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R&D Partnership Portfolios and the Inflow of Technological Knowledge[•]

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R&D Partnership Portfolios and the Inflow of Technological Knowledge

Abstract

This paper links research on parallel search and joint R&D to contribute a portfolio perspective to the study of knowledge flows within interfirm R&D partnerships. In a longitudinal analysis of firms engaged in R&D partnerships relating to information technology between 1975 and 1999, we show that the size of a firm's R&D partnership portfolio and its share of novel partners both have an inverted U-shaped effect on the inflow of technological knowledge from the firm's R&D partners. We also show how these direct effects vary as a function of the level of technological uncertainty within the portfolio.

INTRODUCTION

Firms engaged in technological innovation face great uncertainty about the future value of new technologies, products, and processes (Freeman & Soete, 1997; Wheelwright & Clark, 1992) and crucial knowledge necessary to make research and development decisions in the face of such uncertainty is often scattered across industry segments. Therefore, many firms have assembled portfolios of R&D partnerships to scan multiple external sources of knowledge, allowing them to reduce technological uncertainty, shorten their innovation time span, and increase their performance (Hagedoorn, 1993, 2002; Laursen & Salter, 2006; Leiponen & Helfat, 2010; Powell, Koput, Smith-Doerr, & Owen-Smith, 1999). Recent studies argue that R&D partnership portfolios, more than individual partnerships alone, represent key knowledge-gathering conduits that allow firms to leverage informational complementarities across their various R&D projects (Faems, van Looy, & Debackere, 2005; George, Zahra, Wheatley, & Khan, 2001; Munson & Spivey, 2006). Consistent with this view, several studies have shown empirical associations between R&D partnership portfolios and innovation (Powell et al., 1999; Rothaermel & Deeds, 2006; Soh, 2003; Stuart, 2000; Wuyts, Dutta, & Stremersch, 2004), while others have suggested a link between technological uncertainty and firms' proclivity to engage in multiple simultaneous R&D partnerships (Hagedoorn, 1993; Powell, Koput, & Smith-Doerr, 1996; Rosenkopf & Schilling, 2008).

However, while research to date has provided important insights into R&D partnership portfolios, a number of issues have remained underexplored. For example, though prior studies have tended to assume that knowledge flows represent a proximate consequence of R&D partnership portfolios (e.g., Soh, 2003; Wuyts et al., 2004), direct evidence on such knowledge flows is largely restricted to studies of dyadic partnerships (Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Mowery, Oxley, & Silverman, 1996; Oxley & Wada 2009; Rosenkopf & Almeida, 2003). Empirical research has yet to connect dimensions of R&D partnership portfolios directly to the inflow of technological knowledge from a firm's R&D partners. In addition, the level of technological uncertainty varies considerably across a firm's R&D partnerships, which likely influences the knowledge-gathering effect of its partnership portfolio (e.g., Hagedoorn, 1993; Nelson, 1961). Nevertheless, available evidence provides limited insight into the effects of technological uncertainty on knowledge gathering in R&D partnership portfolios of varying size and composition.

In light of these issues, we aim to contribute to the theoretical and empirical literature on R&D partnerships in two ways. First, we bridge the gap between theory and evidence by providing a direct test of the proposition that an R&D partnership portfolio has predictable and substantive effects on the inflow of technological knowledge from a firm's partners. In particular, we examine whether portfolio size and its composition – i.e., the mix of novel and repeat partners – affect inward knowledge flows. Evidence on such relationships contributes to our understanding of the mechanisms that prior work has assumed, explicitly or implicitly, to drive the performance correlates of R&D partnership portfolios.

Second, we develop and test a contingency perspective that considers how the extent of technological uncertainty characterizing a firm's R&D partnerships affects inward knowledge flows in portfolios of different size and composition. To do so, we first distinguish research- and development-oriented partnerships as indicators of, respectively, higher and lower technological uncertainty. Drawing on the literature on parallel research and development efforts within firms (e.g., Nelson, 1961), we then argue that the extent to which a portfolio is composed of research-oriented partnerships affects the optimal portfolio size and partner mix. This contingency view extends nascent understanding of R&D partnership portfolios by suggesting that optimal portfolio design varies with the types of projects comprising those portfolios.

We define an R&D partnership portfolio as a firm's set of partnerships formed with other firms to share existing technologies and develop new technologies, products, and processes. We define inward knowledge flows as the knowledge flows a firm draws from its R&D partners and that relate to the development of technological innovations. We evaluate our hypotheses using a panel dataset on the innovative and partnering activities of firms engaged in R&D partnerships related to information technology (IT) during 1975-1999. To allow for a conservative test of our theory, we exploit rich longitudinal data by incorporating fixed effects for firms and years, and a wide range of time-varying controls at the firm, portfolio, and partner level.

KNOWLEDGE GATHERING IN R&D PARTNERSHIP PORTFOLIOS

Technological innovation is essential to a firm's commercial and financial performance (Bayus, Erickson, & Jacobson, 2003; Hall, Jaffe, & Trajtenberg, 2005) and so developing valuable innovation projects represents a key managerial challenge (Freeman & Soete, 1997). An important complication in innovation is that the future value of new technologies, products, and processes is inherently uncertain. Among other uncertainty-reduction strategies, the formation of R&D partnerships represents a major factor helping firms to address this challenge (Hagedoorn, 1993; Powell et al., 1999; Stuart, 2000). R&D partnerships help reduce uncertainty in particular because they allow a firm to gather information, by providing access to externally available technological knowledge (Gomes-Casseres et al., 2006; Mowery et al., 1996; Rosenkopf & Almeida, 2003).

Recent studies suggest that R&D partnership portfolios, more than individual partnerships alone, represent key knowledge-gathering conduits because a portfolio allows a firm to leverage informational complementarities across its various R&D projects (Faems et al., 2005; George et al., 2001; Munson & Spivey, 2006; Soh, 2003). This portfolio argument echoes insights provided by the literature on parallel search in research and development projects (Abernathy &

Rosenbloom, 1969; Childs & Triantis, 1999; Krishnan & Ulrich, 2001; Nelson, 1961). These studies have compared the 'classic' sequential project selection model to a parallel search approach. In the sequential model, firms bet all resources on one 'best evidence' R&D project and only consider alternative projects if the initial investments have proven unsuccessful. However, in the face of significant uncertainty – e.g., when the project concerns novel, cutting-edge technologies and the competitive environment forces short development cycles – such a sequential strategy is risky. Sequential evaluation of approaches means that firms lose costly time and resources by investing in new projects only after earlier projects have failed.

Alternatively, under technological uncertainty, a firm can benefit from investment in a portfolio of parallel R&D projects. This way, the firm avoids the risks of a priori decision making about uncertain R&D projects. Instead of picking an early winner and so potentially cutting off promising alternative options, 'parallelism' generates information about the future value of a broader range of products and technologies. Nelson (1961) demonstrated that a parallel investment approach can be cost effective in the long run because it generates an investment decision that is based on more information while, as compared with the later stages of an innovation trajectory, the costs of R&D are still relatively low.

The benefits typically attributed to a portfolio of internal R&D projects (Abernathy & Rosenbloom, 1969) – e.g., long run cost efficiency, information gains, hedging against the risk of individual project failure, generating competing perspectives on novel technologies, and boosting technological competencies – are also relevant for a portfolio of external R&D partnerships. Therefore, convergent with the literatures on parallel search and R&D partnership portfolios, we develop the argument that a portfolio of parallel R&D partnerships will directly help innovating firms gather the requisite technological knowledge to counter technological uncertainty. In particular, we first focus on the effects of portfolio size and composition – i.e., the mix of novel and repeat partners – on the amount of technological knowledge a firm draws from its R&D partners. Second, we argue that these direct effects vary with the level of technological uncertainty within an R&D partnership portfolio.

