00	10.14	7.08	0.98

All correlations ≥ |0.18| are significant at or beyond p=0.05 (two-tailed).

a. Logarithm.

Table 2.

Conditional fixed effects Poisson QML estimates of new product development ($t+1$) (N = 120)[a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model:	H1	H2	H3	H2/3	H1	H2/3	H2/3[b]
Knowledge acquisition	2.817**	0.055	0.068	-0.073	2.403**	0.022	-0.233
	[0.886]	[0.116]	[0.084]	[0.111]	[0.774]	[0.071]	[1.291]
Technological relatedness (TR)	2.451**	0.325**	0.265+	0.141	2.424***	0.232**	0.580
	[0.764]	[0.117]	[0.142]	[0.133]	[0.548]	[0.081]	[0.711]
Product-market competition (PMC)	-0.616	-0.087	-0.148	-0.066	-0.446	-0.057	-0.042
	[0.409]	[0.133]	[0.105]	[0.117]	[0.422]	[0.082]	[0.591]
Knowledge acquisition × TR		0.230**		0.194**		0.164**	9.779***
		[0.078]		[0.070]		[0.050]	[2.603]
Knowledge acquisition × PMC			-0.452***	-0.409***		-0.247**	-3.406
			[0.102]	[0.106]		[0.091]	[5.396]
Firm size	-0.006	0.067	0.880	0.834			-0.024
	[0.837]	[0.785]	[0.695]	[0.677]			[0.898]
Firm age	-1.019	-1.764	-4.000+	-4.251+			-0.881
	[3.023]	[3.269]	[2.305]	[2.513]			[3.014]
Firm patent applications	0.271+	0.230	0.310*	0.273*			0.157
	[0.163]	[0.150]	[0.139]	[0.123]			[0.145]
Firm alliance experience	0.037	0.025	-0.137	-0.134			-0.036
	[0.208]	[0.218]	[0.191]	[0.191]			[0.210]
Firm technological diversity	-0.823	6.369	7.317	12.350*			9.386+
	[7.061]	[7.382]	[5.061]	[5.216]			[5.476]
Joint venture relationships	0.403	0.274	1.486**	1.291*			0.501
	[0.560]	[0.629]	[0.542]	[0.580]			[0.613]
Same-country relationships	0.947	0.328	-0.130	-0.546			0.172
	[0.585]	[0.555]	[0.580]	[0.589]			[0.498]
Research-focused relationships	-0.890+	-0.088	-0.266	0.373			0.293
	[0.531]	[0.572]	[0.365]	[0.450]			[0.459]
Partner citations	0.082	0.114+	0.096	0.125+			0.139+
	[0.070]	[0.061]	[0.078]	[0.065]			[0.071]
Partner new products ($t+1$)	-0.107	-0.031	0.013	0.064			-0.022
	[0.073]	[0.077]	[0.087]	[0.098]			[0.095]
Partner technological diversity	2.294	0.545	0.382	-0.919			0.215
	[1.493]	[0.752]	[1.644]	[1.063]			[1.037]
Log-likelihood	-308.65	-290.00	-278.82	-265.92	-342.85	-291.19	-273.45

Standard errors in brackets; *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. All models include year fixed effects.

a. In Models 2-4 and 6, the main effects for *Knowledge acquisition*, *Technological relatedness*, and *Product-market competition* were standardized prior to calculating the interaction terms.

b. In Model 7, interactions were calculated at the dyadic level and then averaged across a firm's R&D alliance partners.

Table 3.