Portfolio Size

A key premise of the literature on parallel search is that increases in the number of parallel projects generate informational benefits that help firms make better technology-related investment decisions (Nelson, 1961). As Helper, MacDuffie, and Sabel (2000: 471) argue, "the experience of firms in technologically sophisticated industries with extremely short product life cycles shows (…) that pursuit of many alternatives is the best way of understanding the advantages and disadvantages of each, and so contributes to selection of the best current possibilities." Within the R&D partnership literature, some results are consistent with this premise. For example, Ahuja (2000), Powell et al. (1999), and Soh (2003) show correlations between a firm's number of simultaneous R&D partnerships and their patenting and new product performance. In general, firms with a portfolio of R&D partnerships have access to more external technological knowledge, which helps them to improve their estimates of potentially valuable technologies. Such firms will also develop capabilities to learn from a range of partners, which decreases the likelihood that they fail to locate relevant technological knowledge and in turn increases their ability to compare the value of divergent bits of knowledge (Powell et al., 1996).

However, beyond an optimum number of parallel partnerships, added costs should start to outweigh any portfolio benefits (cf. Nelson, 1961: 356-357). If so, then the marginal effect of additional R&D partnerships decreases, and perhaps becomes negative, with an increase in the size of a portfolio. Firms will enter the most promising partnerships first and so the amount of relevant information drawn from additional partners, and the concomitant potential for uncertainty reduction, should gradually decrease (Rothaermel & Deeds, 2006). Moreover, increasing the size of a portfolio increases burdens on their management and monitoring (Deeds & Hill, 1996). Beyond a certain portfolio size, additional R&D partnerships generate an overexposure to information, which in turn increases the cognitive strain on those responsible for inspecting and monitoring such partnerships. Together, these arguments suggest that initial increases in portfolio size increase the inflow of technological knowledge but only up to a point. Beyond an optimum portfolio size, the inflow of technological knowledge gradually decreases.

Hypothesis 1. The inward flow of technological knowledge from a firm's R&D partners first incr*eases and then decreases with the size of the firm's R&D partnership portfolio.*

Portfolio Composition: Combining Novel and Repeat Partners

Apart from the size of an R&D partnership portfolio, its composition in terms of the mix of novel and repeat partners may also influence inward flows of technological knowledge (e.g., Wuyts et al., 2004). In uncertain environments, firms tend to engage in partnerships with firms they have collaborated with before (Gulati 1995). Such repeat collaboration promotes the development of cooperative routines, especially in the area of R&D in which tacit knowledge sharing requires rich interactions among the personnel of the sponsoring firms (Hoang & Rothaermel, 2005; Zollo, Reuer, & Singh, 2002). Thus, the inflow of technological knowledge from R&D partners increases with repeat collaboration.

Although repeat collaboration might initially increase knowledge inflows into the focal firm, there may be decreasing marginal returns to repeated engagements with prior partners. For example, Gulati (1995) shows that the relation between prior partnerships and future partnership formation at the dyad level is an inverted U-shaped one and Hoang and Rothaermel (2005) suggested an inverted U-shaped relationship between repeat partnerships and alliance success. Beyond a certain threshold, additional information benefits of repeat partnerships may thus dry up. Indeed, Hagedoorn and Frankort (2008) indicated that during the 1990s, IBM's extensive

R&D partnerships with firms like Apple, Siemens, Toshiba, and HP appeared to have eventually exhausted opportunities for interfirm learning. This led IBM to engage in partnerships with a new set of firms that had not featured prominently in its R&D partnership portfolio before. Hence, an overdependence on prior partners ultimately eliminates further information benefits.

In high tech industries characterized by continual exit and entry of firms, useful sources for novel perspectives are unlikely to reside infinitely within a firm's group of repeat partners. Consequently, cooperation with R&D partners that have no prior partnerships to the firm provides welcome access to novel technological perspectives (Lavie & Rosenkopf, 2006). Novel partners enrich the opportunity set a firm faces versus its competition, which allows the firm to reduce technological uncertainty and increase its prospects for promising technologies.

At the portfolio level, these arguments imply that though repeat partnerships are valuable due to increasingly fine-grained information sharing, novel partnerships are valuable as they infuse the firm with new information with higher marginal benefits. Hence, a firm maintaining a portfolio with both repeat partners and novel ones balances the informational benefits of relational routines with higher marginal returns of information drawn from novel partners. Repeat partnerships would predominantly deepen a firm's technological understanding, while novel partnerships would instead enrich the focal firms' perspectives on new technologies (Lavie & Rosenkopf 2006). As excessive depth would ultimately lock a firm into one technological direction and excessive breadth would challenge the cognitive abilities of a firm to make sense of disparate bits of technological knowledge, R&D partnership portfolios that mix novel and repeat partners should generate the largest inflow of technological knowledge. Thus, the share of novel partners in a portfolio will have an inverted U-shaped effect on inward knowledge flows.[1]

> Hypothesis 2. The inward flow of technological knowledge *from a firm's partners* first increases and then decreases with the share of novel partners in the *firm's R&D* partnership portfolio.

Research versus Development Focus: the Contingency of Technological Uncertainty

The level of technological uncertainty is a key factor that determines the value of a parallel R&D approach and it varies across the different stages of the innovation process (Abernathy & Rosenbloom, 1969; Nelson, 1961; Wheelwright & Clark, 1992). Specifically, it should decrease over time (Roberts & Weitzman, 1981). Consequently, we expect to observe differences between, on the one hand, firms that focus on early-stage experimental, basic or applied research projects within their R&D partnership portfolios and, on the other hand, firms that focus more on partnerships aimed at the further development and refinement of existing technologies.

Early-stage experimental and applied research is rife with uncertainties. Firms face many technological options and, therefore, many different directions for potential research projects (Freeman & Soete, 1997; Nelson, 1961, 1982). Across these options, the information availability ranges from no information to crude ideas about various technological attributes and their relation to economic payoffs. The sequencing of research steps is unclear ex ante as means-ends connections await establishment and concrete performance information is lacking (Van de Ven & Polley, 1992). Behavioral tendencies of key R&D managers further aggravate the uncertainty because of incentives to over-estimate the rates of return to favored technological paths (Freeman & Soete, 1997). Therefore, even although decision makers may have crude estimates about the merits of several potential research projects early on, these estimates are often highly unreliable. In short, a priori decision making about which research projects to pursue is a misfortune if unreliable estimates can only improve ex post, i.e. during the actual project when additional information has been gathered (Roberts & Weitzman, 1981).

In contrast, development projects are far less uncertain in technological terms because they often start from a set of decisions about which technologies will be developed to commercial ends. These decisions in turn define stricter boundary conditions within which a firm will expend further efforts. During development, firms work increasingly towards the implementation of innovations and, eventually, the introduction of new products and processes. Prior technological choices thus lock firms into development trajectories that become more proprietary and firm specific over time.

With the distinction in mind between research and development, we expect that a portfolio of parallel R&D partnerships is most useful if the partnerships in such a portfolio focus strongly on basic and applied research. A portfolio of parallel R&D partnerships geared towards performing joint research, rather than development, will increase the reliability of estimates of total effort, time-line, costs, and performance prospects of the various technological options, before firms make irreversible investments in downstream development. Over time, firms in turn weed out the options with poor prospects and continue to develop the most promising ones. In line with Nelson (1961), we expect that the parallel pursuit of a number of joint R&D projects gravitating towards joint research is effective to hedge against potentially inaccurate decisions when firms' knowledge about the future is fuzzy.

Because the early stages of research are notoriously uncertain, they offer the clearest motivation for uncertainty reduction. For two reasons, they also seem to offer the best opportunities to reduce uncertainty. First, early-stage basic and applied research has fewer immediate implications for interfirm rivalry in downstream product markets than more close-to commercial activities such as the development and commercialization of concrete technologies, products, or processes (Harrigan 2003 [1985]: 380). Firms thus tend to be more open and perceptive to external knowledge sources during the early stages of research, whereas towards development, firms become increasingly secretive (Faems, Janssens, & Van Looy, 2007).

The second opportunity factor is cost related. The early stage of an R&D effort tends to be significantly less costly than the later stage of an R&D effort. Parallel efforts early in a research trajectory therefore reduce uncertainty in a cost-effective way. For example, data on US industrial R&D expenditures compiled by the US National Science Foundation show that, during the period 1975-1999, only 23 to 31% of firms' total R&D costs related to basic and applied research, whereas roughly 70 to 80% was dedicated to development activities (National Science Foundation, 2006: table 32). Similarly, Freeman and Soete (1997) indicate that the costs of basic and applied research are comparatively low in relation to the total costs of an innovation trajectory. A range of additional activities related to development, such as engineering, prototyping, and design, create major expenses at the later stages of the innovation process.

To summarize, uncertainty reduction through an R&D partnership portfolio should be more effective when uncertainty is higher and so the knowledge-gathering effect of a portfolio of parallel R&D partnerships will be more positive when the portfolio focuses mainly on research rather than development. As in Nelson's (1961: 356-357) model, the marginal benefit of an additional partnership, and the optimum number of projects to run in parallel, will thus be greater when the learning potential is greater. Hence, with increased research focus, the positive slope of the portfolio size effect (Hypothesis 1) will be steeper and the inflection point beyond which additional R&D partnerships have a negative impact will shift to the right. Empirical corroboration of these arguments would support descriptive work by Hagedoorn (1993), suggesting that firms in high tech environments often decrease technological uncertainties through a range of research-focused interfirm partnerships.[2]

Hypothesis 3. The research focus of a firm's R&D partnership portfolio positively moderates the curvilinear relationship between portfolio size and knowledge inflows, such that increasing research focus will increase the portfolio size that maximizes knowledge inflows.

The research focus of a firm's R&D partnership portfolio may also alter the effect that the partner mix within a portfolio has on inward knowledge flows. Early-stage experimental and applied research is rife with uncertainties and requires the combination and recombination of bits of knowledge that are implicit, poorly objectified, and embedded within the context of individual firms (Kogut & Zander 1992; Van de Ven & Polley, 1992). Recognizing, identifying, and understanding the value of such knowledge will require significant efforts and so the more firms can rely on a basic, pre-established, understanding of their partners, the more they can mitigate any potential information-gathering problems (Kale, Singh, & Perlmutter, 2000; Simonin, 1999; Zollo et al., 2002). This understanding is significantly greater when firms have collaborated before and so in a research-focused portfolio, firms should benefit more from a reliance on pre-established routines shared with repeat partners.

A portfolio with fewer novel partners admittedly loses some of its absolute knowledge gathering benefits because the marginal value of knowledge held by novel partners tends to be higher than that of repeat partners. Nevertheless, this knowledge is less useful if the focal firm cannot recognize, identify, and understand it, for example because it is implicit and poorly objectified (Simonin, 1999).

By this logic, the marginal benefit of an additional novel partner, and the optimum number of novel partners, will thus be lower when technological uncertainty is greater. Hence, with increased research focus, the positive slope of the portfolio novelty effect (Hypothesis 2) will be flatter and the inflection point beyond which additional novel partners have a negative impact will shift to the left. Thus, knowledge gathering in a research-focused portfolio peaks at a lower (higher) share of novel (repeat) R&D partners, and its peak reaches a lower level, than knowledge gathering in a development-focused portfolio.

> Hypothesis 4. *The research focus of a firm's R&D partnership portfolio negatively* moderates the curvilinear relationship between the share of novel partners and knowledge inflows, such that increasing research focus will decrease the share of novel partners that maximizes knowledge inflows.

From a knowledge-gathering perspective, these contingency hypotheses suggest that an optimal research-focused R&D partnership portfolio is larger, and its share of novel partners smaller, than an optimal development-focused portfolio. Crucially, these hypotheses assume constant the governance of the R&D partnerships in the portfolio.[3] Transaction cost economics research (e.g., Oxley, 1997) has argued and shown that when technology is difficult to specify and uncertain, firms often choose more hierarchical governance modes to govern their partnerships. If a greater research focus in a firm's R&D partnership portfolio reflects greater uncertainty (Roberts & Weitzman, 1981), then appropriability hazards should be greater and so a larger share of the R&D partnerships in the portfolio should be equity based, ceteris paribus.[4] To account for such transaction cost concerns in our empirical analysis, we hold constant partnership governance (equity versus nonequity partnerships), which is widely recognized as an important 'cure' for transaction costs associated with transactional uncertainty (Mowery et al., 1996; Oxley, 1997).

METHOD

Data

We use data from a database developed by researchers from Brandeis University and Maastricht University (see Gomes-Casseres et al., 2006). This database contains data on R&D partnerships, patents and patent citations in the IT industry for the period 1975-1999. For the current paper, we added information from CATI, Osiris, Datastream, and firms' annual reports. The Brandeis-Maastricht database is a merger of parts of the CATI database on R&D partnerships (Hagedoorn, 2002), the NBER patent data file (Hall, Jaffe, & Trajtenberg, 2002), and Standard & Poor's COMPUSTAT database. CATI contains detailed information on interfirm R&D partnerships starting in 1960, including partner identities, organizational form, and other specifics of the partnerships. The NBER patent data file contains detailed information on all utility patents granted by the USPTO since 1963, the citations among them (1975-2002), and information about inventors and firms. COMPUSTAT contains a wide range of firm-level financial variables.

IT includes segments such as computers, semiconductors, and communications, corresponding to patent classes for communications, computer hardware and software, computer peripherals, information storage and semiconductor devices (patent class subcategories 21-24 and 46 in Hall et al. 2002). We use two rules sequentially for including firms in our estimation sample. First, a firm is included if it had at least one patent in patent classes for communications, computer hardware and software, computer peripherals, information storage and semiconductor devices in 1975-1999. Second, of the selected firms we include only those that had at least one R&D partnership in IT, devised to perform joint R&D and/or joint technology development. These two rules ensure that firms in the sample are, at a minimum, at risk of citing (or being cited by) a partner. The partnership/patent sample contains 152 firms, organized as an unbalanced panel of 1,836 firm-years.

The longitudinal nature of our data necessarily leads to missing values for some of the key control variables. We include only those firm-years for which both firm- and partner-specific data are complete and delete others listwise. In addition, the lagging of independent variables and restrictions imposed by the count data models discard additional firm-year records from the analyses. Taken together, these steps lead to an effective sample size of 1,030 firm-years. Below, we probe the sensitivity of the analyses to this reduction in sample size. Further, our design might raise concerns of left censoring because some firms were already in business prior to our sampling window. However, the sample firms' R&D partnership activity prior to 1975 was negligible. In fact, R&D partnering did not take serious shape until the second half of the eighties, although the IT industry took an early lead (Hagedoorn, 2002).

Dependent Variable

Following work by Gomes-Casseres et al. (2006), Mowery et al. (1996), Rosenkopf and Almeida

(2003), we use patent citations to proxy the inflows of technological knowledge from a firm's R&D partners. Patent citations indicate that existing patents, representing 'prior art', were relevant for a new patent and, therefore, they likely represent the flow of knowledge between the citing and cited party. Some survey-based results indeed indicate that the flow of technological knowledge between actors is significantly larger when they cite each other's patents (Duguet & MacGarvie, 2005; Jaffe, Trajtenberg, & Fogarty, 2000). Jaffe et al. (2000) concluded that aggregated, actor-centric citation measures are reasonable proxies for the intensity of knowledge flow between actors.

We recognize that patents embody codified knowledge, whereas much of the technological knowledge in the innovation process is tacit (Appleyard, 1996). Yet, tracing tacit knowledge empirically is nearly impossible, especially given our longitudinal design. Instead, we align with Almeida et al. (2002: 152), Mowery et al. (1996: 83), and Patel and Pavitt (1997: 143) and assume that flows of codified and tacit knowledge are closely related and complementary. We thus abstract from the codified-tacit distinction and use the pattern of citations between firms' patents to identify the magnitude of inflows of technological knowledge.