Conditional fixed effects Poisson QML estimates of new product development ($t+1$) with alternative time lags for knowledge acquisition (N = 120)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model:	H1	H2	H2	H2	H3	H3	H3
Technological relatedness (TR)	2.762**	2.652*	2.304*	1.850+	3.614**	3.043**	3.312***
	[0.881]	[1.352]	[1.007]	[1.105]	[1.111]	[0.953]	[0.942]
Product-market competition (PMC)	-0.558	-0.709+	-0.846+	-0.707+	-0.509	-0.821	-0.329
	[0.399]	[0.420]	[0.486]	[0.419]	[0.423]	[0.558]	[0.504]
Knowledge acquisition (t)	2.157*						
	[0.992]						
Knowledge acquisition (t-1)	-0.432	-1.894			-0.297		
	[0.281]	[1.572]			[0.265]		
Knowledge acquisition (t-2)	-0.260		-2.614+			-0.680*	
	[0.275]		[1.559]			[0.282]	
Knowledge acquisition (t-2 to t)				-6.402**			-1.537+
				[2.402]			[0.823]
Knowledge acquisition (t-1) × TR		3.187					
		[4.007]					
Knowledge acquisition (t-2) × TR			4.604				
			[3.428]				
Knowledge acquisition (t-2 to t) × TR				10.600+			
				[5.742]			
Knowledge acquisition (t-1) × PMC					-1.968		
					[1.232]		
Knowledge acquisition (t-2) × PMC						0.177	
						[0.927]	
Knowledge acquisition (t-2 to t) × PMC							-3.271
							[2.572]
Firm size	-0.066	0.009	0.370	0.221	-0.246	0.172	0.076
	[0.872]	[0.971]	[0.975]	[0.930]	[0.908]	[0.936]	[0.869]
Firm age	-0.069	1.505	1.858	1.608	0.924	1.879	1.503
	[3.065]	[2.510]	[2.386]	[2.735]	[2.738]	[2.513]	[2.829]
Firm patent applications	0.335+	0.369+	0.395+	0.472*	0.229	0.342+	0.379+
	[0.177]	[0.208]	[0.212]	[0.218]	[0.195]	[0.199]	[0.198]
Firm alliance experience	-0.048	-0.055	-0.156	-0.188	0.019	-0.125	-0.157
	[0.234]	[0.267]	[0.227]	[0.265]	[0.275]	[0.231]	[0.263]
Firm technological diversity	-2.323	0.427	-0.423	-2.076	0.799	0.470	0.385
	[6.757]	[6.269]	[6.536]	[5.941]	[6.325]	[6.649]	[6.028]
Joint venture relationships	-0.037	-0.264	-0.180	-0.596	-0.624	-0.163	-0.485
	[0.722]	[0.746]	[0.688]	[0.787]	[0.798]	[0.687]	[0.775]
Same-country relationships	1.035+	0.716	0.862	1.087+	0.642	0.745	0.753
	[0.629]	[0.580]	[0.547]	[0.634]	[0.570]	[0.551]	[0.657]
Research-focused relationships	-1.246*	-1.183+	-0.934	-1.271*	-1.041	-0.880	-1.233*
	[0.593]	[0.643]	[0.635]	[0.587]	[0.659]	[0.655]	[0.606]
Partner citations	0.111	0.170*	0.164*	0.191*	0.155+	0.159*	0.173+
	[0.084]	[0.083]	[0.073]	[0.088]	[0.083]	[0.078]	[0.090]
Partner new products (t+1)	-0.119	-0.120	-0.105	-0.109	-0.127	-0.116	-0.118
	[0.076]	[0.089]	[0.088]	[0.085]	[0.087]	[0.091]	[0.087]
Partner technological diversity	2.299	1.843	1.773	1.384	2.501	2.505	2.472
	[1.631]	[1.930]	[1.948]	[1.461]	[2.741]	[2.988]	[3.287]
Log-likelihood	-304.23	-318.64	-319.11	-306.68	-317.28	-321.83	-308.78

Standard errors in brackets; *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. All models include year fixed effects.

Table 4.

OLS regressions of the correlation between knowledge acquisition and the logarithm of new product development across 20 groups of firm-years (Figure 2)[a]

Dependent variable:	Corr[Knowledge acquisition; ln(New product development)]	
	(1)	(2)
Technological relatedness	0.207*	0.226*
	[0.094]	[0.099]
(Technological relatedness)^2		-0.056
		[0.078]
Constant	0.472**	0.526**
	[0.092]	[0.119]
N	20	20
R-squared	0.211	0.234
adjusted R-squared	0.167	0.144

Standard errors in brackets; ** $p<0.001$, * $p<0.05$.

a. In both models, *Technological relatedness* was standardized.

Table 5.

Conditional fixed effects Poisson QML estimates of new product development (t+1) including squared technological relatedness (N = 120)[a]

	(1)	(2)
Knowledge acquisition	0.074	0.062
	[0.069]	[0.119]
Technological relatedness (TR)	0.202	0.163
	[0.162]	[0.190]
[Technological relatedness (TR)]^2	0.042	0.150
	[0.086]	[0.121]
Knowledge acquisition × TR	0.218*	0.148
	[0.056]	[0.112]
Product-market competition		-0.456
		[0.480]
Firm size		0.257
		[0.837]
Firm age		-1.838
		[3.046]
Firm patent applications		0.265+
		[0.154]
Firm alliance experience		0.054
		[0.229]
Firm technological diversity		7.529
		[6.976]
Joint venture relationships		0.438
		[0.619]
Same-country relationships		0.330
		[0.546]
Research-focused relationships		-0.246
		[0.580]
Partner citations		0.120+
		[0.065]
Partner new products (t+1)		-0.033
		[0.082]
Partner technological diversity		0.623
		[0.782]
Log-likelihood	-305.15	-290.00

Standard errors in brackets; * p<0.001, + p<0.1. All model include year fixed effects.

a. In both models, the main effects for *Knowledge acquisition* and *Technological relatedness* were standardized prior to calculating the squared and interaction terms.