Nevertheless, some recent work has called for caution when using patent citations to proxy flows of technological knowledge (Alcácer & Gittelman, 2006). For instance, part of the citations on a patent may be 'strategic', to avoid litigation only. More importantly, however, patent examiners or a firm's lawyers might add citations to the patent that the inventors were not aware of themselves. Only since the 2001 change in U.S. patent reporting do patents contain a separate listing of inventor- and examiner-inserted citations. Our sampling period (1975-1999) thus precludes the use of a more fine-grained proxy.

Despite these potential issues, we have five reasons to expect that patent citations are useful in our analyses of technological knowledge flows in the context of interfirm R&D partnerships.

First, interfirm R&D partnerships serve as embedded mechanisms in which people intervene to transfer technological knowledge (Autant-Bernard, 2001; Singh, 2005). As such, cooperating firms are most likely cognizant of partners' relevant lines of research and pending patents. Second, violating a partner's interests by wittingly excluding citations may harm a firm's reputation as a trustworthy partner and, hence, restrict future cooperative possibilities. To illustrate, Harrigan (2003 [1985]: 342) drew from in-depth field studies of interfirm R&D partnerships to conclude that "…if a trusted partner chose to betray its partner by pirating intellectual property, word went out in the industry." Third, to protect its interests a firm has an incentive to monitor the applications of its partners and, if necessary, suggest citations to its own patents. Fourth, we have no reason to expect that examiners pattern their interventions on characteristics of an applicant's R&D partnership portfolio. Hence, in our setting, examiner-inserted citations should only add noise to the knowledge flow measures, without systematically (dis-)favoring particular firms. Finally, examiner-inserted citations appear especially troublesome for analyzing self-citations (Alcácer & Gittelman, 2006), which are beyond our theoretical and empirical focus.

Besides these five reasons, we also cover a period in which the use of R&D partnerships flourished (Hagedoorn, 2002), generating important cross-sectional and longitudinal variation. Given the large number of patents and citations in our data, we expect that annual firm-level citation counts reveal a meaningful signal about the magnitude and direction of technological knowledge flows between partnered firms. We define Inward knowledge flows as the aggregate annual number of patent citations made by the focal firm to patents of its R&D partners. To evade simultaneity, this dependent variable takes a one-year lead to the independent variables and control variables.

Independent Variables

Portfolio size is the count of R&D partnerships a firm maintains in t. To test hypothesis 1, we include in our models both a monotonic and squared portfolio size term. To test hypothesis 3, we interact portfolio size with our measure for portfolio research focus.

We measure Portfolio novelty as a firm's share of partners in t that it has never collaborated with before. This measure ranges between 0 and 1 and a higher value indicates that a firm maintains more partnerships with firms it has never previously collaborated with. For example, a value of 0.4 means that 40% of all of a firm's R&D partners are novel to the firm and the other 60% are repeat partners. To test hypothesis 2, we include in our models both a monotonic and squared portfolio novelty term. To test hypothesis 4, we interact portfolio novelty with our measure for portfolio research focus. Our findings are robust to treating as novel those partners that a firm has not otherwise collaborated with in the past five years (rather than ever).

Whereas much prior work has distinguished R&D partnerships from a variety of other partnership types such as second-sourcing deals, marketing, licensing, royalty and sales agreements (e.g., Lavie, 2007; Lavie, Kang, & Rosenkopf, 2011), we identify an R&D partnership's research focus (we split the R from the D). Convergent with OECD guidelines for distinguishing types of R&D (OECD, 2002: 77-82), we distinguish partnerships that focus on basic and applied research on the one hand from those focusing on development activities on the other. We exploit the granular categorical information about the cooperative forms of the partnerships contained in CATI. In particular, we consider partnerships that fall into one of four categories: (1) joint research pacts, (2) joint development agreements, (3) joint ventures, and (4) research corporations. Categories (1) and (4) unambiguously indicate a focus on basic and applied research. Category (2) unambiguously indicates a focus on development. However, category (3) is ambiguous. For example, detailed inspection of partnership announcements reveals that this category contains partnerships that may focus on either research or development. Therefore, we label partnerships in category (3) as research focused only if the public announcement clearly indicated that the partnership focuses on basic and/or applied research activities rather than the development of existing technologies.

To summarize, we code a partnership as research focused if it is a joint research pact, a research corporation, or if it is a joint venture with an explicit focus on research. Using this dyad-level coding, we calculate Portfolio research focus as a firm's share of partnerships with a distinctive research focus in t. To test hypothesis 3, we evaluate the interaction between portfolio size and portfolio research focus. To test hypothesis 4, we evaluate the interaction between portfolio novelty and portfolio research focus.[5]

Control Variables

We test our hypotheses net of a rich control model of knowledge inflows. This model reflects that knowledge inflows are a function of firm, partner, and portfolio properties (Greve, 2005; Kalaignanam, Shankar, & Varadarajan, 2007) and we include a full set of year dummies (1975-1998, omitting 1999) that capture unobserved temporal effects.

Firm controls. Size is the logarithm of a firm's total sales in t (using values in millions of U.S. dollars). We control for firm size as larger firms tend to have more financial and managerial resources, and more partnerships than smaller ones. This in turn influences their investments and attractiveness for cooperation in R&D partnerships. We define the variable Profitability as the ratio of a firm's operating income to its sales in t. A firm's profitability possibly signals that it successfully commercialized new technologies. In addition, the firm can use profits to invest in new technological activities.

To control for the confounding effects of innovativeness, we include the variable R&D intensity as the ratio of a firm's R&D spending to its sales in t. A firm's innovativeness likely reflects its absorptive capacity (Cohen & Levinthal, 1990), which should ease the assimilation of externally generated technological knowledge. In addition, increases in firms' technological inputs broaden the scope for complementarities to exploit, which may lead to the formation of additional partnerships (Cassiman & Veugelers, 2002). Patent stock measures the size of a firm's patent stock in t. To control for a firm's overall patent citing activity, we include Total citations made, indexing the total number of patent citations made by the focal firm in a given year. Because any unobserved, time varying, factors would be manifest in the total number of citations a firm makes to others' patents, these factors should not confound our analysis and so this control helps us to rule out a number of time-varying sources of unobserved heterogeneity.

We include the variable Partnering experience that measures the count of R&D partnerships a firm has entered by t. Evolutionary theory states that a firm's past pursuit of technological knowledge is important for new searches (Nelson & Winter, 1982). Hence, a firm's partnering experience may ease the search for knowledge. Further, recent work reveals that more experienced firms may develop a dedicated alliance management function, which would enable the coordination of collaborative activities across a portfolio of partnerships (Heimeriks, Duysters, & Vanhaverbeke, 2007; Sarkar, Aulakh, & Madhok, 2009).

Partner controls. We include a number of partner-specific measures that capture their potential value as sources of knowledge. Size is the mean value of partners' logged sales in t. Profitability is the mean value of partners' operating income divided by sales in t. R&D intensity is the mean value of partners' R&D spending divided by sales in t. Patent stock is the mean value of the size of partners' patent stock in t. Finally, to control for partners' overall numbers of patent citations received, we include Total citations received as the mean value of the total number of patent citations received by the patents of a firm's partners in t.

Portfolio controls. Bilateral competition is a firm's proportion of partners active in its own primary 3-digit SIC in t. Firms that cooperate in IT may nevertheless compete in product markets

(Mowery et al., 1996). We thus control for the extent to which partners are active in primary product markets identical to the focal firm (Lavie, 2007). To account for the effects of equity partnerships on technological knowledge flows (Almeida et al., 2002; Mowery et al., 1996), we include the variable Equity partnerships as a firm's share of equity-based partnerships. This variable is bounded by 0 and 1, and a value closer to 1 indicates a higher share of equity-based partnerships. We control for geographic explanations of technological knowledge flows and include the variable Regional concentration, which is the proportion of a firm's partners in its home region. This variable ranges from 0 to 1, and a value closer to 1 indicates a higher share of intraregional partnerships. We use the home country of a firm's headquarters to classify firms in one of four regions: the United States, Europe, Japan, and Other regions.

Statistical Method

Our statistical model allows us to obtain estimates of the determinants of the amount of partnership-related knowledge flowing into firm i in year t+1, K_{it+1}. Specifically:

$$E(K_{it+1} \mid X_{it}, C_{it}, \alpha_t, \delta_i) \propto \exp[\beta_X X_{it} + \beta_C C_{it} + \beta_\alpha \alpha_t + \delta_i] ,$$

where X_{it} is a time-varying vector of independent variables, and their interactions, characterizing firm i; C_{it} is a time-varying vector of control variables characterizing firm i; α_t is a vector of year dummies; and δ_i represents unobserved time-invariant firm effects not captured by the independent and control variables. We use a conditional fixed effects negative binomial specification to estimate this model (Hausman, Hall, & Griliches, 1984), which accommodates the discrete, nonnegative, and overdispersed nature of the dependent variable. Further, it partials out time-invariant unobserved firm heterogeneity by conditioning on firms' total partnership-related inward knowledge flows during the sampling window (Hausman et al., 1984: 923-924). Though this conditioning procedure drops firms for which the dependent variable is zero in the entire sampling period, the estimates are unbiased and consistent (for the proof, see Hausman et al., 1984: 935). Though we also estimated random effects negative binomial models, Hausman (1978) specification tests consistently indicated that the use of random effects specifications would have generated parameter inconsistencies. These inconsistencies are due to correlations between unobserved firm effects and the covariate matrices, providing prima facie evidence for persistent differences between the sample firms. We therefore report results based on fixed effects specifications that produce firm-specific intercepts.

RESULTS

Tables 1 and 2 show descriptive statistics and bivariate correlations. Most correlation coefficients are low in magnitude, though a few are somewhat higher (> .80). Unreported analyses indicated that all variance inflation factors had a value less than 10. To address the potential impact of multicollinearity on the standard errors of the estimates of our key independent variables, we centered these variables on their means prior to calculation of the squared and interaction terms. An average of 16% of firms' R&D partnerships was research focused, which mirrors R&D data provided by the National Science Foundation (NSF 2006: table 32), showing that U.S. firms spent about 20 to 30% of their full R&D budget on basic and applied research during 1975-1999.

--- Insert tables 1, 2, and 3 about here ---

Table 3 shows our findings regarding inward knowledge flows. The control variables show some persistent results. Inward knowledge flows increase with firm size, indicating that larger firms attract more knowledge. In addition, a firm's total citations made correlates positively with inward knowledge flows. Partnering experience also generally increases inward knowledge flows. A firm's profitability, R&D intensity, and patent stock have no significant effects on inward knowledge flows. Of the partner controls, only the size of partners' patent stock affects inward knowledge flows, which perhaps indicates that the other partner controls may matter more at the level of individual partnerships rather than in the aggregate. These results thus suggest that the most important partner-level factor affecting inward knowledge flows is the mere size of the citable stock of knowledge within a firm's R&D partnership portfolio.

Inward knowledge flows increase with the share of equity partnerships in a portfolio, confirming previous findings by Mowery et al. (1996), who show that knowledge flows are greater in equity partnerships. Finally, firms with a high proportion of partners in their home region experience lower inward knowledge flows. This surprising yet consistent finding may reflect that firms' choice of foreign partners is endogenous to expected knowledge flows, which in turn explains why firms that do have international partners face fewer difficulties in attracting knowledge (Lavie & Miller, 2008). Moreover, Peri (2005) shows that technological knowledge in especially the computer sector flows significantly farther internationally than in a number of other sectors.

Hypotheses

In support of hypothesis 1, models 2-6 show a positive and significant main effect, and a negative and significant squared effect, for portfolio size. Models 3, 5, and 6 show a positive and significant main effect, and a negative and significant squared effect, for portfolio novelty, which supports hypothesis 2. Models 4 and 6 show that the interaction between portfolio size and portfolio research focus is significant and positive, in line with hypothesis 3. Figure 1 shows this contingency effect. When a firm focuses its portfolio on development rather than research (i.e., portfolio research focus = 0), the multiplier of inward knowledge flows peaks around a portfolio size of 11, with a multiplier of 1.47 (=exp[0.068*11-0.003*11*11+0.074*11*0]). Yet, when a firm focuses its portfolio on research rather than development (i.e., portfolio research focus = 1), the multiplier of inward knowledge flows peaks around a portfolio size of 24, with a much larger multiplier of 5.37 (=exp[0.068*24-0.003*24*24+0.074*24*1]). Thus, convergent with our theory, parallel partnerships are significantly more valuable for knowledge inflows when the focus of these partnerships is on research rather than development.

--- Insert figures 1 and 2 about here ---

Models 5 and 6 show that the interaction between portfolio novelty and portfolio research focus is significant and negative, in line with hypothesis 4. Figure 2 shows this contingency effect. When a firm focuses its portfolio on development rather than research (i.e., portfolio research focus = 0), the multiplier of inward knowledge flows peaks when the share of novel partners is around 0.5, with a multiplier of 1.37 (=exp[1.291*0.5-1.315*0.5*0.5-0.617*0.5*0]). Yet, when a firm focuses its portfolio on research rather than development (i.e., portfolio research focus = 1), the multiplier of inward knowledge flows peaks when the share of novel partners is around 0.3, with a much smaller multiplier of 1.09 (=exp[1.291*0.3-1.315*0.3*0.3-0.617*0.3*1]). Thus, in line with our theory, the effect of portfolio novelty is less positive when the portfolio focuses on research rather than development.

Robustness Checks

First, as with any model relating interorganizational design to outcomes, endogeneity may affect our estimates (Bascle, 2008). Specifically, knowledge inflows may systematically condition firms' R&D partnership formation. Nevertheless, a generalized Durbin-Wu-Hausman χ^2-test (Davidson & MacKinnon, 1993: 237-240) failed to reject the null hypothesis that the fixed effects negative binomial coefficients for the three potentially endogenous partnership variables of interest (i.e. portfolio size, portfolio research focus, and portfolio novelty) were consistent. As only statistical proof of coefficient inconsistency would suggest endogeneity issues, we are confident that endogeneity has not materially affected our empirical estimates. This finding perhaps indicates that accounting for unobserved heterogeneity has reduced systematic endogeneity to random fluctuations (Heckman, 1979), that there is no feedback, or that knowledge inflows affect R&D partnership formation in multiple ways, resulting in an overall insignificant effect.[6]

Second, we generated alternative estimates to further rule out the influence of unobserved heterogeneity. In the spirit of Blundell, Griffith, and Van Reenen (1995) and Blundell, Griffith, and Windmeijer (2002), we added firms' pre-sample history of knowledge inflows to the conditional fixed effects models in table 3. The rationale for pre-sample fixed effects is that any firm-specific dispositional differences should be manifest in firms' knowledge inflows prior to the study period, making a measure capturing such pre-sample inflows a suitable index of persistent unobserved firm differences. With this additional control complementing the conditional fixed effects estimator, the original results remained identical.[7]

Alternatively, we estimated an unconditional fixed effects negative binomial model – i.e., a cross-sectional negative binomial model with dummies for firms. As Allison and Waterman (2002: 250-252, 255-256) argue, because Hausman et al.'s (1984: 922) parameterization of the negative binomial distribution may not eliminate all time-invariant firm effects, an unconditional estimator should be preferred. Rather than eliminating them from the likelihood function, this estimator captures firm fixed effects through firm dummies. Admittedly inefficient, the unconditional estimator nevertheless generated coefficients and significance levels that were broadly identical to the ones presented in table 3. Together, these two alternative specifications further increase our confidence in the results, as the coefficients of interest are unlikely to be systematic shadows of unobserved firm heterogeneity.

Finally, we investigated if the results were sensitive to the reduction in effective sample size due to missing values. We first ran the complete models excluding the controls with missing values. This increased the effective sample size to 1,322 firm-years. Though none of the coefficients changed direction, previously insignificant effects turned significant, suggesting the importance of the omitted controls. Thus, we probed this issue further because missing values would bias our estimates if they occurred non-randomly. We tested for this potential selection bias by estimating a two-stage selection model (Allison, 2001: 79-81; Heckman, 1979). In the first stage, we estimated the probability of non-missing values in the full panel using robust probit regression. In the second stage, we estimated the full model including the inverse Mills ratio based on the first-stage probit estimates to correct for the probability of non-missing values. Results remained identical, indicating missing values did not bias our parameter estimates.

DISCUSSION AND CONCLUSION

In this paper, we explored how a firm's R&D partnership portfolio affected inward flows of technological knowledge from its partners. We linked research on parallel search and joint R&D to show that the size of a firm's R&D partnership portfolio and its share of novel partners both have an inverted U-shaped effect on the inflow of technological knowledge from the firm's R&D partners. In addition, we showed that these direct effects vary as a function of the level of technological uncertainty within the portfolio. Together, these findings reveal the value of invoking a portfolio perspective to study knowledge flows in interfirm R&D partnerships.

We wish to emphasize two broad contributions. First, our focus on the amount of knowledge a firm gathers from its R&D partners helps us move beyond conclusions about portfolios and knowledge flows deriving from studies connecting partnership portfolios to innovative outputs or those connecting partnership dyads to knowledge flows. Direct attention to knowledge flows as the mechanism connecting R&D partnership portfolios to performance is an important step to bridge the gap between theory on knowledge flows in R&D partnership portfolios and available empirical evidence. Results show that a firm achieves the greatest knowledge inflows with a portfolio of intermediate size and with a balanced mix of novel and repeat partners. The portfolio size result strongly mirrors early research on parallel R&D within firms (Nelson, 1961), suggesting the existence of an optimum portfolio size. While small portfolios do not sufficiently allow for uncertainty reduction through knowledge gathering, those that are too large will provide less useful information and increase burdens on their management.

The result regarding the mix of novel and repeat partners suggests that neither a sole reliance on repeat partners, nor a sole reliance on novel partners leads to the greatest inflow of knowledge in a high tech environment where both firm-specific and industry-level uncertainties blur innovation-related decisions. Though repeat partnering allows a firm to benefit from relational routines that may ease the exchange of technological knowledge, novel partners are likely to carry information with a higher marginal value. Thus, a balanced portfolio should optimally combine the benefits of relational routines with higher marginal returns of information drawn from novel partners. In addition, this finding suggests that an R&D portfolio may serve as an integrating mechanism joining novel and extant knowledge. This is similar to Katila and Ahuja (2002), who suggest that useful innovations emerge in particular when an integrating mechanism joins extant and novel perspectives. We think further study of the integrating capability that appears endogenous to firms' R&D partnership portfolio activities is warranted.

At a more general level, our portfolio perspective on knowledge inflows aligns with recent interest among scholars and practitioners, who increasingly note that partnership portfolios represent an important level of analysis, above and beyond individual partnerships (Bamford & Ernst, 2002; Gulati, 2007; Hoffmann, 2007; Lavie, 2007; Mahnke, Overby, & Nielsen, 2006; Munson & Spivey, 2006; Parise & Sasson, 2002; Wassmer, 2010; Wassmer, Dussauge, & Planellas, 2010). Like internal project portfolios, external partnership portfolios exhibit aggregate compositional properties with crucial implications for understanding firm behavior and performance. Our findings suggest that interfirm knowledge flows can be usefully analyzed and understood when cast as a function of portfolio characteristics like size and partner mix.

The second, and related, contribution concerns our theoretical and empirical treatment of technological uncertainty as a contingency to the relationship between R&D partnership portfolios and knowledge inflows. Consistent with early work on parallel R&D within firms (Abernathy & Rosenbloom, 1969; Nelson, 1961), we find that when firms focus their joint R&D activities on basic and applied research rather than development, the optimum portfolio size, and the absolute amount of knowledge to be gathered, becomes significantly larger. Thus, parallel R&D projects are significantly more beneficial for knowledge gathering in the research stages of innovation projects, when technological uncertainty is greatest.

Moreover, beyond affecting the knowledge gathering effect of portfolio size, technological uncertainty also affects the relationship between the portfolio's partner mix and knowledge inflows. Our findings robustly reveal that knowledge gathering in a research-focused portfolio peaks at a lower share of novel R&D partners than knowledge gathering in a development-focused portfolio. In the face of greater technological uncertainty typical for a research-focused portfolio, firms thus benefit more from pre-established routines because they help mitigate information-gathering problems. In addition, the higher marginal value of information potentially drawn from novel partners is less relevant when technological uncertainty makes that information particularly hard to recognize, identify, and understand (Simonin, 1999).

More broadly, our contingency perspective contributes to recent work on alliance networks and portfolios (e.g., Gilsing et al., 2008; Lavie et al., 2011; Rowley, Behrens, & Krackhardt, 2000), which shows that the performance consequences of firms' embeddedness within a network of partnerships vary with the types of projects comprising those portfolios. These studies test the broader idea that the heterogeneity of projects within a firm's portfolio of partnerships, or across portfolios of different firms, will have implications for optimal portfolio design. In our case, the optimal portfolio for highly uncertain, early-stage basic and applied research differs from the portfolio optimal for less uncertain development projects. We believe that the focus on task contingencies (here, research versus development) within recent work has the potential to generate insight into the functioning of partnership portfolios with much closer applicability in practice than unifying approaches arguing for one optimal portfolio design.

To test our contingency hypotheses, we used granular information drawn from partnership announcements to identify the research versus development focus of the R&D partnerships in our sample. Though each individual partnership represents specific technological problems that are not necessarily captured by our research-development dichotomy, we believe that decomposing R&D partnerships into joint research and joint development is an important step to arrive at a more fine-grained understanding of portfolio effects in firms' external R&D partnership activities. Admittedly posing a research challenge when announcement data are scarce or dubious, we hope that our first look here spurs further study.

Our study does not come without some caveats that might encourage further study beyond the above suggestions. First, measuring technological knowledge flows using patent citations has well-known shortcomings. Despite recent changes enabling the isolation of examiner-added citations, some degree of noise to the information caught in patent citations will remain. Alternative measures with less noise may be found outside the realm of patents. Obviously, standard single-respondent-per-firm survey research runs the risk of single respondent, common methods bias, in particular when it concerns technological knowledge flows for firms with vast R&D resources and multiple R&D units and innovation centers. Although multiple-respondent-per-firm survey research could provide some additional insights, the cost of such research is significant. Nevertheless, for science-based industries such as IT, a combination of patent citations and bibliometric research on joint publications and scientific citations might reveal additional and more in-depth understanding of the technological knowledge flows between firms.

Second, we focused on one industry, albeit a broad one. The pattern of knowledge flow in relation to dimensions of firms' R&D partnership portfolios thus perhaps reflects characteristics of the industry's knowledge base. Even though our theory did not rely on idiosyncratic features of the IT industry, an obvious question for further research is to what extent portfolio effects we found play a role across a range of industries in which uncertainty blurs decisions about the development of novel technologies, products, and processes.

Our understanding of interfirm R&D partnerships has increased considerably in recent years. We further this understanding by presenting and testing a firm-level portfolio perspective on knowledge flows within such partnerships, and by highlighting technological uncertainty as an important contingency within this portfolio perspective. We hope our findings stimulate further research linking dimensions of R&D partnership portfolios to knowledge flows, innovation, and economic performance at the firm level.

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Figure 1: Portfolio Size, Research Focus, and Inward Knowledge Flows

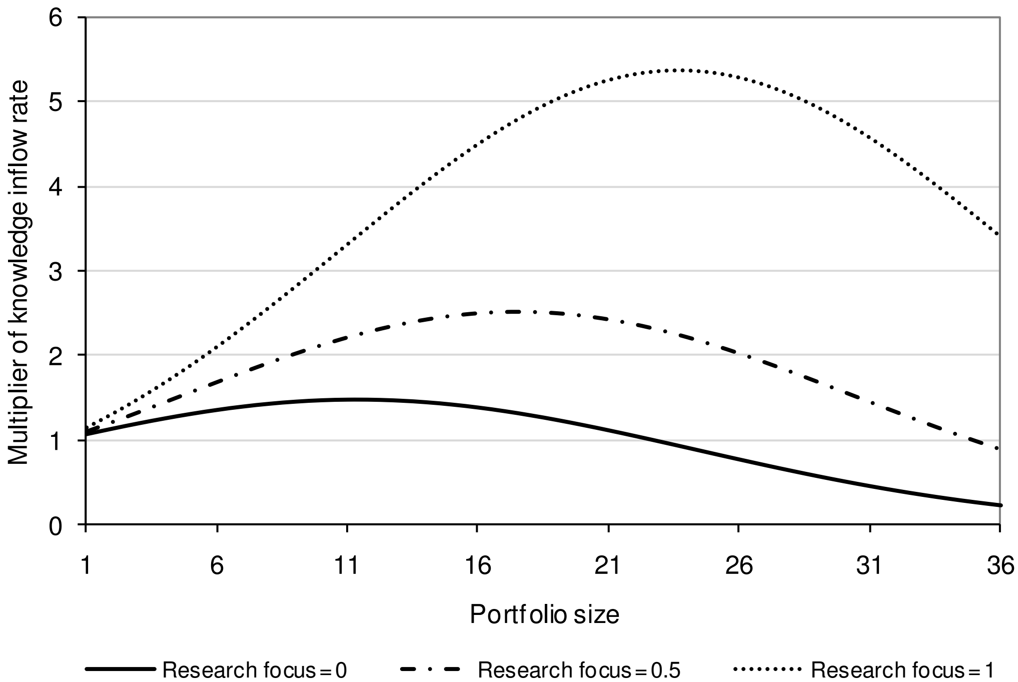

Figure 2: Portfolio Novelty, Research Focus, and Inward Knowledge Flows

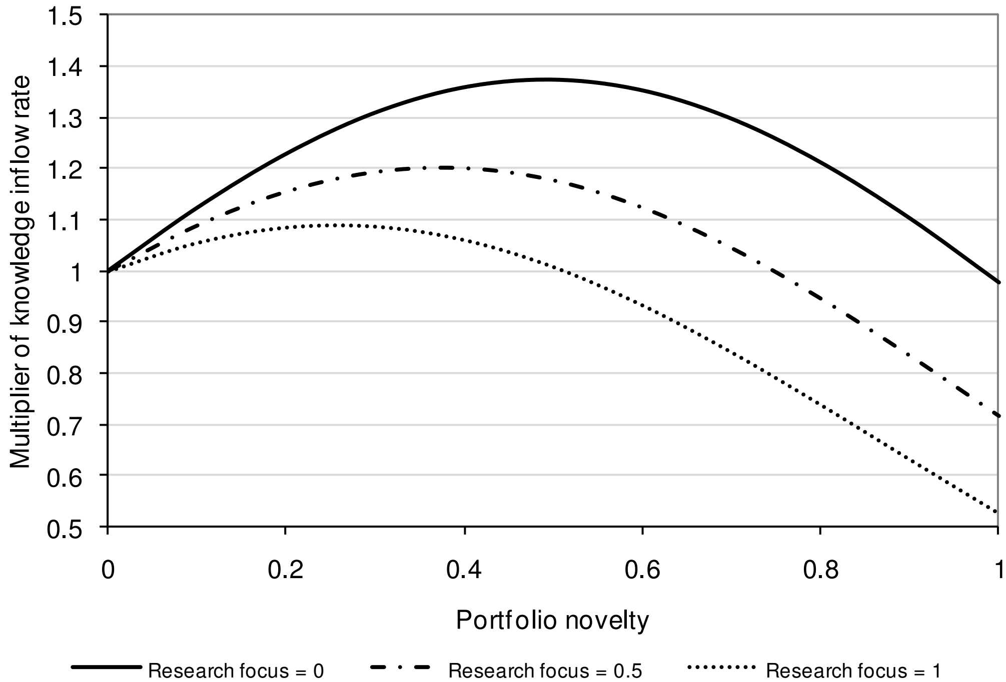

Table 1: Descriptive Statistics

	Mean	SD	Minimum	Maximum
Dependent variable				
Inward knowledge flows	58.416	257.764	0	5,112
Independent variables				
Portfolio size	4.387	5.611	1	36
Portfolio research focus	0.160	0.294	0	1
Portfolio novelty	0.369	0.415	0	1
Firm controls				
Size	3.438	0.888	0.930	5.188
Profitability	0.142	0.132	-1.104	0.624
R&D intensity	0.091	0.099	0	0.708
Patent stock	516.855	1,155.485	1	12,352
Total citations made	260.485	851.618	0	16,205
Partnering experience	7.528	14.336	1	141
Partner controls				
Size	3.907	0.619	1.242	5.188
Profitability	0.148	0.079	-0.560	0.482
R&D intensity	0.086	0.056	0.003	0.893
Patent stock	1,533.404	1,810.209	1	12,352
Total citations received	635.357	1,193.549	0	11,378
Portfolio controls				
Bilateral competition	0.185	0.305	0	1
Equity partnerships	0.152	0.265	0	1
Regional concentration	0.840	0.299	0	1

Table 2: Bivariate Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Dependent variable																	
1	Inward knowledge flows																	
	Independent variables																	
2	Portfolio size	0.56																
3	Portfolio research focus	0.18	0.23															
4	Portfolio novelty	-0.08	-0.19	-0.07														
	Firm controls																	
5	Size	0.24	0.45	0.28	-0.12													
6	Profitability	0.07	0.09	0.04	0.09	0.17												
7	R&D intensity	-0.02	-0.04	0.01	-0.06	-0.38	-0.39											
8	Patent stock	0.59	0.65	0.23	-0.10	0.49	0.07	-0.10										
9	Total citations made	0.85	0.58	0.20	-0.10	0.32	0.08	-0.03	0.77									
10	Partnering experience	0.62	0.93	0.23	-0.20	0.39	0.09	-0.02	0.70	0.67								
	Partner controls																	
11	Size	0.00	0.03	0.03	-0.24	0.01	-0.10	0.00	0.02	0.01	0.03							
12	Profitability	0.04	0.06	-0.01	0.04	-0.04	0.11	-0.01	0.07	0.06	0.06	0.04						
13	R&D intensity	0.00	-0.01	-0.09	0.00	-0.01	0.06	-0.07	0.00	0.01	0.01	-0.36	-0.23					
14	Patent stock	0.02	0.01	-0.09	-0.15	-0.01	0.08	-0.01	0.05	0.06	0.03	0.54	0.08	-0.09				
15	Total citations received	0.05	-0.02	-0.09	-0.12	-0.02	0.09	-0.01	0.00	0.08	0.00	0.37	0.06	-0.04	0.83			
	Portfolio controls																	
16	Bilateral competition	-0.02	-0.01	0.13	0.04	-0.20	0.16	0.09	-0.15	-0.04	0.00	-0.17	0.03	0.08	-0.03	-0.03		
17	Equity partnerships	0.30	0.40	0.33	-0.02	0.35	0.04	-0.03	0.42	0.32	0.36	0.10	0.10	-0.06	0.04	-0.03	-0.06	
18	Regional concentration	-0.05	-0.03	0.03	0.04	-0.07	0.14	-0.15	-0.21	-0.12	-0.02	-0.11	0.07	-0.17	-0.21	-0.08	0.21	-0.08

Correlations ≥ |0.06| are significant at $p < .05$; correlations ≥ |0.08| are significant at or beyond $p < .01$.

Table 3: Conditional fixed effects negative binomial models of inward knowledge flows, 1975-1999

Variables	Hypothesis and sign	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Independent variables							
Portfolio research focus		0.517**	0.305	0.307	0.222	0.356+	0.254
		(0.184)	(0.186)	(0.188)	(0.190)	(0.194)	(0.199)
Portfolio size	1: +		0.098***	0.074***	0.090***	0.073***	0.068***
			(0.016)	(0.017)	(0.016)	(0.017)	(0.017)
(Portfolio size)^2	1: -		-0.004***	-0.004***	-0.004***	-0.003***	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Portfolio novelty	2: +			1.277***		1.351***	1.291***
				(0.311)		(0.316)	(0.316)
(Portfolio novelty)^2	2: -			-1.305***		-1.356***	-1.315***
				(0.320)		(0.323)	(0.321)
Portfolio size × portf. research focus	3: +				0.082**		0.074*
					(0.031)		(0.032)
Portfolio novelty × portf. research focus	4: -					-0.676*	-0.617*
						(0.280)	(0.292)
Firm controls							
Firm size		0.651***	0.456***	0.444***	0.464***	0.428***	0.444***
		(0.103)	(0.106)	(0.106)	(0.105)	(0.106)	(0.106)
Firm profitability		0.552	0.481	0.544	0.547	0.600	0.636
		(0.444)	(0.440)	(0.439)	(0.443)	(0.445)	(0.445)
Firm R&D intensity		1.928*	0.891	0.675	0.839	0.591	0.587
		(0.844)	(0.937)	(0.925)	(0.945)	(0.926)	(0.933)
Firm patent stock (× 10^2)		-0.001	-0.001	0.004	0.000	0.005	0.006
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firm total citations made (× 10^2)		0.007**	0.010***	0.008***	0.009***	0.007***	0.009***
		(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Firm partnering experience		0.008*	0.011*	0.014**	0.007	0.013*	0.009+
		(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Partner controls							
Partner size		-0.216	-0.062	-0.098	-0.003	-0.110	-0.050
		(0.135)	(0.140)	(0.140)	(0.140)	(0.140)	(0.141)
Partner profitability		-1.154	-0.967	-0.854	-0.899	-0.821	-0.740
		(0.732)	(0.729)	(0.728)	(0.723)	(0.726)	(0.722)
Partner R&D intensity		-2.906	-0.771	-0.873	-0.970	-1.188	-1.214
		(1.851)	(1.891)	(1.882)	(1.886)	(1.894)	(1.885)
Partner patent stock (× 10^2)		0.036***	0.040***	0.040***	0.040***	0.042***	0.038***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Partner total citations received (× 10^2)		-0.003	-0.003	-0.010	-0.008	-0.010	-0.003
		(0.008)	(0.009)	(0.010)	(0.010)	(0.009)	(0.008)
Portfolio controls							
Bilateral competition		0.137	0.184	0.157	0.273	0.170	0.253
		(0.237)	(0.242)	(0.243)	(0.241)	(0.242)	(0.242)
Equity partnerships		1.033***	0.627**	0.754***	0.582**	0.807***	0.729***
		(0.205)	(0.211)	(0.212)	(0.213)	(0.216)	(0.219)
Regional concentration		-0.650***	-0.674***	-0.661***	-0.743***	-0.686***	-0.741***
		(0.189)	(0.200)	(0.199)	(0.199)	(0.200)	(0.199)
Constant		-2.191+	-1.893	-1.348	-2.112+	-1.250	-1.505
		(1.229)	(1.249)	(1.262)	(1.249)	(1.261)	(1.263)
Log likelihood (significance versus (1))		-2,689.80	-2,664.50***	-2,656.05***	-2,661.16***	-2,654.40***	-2,652.68***

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1; n = 1,030. Standard errors are in parentheses. All models include year fixed effects. The dependent variable takes a one-year lead. We centered the independent variables on their means prior to calculation of the squared and interaction terms.

Notes

1. Recent work in the literature on teams also emphasizes the importance of team composition for performance. For example, Perretti and Negro (2007) studied the Hollywood feature film industry, showing that film genre innovation increased both with the number of newcomers and with the number of new combinations between newcomers and 'old-timers' within the project team. Another recent study by Ferriani, Cattani, and Baden-Fuller (2009), also studying the Hollywood feature film industry, showed that a film producer's commercial performance first increased and then decreased with the percentage of team members that had previously collaborated. While at a different level of analysis, these results are consistent with our theoretical mechanisms: because newcomers (in our case: novel R&D partners of the focal firm) provide novel perspectives and old-timers (in our case: repeat R&D partners of the focal firm) provide coordination advantages necessary for effective interaction, a mixture of old-timers and newcomers should optimize performance.

2. One might argue that large, research-focused, R&D partnership portfolios should also increase the outflow of technological knowledge to a firm's R&D partners. Though this may be the case, such knowledge outflows disperse across a firm's partners and so individual partners need not benefit from them. Additional analysis using the total partnership-related outflow of technological knowledge as dependent variable indicated that large, research-focused, portfolios did not significantly affect the outflow of technological knowledge. These results are available upon request.

3. We thank an anonymous reviewer for reminding us of the importance of this assumption. Our theoretical focus on coordination and knowledge-gathering benefits within R&D partnership portfolios does not discount the substantive relevance of appropriation concerns inherent in interfirm R&D partnerships.

4. Our measures for research focus and partnership governance indeed correlate at the .33 level. The linear association between the two variables remains strongly significant and positive when the other independent variables are held constant. These results are available upon request.

5. The specification incorporating the interaction between the squared portfolio size term and research focus did not significantly improve the model fit and the additional interaction effect was not significant. This result was identical for portfolio novelty. To conserve space, we present the more parsimonious models incorporating the interactions between the respective main effects instead.

6. Firms with greater knowledge inflows may be motivated to seek more opportunities to learn, by expanding their portfolio of R&D partnerships (Powell et al., 1996). Yet, it is equally plausible that others view fast learners (i.e. expropriators that absorb, rather than reveal, information) as suboptimal partners (Harrigan, 2003 [1985]), which would shrink the opportunity space for potential partnerships. This counterbalances the portfolio-enlarging effect of a firm's search motivation. Thus, theory runs in two directions, which perhaps explains the insignificant effect we find. The logic concerning a possible feedback effect of knowledge inflows to portfolio research focus runs along similar lines. Finally, the feedback effect to portfolio novelty is not obvious. We tested it nevertheless, as some work shows that repeat partnering is a systematic decision (Gulati, 1995). Nevertheless, knowledge inflows do not systematically shift the balance of novel vs. repeat partners in our sample.

7. Frank Windmeijer provided helpful comments on the pre-sample estimator. Blundell et al. (1995, 2002) originally used a pre-sample approach to capture unobserved heterogeneity in dynamic patent rate models. Here, the pre-sample approach complements Hausman et al.'s (1984) conditioning procedure to weed out firm-level unobserved heterogeneity. We added the 4-

year pre-sample mean of inward knowledge flows in the analyses. Patent citation data are not available prior to 1975 and so a 4-year pre-sample period and a one-year lead of the dependent variable only allowed us to predict knowledge inflows from 1980 onwards. Using a Hausman (1978) specification test, we compared the resulting coefficients to the ones of the models for 1980-1999 that omitted the pre-sample mean estimator. With no exceptions, differences were non-systematic, which further increased our confidence in the results reported in table 3.